frontiers | Research Topics

Sustainability of digital transformation for the environment

Edited by
Evgeny Kuzmin, Grigorios L. Kyriakopoulos,
Victoria Akberdina and Vikas Kumar

Published in
Frontiers in Environmental Science

ISSN 1664-8714
ISBN 978-2-8325-4451-8
DOI 10.3389/978-2-8325-4451-8

About Frontiers

Frontiers is more than just an open access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers journal series

The Frontiers journal series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the *Frontiers journal series* operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews. Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the *Frontiers journals series*: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area.

Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers editorial office: frontiersin.org/about/contact

Sustainability of digital transformation for the environment

Topic editors
Evgeny Kuzmin — Institute of Economics, Ural Branch of the Russian Academy of Sciences, Russia
Grigorios L. Kyriakopoulos — National Technical University of Athens, Greece
Victoria Akberdina — Institute of Economics of the Ural Branch of the Russian Academy of Sciences, Russia
Vikas Kumar — Birmingham City University, United Kingdom

Citation
Kuzmin, E., Kyriakopoulos, G. L., Akberdina, V., Kumar, V., eds. (2024). *Sustainability of digital transformation for the environment*. Lausanne: Frontiers Media SA.
doi: 10.3389/978-2-8325-4451-8

Table of contents

Frontiers in Environmental Science

TYPE Editorial
PUBLISHED 31 January 2024
DOI 10.3389/fenvs.2024.1371047

OPEN ACCESS

EDITED AND REVIEWED BY
Aleksy Kwilinski,
The London Academy of Science and Business,
United Kingdom

*CORRESPONDENCE
Evgeny Kuzmin,
kuzmin.ea@uiec.ru
Grigorios L. Kyriakopoulos,
gregkyr@chemeng.ntua.gr

RECEIVED 15 January 2024
ACCEPTED 22 January 2024
PUBLISHED 31 January 2024

CITATION
Akberdina V, Kuzmin E, Kyriakopoulos GL and Kumar V (2024), Editorial: Sustainability of digital transformation for the environment.
Front. Environ. Sci. 12:1371047.
doi: 10.3389/fenvs.2024.1371047

Editorial: Sustainability of digital transformation for the environment

Victoria Akberdina[1], Evgeny Kuzmin[1]*, Grigorios L. Kyriakopoulos[2]* and Vikas Kumar[3]

[1]Institute of Economics of the Ural Branch of the Russian Academy of Sciences, Ekaterinburg, Russia, [2]School of Electrical and Computer Engineering, National Technical University of Athens (NTUA), Athens, Greece, [3]Faculty of Business, Law and Social Sciences, Birmingham City University, Birmingham, United Kingdom

KEYWORDS

digital transformation, environment, social, and governance, digital technologies, sustainable development goal, corporate social responsibility, green transition

Editorial on the Research Topic
Sustainability of digital transformation for the environment

Digital transition and green transition are two major simultaneous processes unfolding today. Both of them play a key role in transforming the development paradigm. In our previous publications, digital transformation was interpreted as "the process of a system transition of the industry from one technological mode to another through the large-scale use of digital and ICT in order to increase its efficiency and competitiveness significantly" (Akberdina et al., 2023a). It is also noteworthy that sustainability, green economy, circular economy, and environmental, social, and governance (ESG) concepts are also an integral part of the new paradigm positively affecting the economy of companies, regions, and countries focusing on how low-carbon, resource-efficient, and socially inclusive economy can improve human wellbeing and provide social justice while reducing environmental threats and resource scarcity. While digitalization enhances productivity, reduces energy intensity, and stimulates economic growth, digital technologies utilize big data that increases energy consumption and digital equipment. Subsequently, natural environment damage occurs with production, maintenance, and disposal. Considering this imperative need to open up a scientific discussion, our Research Topic "*Sustainability of Digital Transformation for the Environment*" includes fifteen articles that are pictorially depicted in the form of a keyword cloud in Figure 1.

Five papers addressed the challenges of *assessing the influence of digital transformation on sustainability in countries and regions*.

Among them, researchers from Northwest Normal University, Key Laboratory of Resource Environment and Sustainable Development of Oasis, and Lanzhou University investigated the interregional and intersectoral interactions of the digital economy in China. Self-generating ability in the digital industry sector was the most significant and influential factor in the industrial growth of China's digital economy, followed by the interrelated effect between industry sectors. Contrarily, the inter-industry feedback effect weakly affects the economic system (Ma et al.).

Researchers from Huaqiao University and Minnan Normal University demonstrated the prevailing role of digital industrialization in the low-carbon development in the manufacturing industry (Lyu et al.). These authors claimed that digital transformation

FIGURE 1
Keyword cloud of the Research Topic "*Sustainability of Digital Transformation for the Environment*." Source: editorial own study.

can satisfactorily promote low-carbon manufacturing development in underdeveloped regions, and medium– and low-energy-consuming industries, but not in high-energy-consuming industries. This was evident not only in the China's provinces but also in other countries around the world.

Regarding the digitalization of the economy and air pollution, a bilateral effect on air pollution was reported, since air pollution can be characterized by emission reduction due to digitalization, but, along with the development of the digital economy, human capital levels, and general economic levels, the emission reduction effect of the digital economy on air pollution was strengthened such that the net effect changed from positive to negative, as mentioned by researchers from Anhui University of Science and Technology and Hohai University (Wang and Ding). Another significant study proved a non-linear relationship between the digital economy and green total factor productivity (GTFP), where the overall effect of the digital economy on GTFP was negative, implying that the growth of the digital economy inclines to a GTFP decline, as pointed out by researchers from Hunan University and Hunan Provincial Tax Service of State Taxation Administration (Wang and Ren). It is also noteworthy that energy transition can mitigate the negative impact of digital economic growth on GTFP, confirming the spatial heterogeneity of digitalization effects (Ma et al.).

Researchers from the Institute of Economics of the Ural Branch of the Russian Academy of Sciences and Ural Federal University identified the relationship between digital financing and environmental financing (Akberdina et al.). The authors proved that digital investments stimulate a comparable increase in environmental investment due to the effects created by digital technologies penetrating into environmental protection technologies.

Five studies on in the Research Topic were devoted to the *relationship between digital transformation and green innovation*.

Xiao et al. argued that the digital economy significantly improves GTFP, which is still valid after testing for robustness, including instrumental variables, taking the "Broadband China" pilot policy as a quasi-natural experiment. The authors proved that the digital economy promotes GTFP through green technological innovation, industrial structure upgrading, and energy conservation provision.

Yang and Liang from Nanjing Audit University explored the digital economy, environmental regulation, and green eco-efficiency and proposed that the moderating role of environmental legislation toward the growth of the digital economy can greatly increase green eco-efficiency. In addition, the authors assessed the regulating role of the government in converging the differences between regions as well as in promoting green sustainable development of a local economy.

Liu et al. from Zhongnan University of Economics and Law assessed the impact of the digital economy and city size on GTFP and proved that city size can positively modify the relationship between GTFP and the digital economy. Moreover, the growth of the digital economy and the full exploitation scale of the digital industries in first-tier cities can generate the spillover effect caused by digital technology in cities of the other tiers.

Researchers from Dhurakij Pundit University and Lanzhou University examined whether the digitalization of enterprises could promote corporate green innovation (Fan et al.) and concluded that digital transformation encourages corporate green innovation by easing corporate financing constraints and enhancing corporate awareness through a high perception of social responsibility. Green innovation can be further promoted not only through corporate digitalization but also through the human capital of other high-tech companies, as stated by researchers from Qingdao University (Li et al.).

The topic of corporate governance was the research focus on three articles, devoted to the digitalization effect on corporate goals, namely ESG and corporate social responsibility (CSR).

The asymmetric effect between executive compensation stickiness (ECS) and ESG goals has encouraged executives to improve the ESG indices through digital transformation activities, as denoted by researchers from Hangzhou City University and Pingdingshan University (Chen et al.).

CSR, digital transformation, and innovation performance were jointly examined, and the results revealed that CSR positively moderates the role of digital transformation in innovation performance and that there is a time lag effect on the innovation performance (both product and process innovation performance), as demonstrated by researchers from Hangzhou City University and Pingdingshan University (Wang and Yan).

Fu and Li from the School of Urban Economics and Management and Beijing University of Civil Engineering and Architecture investigated whether ESG affects corporate financial performance and whether this relationship is moderated by digital transformation. They showed that ESG positively and significantly affects corporate financial performance and digital transformation drives this promoting effect. The authors also proved that the positive effect of current ESG on financial performance in the lag period will gradually weaken.

The topics of agriculture development amid digitalization with a special emphasis on behavioral aspects were the research objectives of two more publications. Indeed, the empirical evaluation of ethical practices and digitalization of the agricultural system was employed in the case of Pakistan by researchers from Zhejiang University while defining the ethical practices (knowledge-sharing, trustworthiness in loan providing, loyalty in professionalism, responsibility of actions, and accountability) that primarily affected the digitalization development of the agricultural system (Manzoor et al.).

Wang and Dong from the Institute of Land Engineering and Technology utilized agricultural digital services to investigate farmers' behavior based on the rural revitalization strategy and verified the dominant digital-use behavior factors, such as adoption intention and facility conditions. Performance expectation, social influence, and data quality were importantpre-factors affecting farmers'behavior.

Digital transformation is a rapidly transforming and adaptable tool for the environment and sustainability, though it also involves challenges that are both complementary and convergent to each other. Among them is the digital transformation industry (DTI) that is extended to a plethora of applications, including those in the hospitality industry and "smart" cities, focusing on responding to environmental concerns about industrial innovations (Kyriakopoulos, 2023) and rethinking policies for clean energy supply that are scrutinized by decision-makers or policymakers who are looking at the potential of smart technologies (like that of Industry 4.0) in creating a green economy (Saraji et al., 2021). All these applications showed that digital transformation can play a decisive role in other, rather than purely environmental, contexts of everyday living like socialization, micro- and macro-economy, as well as the circular economy (Kyriakopoulos et al., 2019), and entrepreneurship issues (Kyriakopoulos, 2023). The proposals and the future prospects voiced in our Research Topic and the adoption of appropriate policy measures should be predominately focused on the following:

- Synchronising the digital and green transitions is more of a positive nature.
- Coordinating the digital and green transitions toward a sustainable and prosperous future.
- Identifying challenges and employing integrated methodological–managerial tools for a sustainable digital transformation.

Author contributions

VA: investigation, conceptualization, data curation, formal analysis, methodology, project administration, visualization, writing–original draft, and writing–review. EK: investigation, data curation, formal analysis, project administration, writing–original draft, and writing–review and editing. GK: investigation, supervision, validation, writing–original draft, and writing–review and editing. VK: investigation, supervision, validation, writing–review and editing.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors, and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Akberdina, V., Kumar, V., Kyriakopoulos, G. L., and Kuzmin, E. (2023a). "Editorial: what does industry's digital transition hold in the uncertainty context?," in *Digital transformation in industry. DTI 2022. Lecture notes in information systems and organisation*. Editors V. Kumar, G. L. Kyriakopoulos, V. Akberdina, and E. Kuzmin (Cham: Springer), 61, 1–4. doi:10.1007/978-3-031-30351-7_1

Kyriakopoulos, G. L. (2023). "The contribution of digital transformation industry (DTI) in micro- and macro- economy. The contribution of digital transformation industry (DTI) in micro- and macro- economy. Chapter 9," in *Digital transformation in industry. DTI 2022. Lecture notes in information systems and organisation*. Editors V. Kumar, G. L. Kyriakopoulos, V. Akberdina, and E. Kuzmin (Cham: Springer), 61, 101–108. doi:10.1007/978-3-031-30351-7_9

Kyriakopoulos, G. L., Kapsalis, V. C., Aravossis, K. G., Zamparas, M., and Mitsikas, A. (2019). Evaluating circular economy under a multi-parametric approach: a technological review. *Sustainability* 11 (21), 6139. doi:10.3390/su11216139

Saraji, M. K., Streimikiene, D., and Kyriakopoulos, G. L. (2021). Fermatean fuzzy critic-copras method for evaluating the challenges to industry 4.0 adoption for a sustainable digital transformation. *Sustainability* 13 (17), 9577. doi:10.3390/su13179577

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 January 2023
DOI 10.3389/fenvs.2023.1113293

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Crenguța-Ileana Sinisi,
University of Pitești, Romania
Manuela Tvaronaviciene,
Vilnius Gediminas Technical University, Lithuania

*CORRESPONDENCE
Qiye Liang,
liangqiye@163.com

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management,
a section of the journal Frontiers in Environmental Science

RECEIVED 01 December 2022
ACCEPTED 09 January 2023
PUBLISHED 20 January 2023

CITATION
Yang Y and Liang Q (2023), Digital economy, environmental regulation and green eco-efficiency—Empirical evidence from 285 cities in China.
Front. Environ. Sci. 11:1113293.
doi: 10.3389/fenvs.2023.1113293

Digital economy, environmental regulation and green eco-efficiency—Empirical evidence from 285 cities in China

Yiwen Yang and Qiye Liang*

School of Economics, Nanjing Audit University, Nanjing, China

Strengthening green eco-efficiency has emerged as one of China's key objectives for its present economic green development. All walks of life have progressively begun to pay attention to how to leverage the rapidly developing digital economy to promote regional green eco-efficiency upgrading. This work first develops a mathematical model to investigate the inherent mechanism of digital economy development on green eco-efficiency enhancement and presents a research hypothesis, which is then followed by a fixed-effects model and a spatial econometric model to evaluate the geographic spillover effect of digital economy development on green eco-efficiency enhancement and the moderating influence of environmental regulation. According to the test results, the growth of the digital economy can greatly increase green eco-efficiency, with environmental legislation acting as a helpful moderator. Additional empirical research revealed that environmental regulation and the development of the digital economy both favourably promote and adjust green eco-efficiency. However, there are various effects of different regions and different time periods, it shows that there are "strong in the East and weak in the west," "weak in the East and weak in the west" and "weak first and then strong." Therefore, each region in China should promote the development of digital economy, accelerate the digitization of industry, and promote the green ecological efficiency of China's industry with the digital economy a grip. At the same time, the regulating role of government environmental regulations should be given full play to narrow the differences between regions and promote the green, coordinated, and sustainable development of each regional economy.

KEYWORDS

digital economy, green development, environmental regulation, eco-efficiency, moderating effects

1 Introduction

As China's economy has gradually shifted to high-quality development after a period of rapid development, the issue of coordination of economy, environment, and resources has become particularly important. The rough and loose development model of the early reform and opening-up period promoted rapid economic growth while destroying the natural environment and disturbing the ecological balance, making natural disasters and environmental pollution problems increasingly prominent. In September 2020, President Xi Jinping, at the 75th session of the United Nations General Assembly, proposed for the first time a "double carbon goal" and announced the "carbon peak" and "carbon neutral" targets. This shows that adopting green development and enhancing the ecological environment have grown to be critical issues that China must deal with. Enhancing green eco-efficiency is the key to resolving the ecological environment and implementing green development because it is a crucial indicator of the harmonious relationship between the economy, resources, and environment as well as one of the indicators to measure the green development of industry.

Technological progress and innovation can reduce pollution emissions and environmental pollution by enhancing resource utilization efficiency, reducing resource waste in production processes, and promoting resource recycling (Bosseboeuf and Richard, 1997; Liu et al., 2021). At the level of environmental governance, technological progress and innovation have improved ecology and alleviated environmental pressure by enhancing environmental monitoring and governance (Ding, 2019). With significant advancements in big data, cloud computing, blockchain, the Internet of Things, and artificial intelligence, the expansion of the digital economy has recently emerged as the primary factor driving scientific and technical advancement. The implementation of environmental monitoring is effectively supported by big data and artificial intelligence technologies, and resource utilization efficiency is increased through the use of the Internet of Things and cloud computing technologies. The development of these technologies has produced favorable environmental externalities in a variety of fields. The interaction between the economy, environment, and resources in production life has gradually changed as a result of digital technology, a major current factor of production. Additionally, since the beginning of the new crown epidemic at the end of 2019, when the movement of labor factors was restricted and travel and business activities were impacted, digital technologies started to replace traditional technologies widely. During this time, the digital economy developed quickly, the scale of the digital economy increased, and the impact it had gradually grew. Has the growth of the digital economy improved green eco-efficiency from an ecological perspective? This has become the focus of analysis in this paper.

The government's implementation of environmental regulations has an effect on the ecological environment and manufacturers' emissions on the one hand, and on economic activity due to the increased costs of emissions, and the digital economy as a significant component of economic activity may also be affected. This paper will also examine the crucial role played by government environmental regulation in the regulation of the green eco-efficiency of the digital economy in order to determine whether the actions of government environmental regulation have an effect on the scope and direction of the role of the digital economy. In order to assess the mechanism by which the digital economy impacts green eco-efficiency and how environmental regulation affects that influence, this study will first conduct a review of the relevant literature. We then employ a variety of econometric techniques to empirically test the impact of the digital economy on green eco-efficiency. We also concentrate on the regulatory function of environmental regulation in order to provide China with theoretical points of reference for achieving its "double carbon" and green development goals.

2 Literature review

At present, issues related to digital economy, environmental regulation and green eco-efficiency have become hot spots in academic circles. In-depth research has been done on the connections between the green eco-efficiency movement, environmental regulation, and the digital economy, with the following topics receiving the majority of attention.

First, studies on the connotation, measurement and key influencing factors of green eco-efficiency. According toSchaltegger and Sturm (1990), green eco-efficiency can be used to gauge the extent of regional green growth by comparing value rise to environmental effect. Some other scholars consider green eco-efficiency as the ability to achieve maximum economic value with minimum environmental cost (Schmidheiny and Timberlake, 1992; Peng et al., 2017; Su et al., 2021). The previous years, the methods of green eco-efficiency measurement have been improved and improved, and the early measures of green eco-efficiency mainly used the single ratio method, which uses the ratio of economic and environmental indicators to measure eco-efficiency, but it has the disadvantage of not being able to estimate the environmental impact in detail and accurately (Yin et al., 2012). Later, some scholars constructed indicator systems to estimate green eco-efficiency more accurately, for example, Jiansu Mao et al. (2010) used industrial output value, pollution emission and energy consumption to construct an indicator system to measure industrial eco-efficiency, and Michelsen (Michelsen et al., 2006) selected nine environmental indicators to assess the eco-friendliness of furniture products. To quantify green eco-efficiency, some academics have recently used the data envelopment analysis (DEA) method (Yin et al., 2012). Some academics have also performed more thorough research in recent years on the critical elements influencing green eco-efficiency. Some researchers have examined the impact of low-carbon city pilot on green eco-efficiency using a quasi-natural experiment and found that low-carbon city pilot policies can significantly improve urban eco-efficiency (Yang and Deng, 2019), while other researchers have found that both resource inputs and social inputs have a positive effect on eco-efficiency, but there is an uneven growth trend of green eco-efficiency among different regions (Feng and Zhang, 2021). Sneideriene et al. (2020) evaluated green growth based on a mixed method of data analysis, generalization and index assessment and measured green growth indices for developing and developed countries, and found that green growth was uneven in European countries and the indices varied greatly in lagging countries. Rybalkin et al. (2021) constructed EEPSE green economy indicators using a five-fold helix model, which combines five dimensions—educational, economic, social, political and environmental—to assess the green economy trends in EU countries. Furthermore, Andryeyeva et al. (2021) constructed a new system of indicators using economic and environmental indicators to assess the process of green growth and provide recommendations for the management of the natural environment.

Secondly, the study of the meaning of the digital economy and how it affects environmentally friendly efficiency. Data has recently risen to the top of the list of production elements, having a significant impact on life, production, and ecology (Wang et al., 2021). Numerous literatures have been published to define the connotation of digital economy. Some scholars define it in terms of the scope of the digital economy, which encompasses the hardware facilities of e-commerce, the processes of e-commerce and e-business (Mesenbourg, 2001), the digital economy is that part of output that is increased by producing products and providing services based on digital technologies (Bukht and Heeks, 2017), and there are definitions that view the digital economy as an economic activity. According to the G20 Digital

Economy Development and Cooperation Initiative, the digital economy is, for instance, “a set of economic activities that use digital knowledge and information as key factors of production, modern information networks as important carriers, and the effective use of information and communication technologies as an important driving force for efficiency improvement and economic structure optimization.” Knickrehm et al. (2016) considers the digital economy as the output brought by the input of digital skills and digital facilities. The digital economy is characterized by “economies of scope, decreasing transaction costs and creative destruction” (Pei et al., 2018). The majority of studies on the relationship between the digital economy and green eco-efficiency primarily employ econometric techniques to test this relationship. For instance, He et al. (2022) used provincial panel data and a two-way fixed effects model to test the influence of digital economy development on eco-efficiency enhancement. Liu et al. (2022) also used empirical methods to verify the effect of digital economy on green eco-efficiency enhancement, in addition, it was found that digital industrialization promotes green eco-efficiency more than digitalization of industry, and at the same time, digital economy development needs to reach a threshold value to promote green eco-efficiency.

Third, study on how environmental regulation affects sustainable development. For example, Lei and Yu (2013) discovered that environmental regulation measures, primarily pollution control investment and emission permits, would impede the improvement of the green total factor productivity of industry. Li and Bi (2012) demonstrated that environmental regulation would increase the cost of enterprises’ development and thus indirectly result in a decrease in the level of green development. According to Luo and Wang (2017), different environmental regulations have different relationships with green eco-efficiency, with governance-input-based regulations and green eco-efficiency having a U-shaped relationship. However, the impact of economic incentive-based regulations on green eco-efficiency is minimal. Other researchers think that environmental regulation will boost local green total factor productivity or green eco-efficiency. For instance, Li et al. (2013) used industry-level data to conduct an empirical test and discovered that environmental regulation can successfully boost green total factor productivity once its level of intensity reaches a specific value. Higher levels of government environmental governance can promote green total factor productivity in regional industries, but there is regional heterogeneity in the green eco-efficiency of environmental governance or environmental regulation (Wang and Sheng, 2015), while other scholars have examined the effect of environmental regulation on economic growth under environmental constraints. Klimas, E. (2020) analyzed the impact of spatial planning regulations on climate change management using the latest sustainable development principles in Lithuania and found that spatial planning regulations should provide for specific measures to effectively enhance climate management.An empirical study of the pilot policy’s impact on civilized cities discovered that environmental regulation by the government can lower pollution levels and encourage the growth of green urban areas.

Our analysis of the existing literature shows that few researchers have examined the digital economy, environmental regulation, and green eco-efficiency within a single theoretical analytical framework. Instead, the majority of the literature primarily focuses on the connections between the digital economy and green eco-efficiency as well as the relationship between the two. This study will fill a research gap, analyze the relationship between the digital economy, environmental regulation, and green eco-efficiency, and focus on the regulatory role of environmental regulation in that relationship. The goal is to unleash the development potential of the digital economy, improve green eco-efficiency, support green development, and advance the construct. The structure of this essay is as follows. This paper’s precise structure is as follows: Part IV will use data from 285 Chinese cities to empirically test the internal logical relationship between the digital economy and green eco-efficiency and test the heterogeneity by period and region. Part V will draw a conclusion. Part III will build a mathematical model to investigate the internal logical relationship between the digital economy and green eco-efficiency and put forward the corresponding research hypotheses.

3 Theoretical model

In order to build a theoretical model about the relationship between the digital economy and green eco-efficiency, this paper primarily draws on Acemoglu et al. (2012) and Jing and Zhang (2014) mathematical modeling ideas. It focuses on exploring the internal logical relationship between the digital economy and green eco-efficiency.

Assume that two production sectors a and b exist in a country or region for the digital technology sector and the traditional technology sector, respectively, and that the production function for the total capacity Y_t of the two sectors is as follows:

$$\boldsymbol{Y_t} = \left(\boldsymbol{Y_{at}^{\frac{\varepsilon-1}{\varepsilon}}} + \boldsymbol{Y_{bt}^{\frac{\varepsilon-1}{\varepsilon}}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

where Y_{at} is the input produced using digital technology, Y_{bt} is the input produced using traditional technology, and ε represents the elasticity of substitution between the two production inputs. When $\varepsilon > 1$, there is a substitution effect between the two inputs; when $\varepsilon < 1$, there is a complementary effect between the two inputs. In addition, both sectors require the use of labor and related equipment for production, and their production functions are:

$$\boldsymbol{Y_{jt}} = \boldsymbol{L_{jt}^{1-\alpha}} \int_0^1 \boldsymbol{A_{jit}^{1-\alpha} X_{jit}^{\alpha}}\, \boldsymbol{di} \tag{2}$$

$$\boldsymbol{G}(\boldsymbol{A_{jt}}, \boldsymbol{Y_{jt}}) = \boldsymbol{\tau}(\boldsymbol{A_{jt}})\boldsymbol{Y_{jt}} = \boldsymbol{\tau}(\boldsymbol{A_{jt}})\boldsymbol{L_{jt}^{1-\alpha}} \int_0^1 \boldsymbol{A_{jit}^{1-\alpha} x_{jit}^{\alpha}}\, \boldsymbol{di} \tag{3}$$

where A_{jit} represents the mass of type i machines used in sector $j \in \{a, b\}$ at time t, and L_{jt} represents the amount of labor input in sector j at time t. $G(A_{jt}, Y_{jt})$ is the total pollution reduction in sector j due to technological progress, and $\tau(A_{jt})$ is the abatement capacity of technological progress while satisfying $\frac{\partial \tau(A_{jt})}{\partial A_{jt}} > 0$. This indicates that the abatement capacity increases with technological progress. Set the green eco-efficiency $g(A_{jt}) = \frac{\partial G(A_{jt}, Y_{jt})}{\partial A_{jt}}$, meaning the rate of change of marginal emission reduction triggered by the improvement of machine quality in sector j, i, technological progress.

The market clearing condition demands that the total labor supply be normalized to 1, with the total labor demand being smaller than the entire labor supply, resulting in:

$$\boldsymbol{L_{at}} + \boldsymbol{L_{bt}} \leqslant \boldsymbol{1} \tag{4}$$

Also set the average productivity A_{jt} for period t of the equipment in sector j as:

$$A_{jt} = \int_0^1 A_{jit}\, di \tag{5}$$

The difference equation between A_{jt} and A_{jt-1} as time progresses is:

$$A_{jt} = (1 + \gamma\delta_j e_{jt}) A_{jt-1} \tag{6}$$

γ is the coefficient of the increase in machine quality due to innovation, δ_j is the probability of successful innovation in sector $j \in \{a, b\}$, and e_{jt} is the number of vendors involved in R&D of digital or traditional technologies in sector j at time t.

In addition, the market in which the two sectors compete is assumed to be perfectly competitive. Thus, the final product is produced under perfectly competitive conditions and the relative prices of the two intermediate input products satisfy.

$$\frac{p_{at}}{p_{bt}} = \left(\frac{Y_{at}}{Y_{bt}}\right)^{-\frac{1}{\varepsilon}} \tag{7}$$

where p_{at} and p_{bt} represent the prices of intermediate input products in the digital technology sector and the traditional technology sector, respectively. Then the profit maximization problem for intermediate input production in sector j is:

$$\max_{x_{jit}, L_{jt}} \left\{ p_{jt} L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha}\, di - w_t L_{jt} - \int_0^1 p_{jit} x_{jit}\, di \right\} \tag{8}$$

w_t is the price of hired labor in period t and p_{jit} is the price of machine i in period t. This leads to the following isoelastic inverse demand function:

$$x_{jit} = \left(\frac{\alpha p_{jt}}{p_{jit}}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jit} \tag{9}$$

Substituting Eq. 9 into the first-order condition of labor $(1-\alpha) p_{jt} L_{jt}^{-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha}\, di = w_t$, and then associating Eq. 5 yields the relative prices of digital technology products and traditional technology products as:

$$\frac{p_{at}}{p_{bt}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-(1-\alpha)} \tag{10}$$

Assuming that the unit cost of machine production is a constant ψ, the problem of profit maximization for a monopoly producer of machine type i in sector j is:

$$\max_{p_{jit}} \left\{ (p_{jit} - \psi) x_{jit} \right\} \tag{11}$$

Due to this elasticity of demand, the price of the machine when profit is maximized is an equal proportional markup of marginal cost, thus:

$$p_{jit} = \frac{\psi}{\alpha} \tag{12}$$

Substituting Eq. 10 into Eq. 8 yields the demand for machine i in sector j at equilibrium as:

$$x_{jit} = \left(\frac{\alpha^2 p_{jt}}{\psi}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jt} \tag{13}$$

This leads to the equilibrium profit of the machine manufacturer under monopoly conditions as:

$$\pi_{jit} = (1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \tag{14}$$

Using the definitions in Eqs 5, 6, the expected profit of a manufacturer in sector j at time t is derived as:

$$\pi_{jt} = (1 + \gamma\delta_j e_{jt})(1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1} \tag{15}$$

Thus the relative returns of the two sectors are obtained as:

$$\frac{\pi_{at}}{\pi_{bt}} = \frac{(1 + \gamma\delta_a e_{at})}{(1 + \gamma\delta_b e_{bt})} \left(\frac{p_{at}}{p_{bt}}\right)^{\frac{1}{1-\alpha}} \frac{L_{at}}{L_{bt}} \frac{A_{at-1}}{A_{bt-1}} \tag{16}$$

When the relative returns $\frac{\pi_{at}}{\pi_{bt}}$ are higher, the stronger is the willingness of R&D in the digital technology sector. Where $(\frac{p_{at}}{p_{bt}})^{\frac{1}{1-\alpha}}$ represents the price effect, which promotes innovation in sectors with higher input prices. $\frac{L_{at}}{L_{bt}}$ represents the labor market size effect, which promotes innovation in sectors with high employment. $\frac{A_{at-1}}{A_{bt-1}}$ is the direct productivity effect, which promotes innovation in sectors with higher productivity. Substituting the demand function (13) at equilibrium into Eq. 2 yields the equilibrium production level:

$$Y_{jt} = \left(\frac{\alpha^2 p_{jt}}{\psi}\right)^{\frac{\alpha}{1-\alpha}} A_{jt} L_{jt} \tag{17}$$

Then, by associating Eqs 5, 7, the relationship between relative productivity and relative employment is:

$$\frac{L_{at}}{L_{bt}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-1-(1-\alpha)\varepsilon} \left(\frac{p_{at}}{p_{bt}}\right)^{\frac{-\alpha}{1-\alpha}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-(1-\varepsilon)(1-\alpha)} \tag{18}$$

According to Eq. 18 and then linking Eqs 10, 16, it follows that:

$$\frac{\pi_{at}}{\pi_{bt}} = \frac{\delta_a}{\delta_b} \left(\frac{1 + \gamma\delta_a e_{at}}{1 + \gamma\delta_b e_{bt}}\right)^{-1-(1-\varepsilon)(1-\alpha)} \left(\frac{A_{at-1}}{A_{bt-1}}\right)^{-(1-\varepsilon)(1-\alpha)} \tag{19}$$

The following conclusions can be drawn from Eq. 19:

When $\varepsilon > \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ is accompanied by increasing e_{at}, if innovation in a country or region occurs in the digital technology sector, technological progress is biased toward digital technology, and at this time it is the technological progress in the digital technology sector that drives green eco-efficiency growth.

When $\varepsilon < \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ decreases along with e_{at}. Technology progress favors traditional technology if innovation in a nation or region happens in the traditional technology sector, and the rise of green eco-efficiency is fueled by technological advancement in the traditional technology sector.

When $\varepsilon = \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ is accompanied by increasing e_{at}. If innovation in a country or region occurs in both sectors, technological progress is biased by uncertainty, and technical progress in both sectors jointly propels green eco-efficiency growth at this time.

On the basis of the results mentioned above, the following research hypothesis can be developed: Green eco-efficiency will be encouraged as a nation or region's digital economy grows.

4 Data sources and study design

4.1 Data sources and sample selection

Data from 285 cities between 2011 and 2019 will be used in this study. The reason for choosing this time period is that, although digital technology was invented in the late 20th century, it was not widely adopted until the early 21st century, and it was not until 2010 that provinces and cities all over the country started to fully explore digital practices, making this period a time of rapid development for the digital economy. City-level data were selected because provincial samples cannot more accurately observe inter-city spillover effects and regional heterogeneity. Municipalities that fall under the direct control of the national government are included as city-level samples in this paper's sample selection process. In this study, the sample of cities with administrative areas that merged after 2019 is kept, while the sample of cities with missing data is excluded. The sample data sources in this paper are mainly statistical yearbooks and government work reports.

4.2 Variable description and descriptive statistics

4.2.1 Explained variable: Green eco-efficiency (gee)

By studying the existing literature on measuring green eco-efficiency, we found that there are several methods to measure it: first, by constructing an indicator system and using the Super-SBM model or Super-EBM model (Pan and Xie, 2019; Feng and Zhang, 2021); second, using the factor decomposition method to measure green energy efficiency and green environmental efficiency from (He et al., 2022); third, the super-efficient EBM model is used to quantitatively evaluate green efficiency by adding non-expected output factors and considering non-oriented, constant payoffs of scale (Zhao et al., 2021); fourth, the DEA model is used to address the input-output inconsistency problem, while environmental pollution is treated as a non-consensual factor (Grosskopf et al., 1989). Among the above methods, the super-efficient SBM model is the most widely used and has a more comprehensive assessment of green eco-efficiency.

In this study, we make extensive use of the existing literature to calculate the green eco-efficiency using the methodology of Hu and Yang (2011), which is based on the global reference DEA analysis framework. We then calculate the green eco-efficiency by taking the Super-SBM model of undesired output and the Malmquist productivity index into account. The China Statistical Yearbook, China Statistical Yearbook of Industrial Economy, China Statistical Yearbook of Environment, and China Statistical Yearbook of Regional Economy were the primary sources of the data used. The regional GDP at constant prices was chosen as the expected output indicator, while the set input indicators were the amount of electricity consumed, the number of people employed, and the capital stock. The unanticipated output indicators were wastewater emissions, industrial soot emissions, sulfur dioxide emissions, and PM2.5.

4.2.2 Explanatory variables: Development stage of the digital economy (dig)

The majority of studies currently in existence on the measurement of digital economy development level indicators are centered on the provincial level, for example, the digital economy is divided into three dimensions for measurement: information development, Internet development, and digital transaction development (Liu et al., 2020). As a result, some indicators for the prefecture-level cities' digital economy measurement have to be reduced. In order to improve the measurement of the digital economy at the municipal level, this article refers to Zhao et al. (2020) and assesses the level of development of the digital economy from two perspectives: digital finance and Internet development. The Digital Finance Research Center of Peking University's Digital Inclusive Finance Index is used to measure one of them, the digital finance dimension. Four variables were utilized to measure the growth of the internet: mobile phone penetration, related practitioners, related output, and Internet penetration rate. The data were primarily taken from the China Urban Statistical Yearbook. The digital economy index was then calculated using the coefficient of variation approach. The basic idea behind the coefficient of variation method, an objective assignment based on the size of the difference between indicators, is that in the indicator system for evaluating the digital economy, the bigger the difference between the indicator values, the more it reflects the variation of the evaluated target. This is the precise computation process.

By removing the impact of the magnitude difference, the coefficient of variation is computed. Each index's coefficient of variation is determined as follows:

$$\boldsymbol{Z_i = \delta_i \Big/ \overline{x_i} \, (i = 1, 2, \ldots, n)} \tag{20}$$

where, Z_i refers to the coefficient of variation of the ith indicator, i.e., the standard deviation coefficient; δ_i is the standard deviation of the ith indicator; and $\overline{x_i}$ the mean value of the ith indicator. After that, the weights of each indicator are calculated as follows:

$$\boldsymbol{w_i = z_i \Big/ \sum\nolimits_{i=1}^{n} z_i} \tag{21}$$

Finally, the individual values of the system can be evaluated according to the calculated weights.

4.2.3 Moderating variable: Intensity of environmental regulation (err)

The approach used by Chen et al. (2018) to calculate the environmental regulatory intensity indicator is used in this work. These are the precise steps: Collect all the terms that are related to the environment in the government work report, count how often they occur, and then determine what percentage of the total number of words in the report are related to the environment. The phrases connected to the environment are: pollution, energy use, emission reduction, emissions, ecology, low carbon, air, chemical oxygen demand, sulphur dioxide, carbon dioxide, PM10, and PM2.5 (Chen and Chen, 2018).

4.2.4 Control variables

The degree of economic development (eco), the volume of foreign investment (fdi), the level of industrial structure (ind), the level of financial development (fin), and the level of government intervention (gov) were chosen as control variables in this paper by drawing on studies on factors affecting green eco-efficiency (Chen and Tang, 2018; Liu et al., 2018; Ji et al., 2022). The gross domestic product (GDP) *per capita* for the area is used to gauge its level of economic development. The ratio of actual foreign investment used to GDP serves as a gauge for the extent of foreign investment. The ratio of tertiary sector output to overall output indicates the level of industrial structure. The ratio of the total deposits and loans to the regional GDP is used to gauge the region's level of financial development. The proportion of public finance spending to regional GDP indicates the degree of government intervention. Table 1 provides explanations for each variable.

TABLE 1 Definition and interpretation of variables.

Variable category	Variable symbols	Variable name	Explanation of variables
Explained variables	Gee	Green	Using the Super-SBM model and the Malmquist productivity index, and based on the DEA framework
		Eco-efficiency	
Explanatory variables	Dig	Level of development of the digital economy	The system of indicators was constructed from two perspectives: digital finance and Internet development, and was measured using the coefficient of variation method
Adjustment variables	Err	Environmental regulation intensity	Statistics on the frequency of words related to the environment as a percentage of all words according to the government work report
Control variables	Eco	Level of economic development	GDP *per capita* in the region (in million)
	Fdi	Scale of foreign investment	Real use of foreign investment in the region as a percentage of GDP
	Ind	Level of industrial structure	Tertiary sector output as a proportion of total output
	Fin	Level of financial development	Total deposits and loans as a percentage of GDP at the end of the year
	Gov	Level of government intervention	Public finance expenditure as a proportion of regional GDP

TABLE 2 Variables' descriptive statistics.

Variable name	Sample size	Mean	Sd	Mid	Min	Max	1/4 quartile	3/4 quartile
Gee	2,565	1.01	0.24	1.01	0.96	4.63	0.98	1.03
ln_dig	2,565	10.55	2.15	10.79	7.81	14.94	10.25	11.39
Err	2,565	0.01	0.00	0.01	0.00	0.02	0.00	0.01
Ind	2,565	0.38	0.15	0.39	0.1	0.83	0.32	0.46
Gov	2,565	0.2	0.11	0.17	0.04	1.59	0.13	0.24
Fin	2,565	2.41	1.2	2.09	0.5	21.3	1.65	2.81
Fdi	2,565	0.02	0.02	0.01	0.00	0.13	0.00	0.02
Eco	2,565	3.63	3.53	3.07	0.69	21.55	1.67	5.33

The level of economic development is chosen as a control variable because the process of economic development, especially the rapid expansion of industry, brings pollution, which leads to a decline in green eco-efficiency, while the pursuit of sustainable development at a higher level of economic development is likely to focus on green eco-efficiency. The indicator of industrial structure level is chosen because most of the development of cities is the continuous transformation from primary industry to tertiary industry, and the higher the proportion of tertiary industry in a city, the higher the environmental efficiency and green eco-efficiency are likely to be. The indicator of the level of financial development is chosen because financial institutions can provide financial support for the development of enterprises, which is conducive to upgrading machinery and equipment, strengthening technological investment, eliminating backward production capacity and improving energy utilization efficiency, as well as financing for the service industry, supporting the rapid development of the tertiary industry, and continuously promoting the upgrading of industrial structure, which in turn has an indirect impact on green total factor productivity. The variable of the degree of government intervention is chosen because the government, through scientific and reasonable planning, guides the adjustment and transformation of the industrial structure in each region, gradually eliminates backward production capacity and reduces the existence of environmentally polluting industries, which also affects green eco-efficiency. FDI is selected as a control variable because according to the "pollution paradise" hypothesis, the level of environmental regulations in China as a developing country is often lower than that in developed countries, which makes developed countries' high pollution and high energy consumption industries move to developing countries, especially those developing countries that are desperate for development and lower environmental regulations, which will become the gathering place of high pollution industries, so the increase of FDI may affect the green eco-efficiency.

Table 2 provides more information on the outcomes of the descriptive statistics. Although there are significant variances between cities, the median and mean values indicate that the level of digital economy development is generally high. This is mainly because different regions are at different phases of this growth. The highest value is significantly bigger than the mean, showing the existence of a limited number of cities with high green eco-efficiency. The values of most cities' green eco-efficiency are focused around the mean. The low mean and variance of environmental regulation intensity show that the values are more concentrated and that total environmental regulation intensity varies relatively little.

TABLE 3 Baseline regression results.

Variables	(1)	(2)	(3)	(4)
	Gee	Gee	Gee	Gee
ln_dig	0.0800***	0.0436***	0.0801***	0.0789***
	(33.4632)	(20.2817)	(33.5520)	(32.8407)
Eco		0.0131***	0.0034	0.0117***
		(9.8196)	(1.5271)	(4.4706)
Ind		0.1572***	−0.0821*	0.1126*
		(4.4597)	(−1.8375)	(1.9065)
Fin		−0.0099**	−0.0034	0.0021
		(−2.1930)	(−0.6133)	(0.3732)
Fdi		0.4761*	−0.1443	−0.4333
		(1.8746)	(−0.4155)	(−1.2268)
Gov		0.3927***	−0.0194	0.0357
		(8.5836)	(−0.2754)	(0.5045)
constant	0.3002***	0.4250***	0.3248***	0.2348***
	(5.4935)	(14.7434)	(5.4364)	(3.7910)
City Effect	YES	NO	YES	YES
Year Effect	YES	YES	NO	YES
Number of samples	2,565	2,565	2,565	2,565
adj. R-sq	0.6257	0.2028	0.6219	0.6283

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively.

4.3 Model setting

The baseline regressions were first conducted using controls for city fixed effects, year fixed effects and two-way fixed effects, and the model was set up as follows:

$$gee_{it} = \beta_0 + \beta_1 ln\_dig_{it} + \sum\nolimits_{i=1}^{n} X_{it} + v_i + v_t + \varepsilon_{it} \tag{22}$$

where $\sum_j X_{it}$ is the control variable, v_i represents the city fixed effect, v_t represents the year fixed effect, and ε_{it} represents the random error term. If the digital economy has an enhancing effect on green eco-efficiency, the sign of β_1 should be significantly positive. To demonstrate that environmental regulation has a moderating effect on the digital economy and green eco-efficiency, the econometric model is set as follows:

$$gee_{it} = \beta_0 + \beta_1 ln\_dig_{it} + \beta_2 err_{it} + \beta_3 ln\_dig_{it} \times err_{it} + \sum\nolimits_{i=1}^{n} X_{it} + v_i + v_t + \varepsilon_{it} \tag{23}$$

If environmental legislation has a major moderating effect but the digital economy still has a significant capacity to boost green eco-efficiency, then β_3 will be significantly positive and β_1 will also continue to be significantly positive. To further examine the spatial spillover effect among cities, we will also put up a spatial econometric model in this work.

5 Empirical results

5.1 Baseline regression

The outcomes of the benchmark regressions are presented in Table 3. Without adjusting for the control variables but for the city impact and the year effect, the regression findings in Column (1) reveal that the level of development of the digital economy greatly increases green eco-efficiency. Columns (2) and (3) show the regression findings after adjusting for the city effect and the year effect, respectively. Even with the addition of control factors, the digital economy still significantly improves green eco-efficiency. The results of column (4), where the year effect, city impact, and control factors are all taken into account, reveal that the degree of development of the digital economy is considerably and favorably associated to green eco-efficiency.

5.2 Moderating effect analysis

This paper includes the intensity of environmental regulation (err) and its cross-product term with the level of digital economy development (ln dig) into the econometric model for regression to analyze the moderating effect of environmental regulation on the digital economy and green eco-efficiency. Table 4 displays the results of the regression. The digital economy significantly enhances green

TABLE 4 Regression results of moderation effects.

Variables	(1)	(2)	(3)
	Gee	Gee	Gee
ln_dig	0.0208***	0.0598***	0.0591***
	(5.0387)	(11.3129)	(11.2209)
ln_dig_err	3.5558***	2.7508***	2.6901***
	(6.4392)	(4.3008)	(4.2293)
Err	−34.0871***	−28.4229***	−27.3366***
	(−6.0041)	(−4.1792)	(−4.0327)
Eco	0.0124***	0.0030	0.0112***
	(9.2876)	(1.3413)	(4.2796)
Ind	0.1506***	−0.0727	0.1177**
	(4.2883)	(−1.5910)	(1.9962)
Fin	−0.0084*	−0.0038	0.0018
	(−1.8507)	(−0.6702)	(0.3108)
Fdi	0.5072**	−0.1452	−0.4375
	(2.0118)	(−0.4195)	(−1.2411)
Gov	0.3911***	−0.0208	0.0333
	(8.6064)	(−0.2968)	(0.4728)
constant	0.6473***	0.5212***	0.4257***
	(14.0794)	(6.9473)	(5.5484)
City Effect	NO	YES	YES
Year Effect	YES	NO	YES
Number of samples	2,565	2,565	2,565
adj. R-sq	0.2150	0.6246	0.6309

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

eco-efficiency, i.e., the higher the level of the digital economy, the higher the green eco-efficiency, even when controlling for the year impact, urban effect, and two-way fixed effect. Additionally, environmental legislation has a substantial positive moderating effect, meaning that the more environmental control there is, the more the digital economy will boost green eco-efficiency.

6 Spatial spillover effect test

6.1 Spatial measurement model setting

There may be regional movements of pertinent components and an impact on surrounding cities in the process of the development of the digital economy in cities, which means that the growth of the digital economy is not occurring in isolation in each city. Therefore, this article employs a spatial econometric model to estimate the spatial spillover effect in order to more precisely assess the relationship between digital economy, environmental regulation, and green eco-efficiency and to take into account the effects of spatial correlation. The spatial econometric model can be used for estimate once more because the Moran indices are all integers, all significant at the 10% level, and all show a clear positive spatial correlation.

The binary spatial adjacency matrix is chosen as the spatial weight matrix in this study. When cities I and j share a boundary in the spatial cross section, the matrix is set to have a value of 1; otherwise, it has a value of 0, and all diagonal values are set to 0. The spatial weight matrix is normalized in the estimation process. The specific form of the matrix is:

$$W_{ij} = \begin{cases} \mathbf{1}; & \textbf{\textit{City i shares a common border with city j}} \\ \mathbf{0}; & \textbf{\textit{Other}} \end{cases} \tag{24}$$

In recent years, spatial econometric techniques have been widely used in research in the field of economics. The more frequently used models are the spatial autoregressive model (SAR), which contains lagged terms of explanatory variables, and the spatial error model (SEM), which contains only spatial error terms, and the spatial Durbin model (SDM), which combines the two models (Li et al., 2010). The spatial transmission mechanisms used in the different models selected are not the same, and there are differences in the practical implications of their inclusion (Bai et al., 2017). In order to select a more appropriate econometric model, LM test and robust LM test were

TABLE 5 Results of selected tests of the model.

Test	SAR model	SEM model
LM Test	23.891***	142.789***
Robust LM Test	0.787	119.685***
WALD Test	101.89***	199.29***
LR Test	101.65***	204.48***
Joint city and time fixed effects test Statistical quantities *p*-value	Time fixed effects 2197.85 0	City fixed effects 28.89 0.0013

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively.

TABLE 6 Spatial econometric regression results.

Variables	SAR		SEM		SDM	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0622***	0.0474***	0.0694***	0.0544***	0.0478***	0.0350***
	(25.2639)	(9.8634)	(25.2589)	(11.1050)	(16.5523)	(7.1094)
Err		−21.1858***		−22.2633***		−18.6187***
		(−3.4674)		(−3.5625)		(−3.0509)
ln_dig*err		2.0514***		2.1411***		1.7361***
		(3.5760)		(3.6596)		(3.0355)
Eco	0.0100***	0.0096***	0.0127***	0.0122***	0.0117***	0.0115***
	(4.2283)	(4.0795)	(4.7743)	(4.6311)	(4.2331)	(4.1729)
Ind	0.1070**	0.1114**	0.1290**	0.1361**	0.1173*	0.1219*
	(2.0180)	(2.1026)	(2.1217)	(2.2510)	(1.6756)	(1.7432)
Fin	0.0002	0.0000	−0.0007	−0.0008	0.0001	−0.0002
	(0.0455)	(0.0023)	(−0.1367)	(−0.1504)	(0.0213)	(-0.0406)
Fdi	−0.5425*	−0.5399*	−0.5796*	−0.5696	−0.8014**	−0.8321**
	(−1.7105)	(−1.7033)	(−1.6624)	(−1.6401)	(−2.2312)	(−2.3214)
Gov	0.0416	0.0396	0.0361	0.0296	0.0505	0.0549
	(0.6554)	(0.6254)	(0.5454)	(0.4490)	(0.7866)	(0.8568)
W*ln_dig					0.0458***	0.0240**
					(9.4695)	(2.5602)
W*err						−22.6917**
						(−2.0231)
W*ln_dig*err						2.7631***
						(2.6090)
ρor λ	0.3179***	0.3118***	0.2561***	0.2448***	0.2028***	0.1976***
	(13.9972)	(13.6755)	(8.9288)	(8.4797)	(7.6281)	(7.4271)
Log-L	1,509.647	1,516.039	1,457.914	1,464.624	1,557.692	1,566.863
Number of samples	2,565	2,565	2,565	2,565	2,565	2,565
R-sq	0.1754	0.1876	0.1694	0.1769	0.1511	0.1915

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

TABLE 7 Direct, indirect and total effects.

Variables	Direct effects		Indirect effects		Total effects	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0504***	0.0366***	0.0654***	0.0373***	0.1158***	0.0739***
	(17.6695)	(7.2070)	(14.4027)	(3.5512)	(29.0940)	(6.0678)
Err		−19.7267***		−29.8516**		−49.5784***
		(−3.2277)		(−2.3105)		(−3.2756)
ln_dig_err		1.8803***		3.5359***		5.4161***
		(3.2464)		(2.8529)		(3.6856)
Eco	0.0114***	0.0113***	−0.0048	−0.0051	0.0066*	0.0062
	(4.3793)	(4.3159)	(−1.2174)	(−1.1801)	(1.7723)	(1.4804)
Ind	0.1201*	0.1176*	−0.0871	−0.1167	0.0329	0.0010
	(1.8548)	(1.7889)	(−0.7997)	(−1.0463)	(0.3546)	(0.0097)
Fin	0.0009	0.0009	0.0229*	0.0217*	0.0238*	0.0226*
	(0.1786)	(0.1716)	(1.9429)	(1.7771)	(1.8764)	(1.7313)
Fdi	−0.7582**	−0.7904**	1.0273*	1.0393*	0.2690	0.2489
	(−2.2104)	(−2.1628)	(1.6778)	(1.6920)	(0.4401)	(0.4058)
Gov	0.0535	0.0529	0.0030	0.0337	0.0565	0.0866
	(0.8348)	(0.8992)	(0.0205)	(0.2280)	(0.3437)	(0.5562)

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

conducted in this paper. The results of LM test showed that both LM-error and LM-lag statistics were significant, indicating that both spatial autoregressive model and spatial error model were supported, so the spatial Durbin model (SDM), which combined the two, could be chosen. The results of the robust LM test, on the other hand, significantly support the use of the spatial error model (SEM). In this paper, the WALD test and the LR test were conducted again, and the test results significantly rejected the degeneration to SEM model or SAR model. The results of the tests are shown in Table 5.

Under comprehensive consideration, the spatial Durbin model is used for estimation in this paper. Subsequently, the Hausman test concludes that a fixed-effects model is appropriate over a random effect. In order to select the appropriate fixed effects, this paper also conducts a joint significance test for urban and temporal fixed effects, and the results are shown in Table 5 strongly support the dual fixed effects model. The spatial Durbin model was set as follows:

$$gee_{it} = \alpha + \beta W gee_{jt} + \gamma \sum_{i=1}^{n} X_{it} + \delta \sum_{i=1}^{n} W X_{it} + v_t + z_i + \varepsilon_{it} \quad (25)$$

Where W is the spatial weight matrix, gee_{jt} is the lag term, δ is the spatial regression coefficient, v_t denotes the time fixed effect, z_i denotes the city fixed effect, and ε_{it} is the random disturbance term.

6.2 Analysis of spatial Durbin model results

Table 6 displays the geographic regression findings, where columns (5) and (6) represent the spatial Durbin model regression results. There is a strong regional spillover effect, as evidenced by the spatial autocorrelation coefficients of green eco-efficiency (gee), which are all significantly greater than zero in the regression results. ln_dig regression coefficients are all positive and pass the 1% significance level test, indicating that the development level of digital economy has a strong positive effect on green eco-efficiency. After adding the moderating variable environmental regulation (err), its cross product term with the digital economy (ln_dig) is significantly positive, indicating that environmental regulation plays a significant positive moderating role in the relationship between the digital economy and green eco-efficiency. At the same time, the spatial regression coefficients of the cross-products of digital economy, environmental regulation and digital economy are also significantly positive, which indicates that the digital economy has positive spatial spillover effects and environmental regulation in neighboring cities also has spatial transmission effects on the local area. To specifically explain the degree of impact of the digital economy on green eco-efficiency and the moderating effect of environmental regulation, the effect decomposition of the Durbin model is performed below.

6.3 Spatial Durbin model effect decomposition

After the effect decomposition of the spatial Durbin model, the results of the direct effect, indirect effect and total effect are shown in Table 7. The results show that the coefficients of the cross product terms of explanatory and moderating variables in the direct effect are significantly positive, which indicates that the digital economy in the region can significantly improve the green eco-efficiency, and the

TABLE 8 Robustness test results.

Explanatory variables	Replacement weight matrix		Supplementary variable method	
	Gee	Gee	Gee	Gee
ln_dig	0.0483***	0.0361***	0.0485***	0.0374***
	(16.8052)	(7.3552)	(17.0039)	(7.6753)
Err		−17.5645***		−16.1190***
		(−2.8850)		(−2.6679)
ln_dig*err		1.6943***		1.5329***
		(2.9666)		(2.7031)
W*ln_dig	0.0418***	0.0275***	0.0432***	0.0311***
	(8.6611)	(3.6302)	(9.0011)	(4.1266)
W*err		−15.6955**		−14.4295*
		(−1.9682)		(−1.8233)
W*ln_dig*err		1.7635**		1.4621*
		(2.2455)		(1.8726)

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

environmental regulation effectively improves the effect of the digital economy on the green eco-efficiency. The results of the indirect effects show that the development of digital economy also has a significant effect on the green eco-efficiency of neighboring cities, and environmental regulation also plays a positive moderating role in it. The spatial spillover effects of the cross-products of the digital economy and the regulating variables account for more than half of the total effects, indicating that the spatial spillover effects of the regulating effects of the digital economy and environmental regulations play an important role in the improvement of green eco-efficiency. At the same time, the estimated coefficients of the cross-products of digital economy and regulatory variables in the spatial Durbin model are smaller than the estimated coefficients of OLS in the previous section, indicating that the spatial effects are underestimated without considering the spatial effects on the enhancement of green eco-efficiency and the regulatory effects of environmental regulation.

6.4 Robustness tests

6.4.1 Replacement of the weight matrix

The adjacency matrix used in the spatial effects test can estimate the spatial spillover effects among neighboring cities, and to test the robustness of the results, the adjacency matrix is replaced with the inverse distance matrix for estimation again. The results are shown in columns (1)(2) in Table 8. The level of digital economy development significantly enhances green eco-efficiency, and environmental regulation has a positive moderating effect, so the regression results are still robust.

6.4.2 Supplementary variable method

According to Liu et al. (2022), the density of population may also have an impact on green eco-efficiency. The denser the population, the greater the environmental impact from economic activities will be, and the greater the ecological pressure faced by that city will be, so this paper takes population density into account to test the robustness of the results. As the results in columns (3)(4) in Table 8 show, the digital economy can still significantly improve green eco-efficiency after adding control variables, while environmental regulation also has a significant positive moderating effect.

7 Further analysis

7.1 Spatial Durbin model estimation by period

At the Second World Internet Conference held in December 2015, General Secretary Xi Jinping formally proposed to build "Digital China." Since then, the construction of digital economy has risen to the level of national strategy and has been developed rapidly. There may be differences in the development of digital economy before and after this point in time, so there may be different impacts of digital economy on green eco-efficiency in different periods. In this paper, we take 2015 as the time point and estimate the sample in groups, and the results are shown in Table 9.

The results in Table 9 show that the digital economy did not have an enhancing effect on green eco-efficiency between 2011 and 2015, and the regulating effect of environmental regulation was not significant. This is because in that period, the digital economy was in its infancy, digital technology was not widely applied, and the digital economy was being explored in various places, which made the digital economy did not reach the scale effect. However, from the spatial autoregressive coefficients, the digital economy is negatively significant, which may be because the digital economy first produces scale effects in larger cities or more economically developed regions, and has a siphoning effect on the surrounding areas. For a deeper analysis, it will be re-estimated by region below.

Between 2016 and 2019, the digital economy played a significant role in enhancing green eco-efficiency. This may be due to the rapid

TABLE 9 Estimation results by period.

Variable Name	2011–2015		2016–2019	
	(1)	(2)	(3)	(4)
ln_dig	−0.0015	−0.0022	0.0386***	0.0339***
	(−0.8554)	(−1.0960)	(7.5443)	(2.9024)
Err		−0.0373		−6.6402
		(−0.0179)		(−0.4265)
ln_dig_err		0.1101		0.4646
		(0.5632)		(0.3241)
W*ln_dig	−0.0071**	−0.0084**	0.0756***	0.0264
	(−2.1351)	(−2.2594)	(8.9412)	(0.9244)
W*err		−1.8017		−58.6609
		(−0.5659)		(−1.5634)
W*ln_dig_err		0.2178		6.1789*
		(0.7153)		(1.8040)
P	−0.0278	−0.0300	0.1609***	0.1667***
	(−0.7097)	(−0.7647)	(3.9419)	(4.0819)
Log-L	3059.127	3061.563	353.0389	355.2259
Control variables	YES	YES	YES	YES
Double fixed effect	YES	YES	YES	YES
R-sq	0.002	0.0019	0.2262	0.2844
N	1,425	1,425	1,140	1,140

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

development of the digital economy after 2015, when "Digital China" was formally elevated to the level of national strategy(Huang and Pan, 2021). It may be because the level of development of the digital economy reached a certain threshold and had a growth effect on green eco-efficiency. At the same time, the spatial autoregressive coefficient ρ for this period is significantly positive, which indicates that the growth of green eco-efficiency in this region also has a "radiative effect" on the surrounding regions, i.e., a positive spatial spillover effect.

7.2 Spatial Durbin model estimation by region

Due to the "insufficient and uneven" development, the relationship between digital economy, environmental regulation and green eco-efficiency may also differ among regions. Most of the eastern regions are coastal regions with strong economic power and are at the forefront of development in all aspects. The digital economy started earlier and has already formed a scale, but the developed manufacturing industries in the early stage are more polluting. The central region has accepted the transfer of manufacturing industries from some developed regions in recent years, which also brings pollution problems, and green development has become particularly important. Most cities in the western region originally have good ecological environment and relatively single industry, less serious pollution problems, while the development of digital economy lags behind, may have less marginal effect on green eco-efficiency. To analyze the inter-regional differences in depth, this paper divides 285 cities into three regions, East, West and Central, according to the division of regions by the Development and Reform Commission, and the estimation results are shown in Table 10.

The results in column (1) of Table 9 show that the digital economy has a positive and significant effect on green eco-efficiency in the eastern region, and there is also a positive spatial spillover effect. The positive moderating effect is more significant with the addition of the moderating variable environmental regulation in column (2), but there is no significant positive spatial spillover effect, probably because the digital economy in the eastern region is maturing and its marginal effect on green eco-efficiency decreases to a lower level. In the central region, the digital economy significantly enhances green eco-efficiency and jointly has a positive effect on green eco-efficiency under the regulation of environmental regulations. The digital economy produced a significant positive spatial spillover effect before the inclusion of the moderating variables, but this effect became insignificant after the inclusion of the moderating variables. However, there is no significant effect of both digital economy and environmental regulation in the western region, which may be due to the late start and small scale of digital economy in the western region, which does not produce scale effect, and the environmental problems

TABLE 10 Estimation results by region.

Variable Name	Eastern region		Middle region		Western region	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0248***	0.0023	0.0790***	0.0667***	−0.0058	−0.0106
	(4.7721)	(0.2012)	(47.9507)	(24.2983)	(−0.5080)	(−0.7812)
Err		−36.9308**		−16.7759***		−4.2564
		(−2.1001)		(−5.6467)		(-0.3830)
ln_dig*err		3.2924**		1.5337***		0.6457
		(2.1020)		(5.3724)		(0.5898)
Wx ln_dig	0.0763***	−0.0463*	0.0082*	−0.0053	−0.0171	−0.0175
	(8.8801)	(−1.7972)	(1.8129)	(−0.7945)	(−0.7407)	(−0.6781)
Wx err		−195.8396***		−16.2633**		−3.1377
		(−4.7401)		(−2.2786)		(−0.1882)
Wx ln_dig_err		18.3571***		1.6982**		0.0930
		(5.0530)		(2.4995)		(0.0552)
P	0.2482***	0.2095***	0.0844*	0.0698	−0.0481	−0.0485
	(6.1503)	(5.0779)	(1.8551)	(1.5177)	(−0.8733)	(−0.8805)
Log-L	431.9840	447.3082	1831.4237	1847.7704	262.3563	262.7100
Control variables	YES	YES	YES	YES	YES	YES
Double fixed effect	YES	YES	YES	YES	YES	YES
R-sq	0.0891	0.1990	0.3841	0.4254	0.0451	0.0416
N	1,035	1,035	981	981	549	549

Note: "*," "**" and "***" denote "10%," "5%" and "1%" levels of significance. The t-values are in parentheses.

are not very serious, so the effect of environmental regulation is not obvious. Therefore, this paper suggests that the eastern region may be in the "green development maturity period," the central region is in the "green development growth period," and the western region may be in the "green development start-up period The western region may be in the initial stage of green development."

8 Conclusion

This study first investigated the inherent mechanisms of the development of the digital economy to improve green eco-efficiency by building a theoretical model and proposing the research hypothesis that the development of the digital economy in a nation or region can foster green eco-efficiency. Next, the research hypothesis was empirically tested using data from 285 cities from 2011 to 2019 and environmental regulation variables were added to test the moderating effect of environment. This paper uses the spatial Durbin model to test the spatial spillover effect, as well as to investigate the heterogeneity of different regions and different periods, and to make the regression results more robust, this paper also conducts a robustness test. These investigations are done in order to further investigate the spatial spillover effect of digital economy development on green eco-efficiency and the moderating effect of environmental regulation.

This study reveals that environmental legislation and the growth of the digital economy both have the potential to dramatically increase green eco-efficiency. This indicates that the rapid development of the digital economy in recent years is conducive to enhancing green eco-efficiency, and that the development of the digital economy is consistent with green sustainability goals. After accounting for the spatial effect, it is still clear that environmental legislation has a regulatory effect and that the digital economy continues to have a facilitative effect. After breaking down the spatial effect, we discover that environmental regulation and the development of the digital economy both have a significant impact on the green eco-efficiency of nearby cities. Additionally, the spatial spillover effect of these two regulating factors also contributes significantly to the improvement of green eco-efficiency. The heterogeneity test also revealed that the digital economy did not contribute to increased green eco-efficiency during its early stages, from 2011 to 2015, and that the regulatory impact of environmental regulation was not statistically significant. But between 2016 and 2019, when the digital economy was at its most developed level, it significantly contributed to the growth of green eco-efficiency. The enhancing effect of the digital economy and the regulating effect of environmental regulation are again most noticeable in the central-eastern region, followed by the central region, and least noticeable in the western region, due to differences in economic development levels and environmental resource endowments of different regions. This result illustrates that there is an uneven impact of the digital economy development process on green eco-efficiency.

For China to explicitly encourage green growth and build its digital economy, the aforementioned findings serve as critical benchmarks.

On the one hand, every region in China needs to work to encourage the growth of the digital economy and fully utilize this sector's contribution to environmental improvement and the improvement of green ecological efficiency, to rationalize the use of digital economy development to achieve green and sustainable goals. The growth of a regional digital economy can help industries digitize, increase their rate of resource utilization and production efficiency, and realize industry management refinement. This will lessen the detrimental effects of economic activity on the environment. Each region should combine market demand and local factor endowment, improve digital infrastructure, and promote the development of digital economy with the implementation and construction of digital infrastructure in order to achieve the goal of green, coordinated a digital economy. Of course, in order to apply digital technology, complete digital infrastructure is a prerequisite. At the same time to promote the balanced development of the digital economy in regions with different levels of development.

On the other hand, each region in China should fully utilize the regulatory function of the government's environmental rules in the process of encouraging the digitalization and greening of the economy. To guide the development of the digital economy and prevent its harmful effects on the environment, all regions of China should therefore constantly improve their environmental regulation policies. For instance, in recent years, "mining" activities have had both a negative impact on the environment due to their high energy consumption and a lack of any actual output. For example, in recent years, "mining" activities not only have no actual output but also have a negative impact on the environment due to high energy consumption. Therefore, through policies and administrative orders, the government should limit the output of high energy consumption and high pollution in the digital economy, promote the development of green technology, and encourage businesses to change their production processes in a green and sustainable way. Additionally, it should integrate market dynamics for investments in pollution prevention and control, enhance and optimize the emission trading system, and fully exploit the regulatory role of environmental regulation in the advancement of the digital economy for the improvement of green eco-efficiency.

There are also some limitations in this study. Due to the limitation of data this study cannot take all the influencing factors of green eco-efficiency into consideration, and there is still room for improvement regarding the evaluation method of green eco-efficiency. In addition, more detailed research is needed on how the digital economy affects green eco-efficiency.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The sample data sources in this paper are mainly statistical yearbooks and government work reports.

Author contributions

YY and QL contributed to conception and design of the study. QL organized the database. QL performed the statistical analysis. QL wrote the first draft of the manuscript. YY wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Funding

This work was supported by The Major Project of Philosophy and Social Science Research in Colleges and Universities in Jiangsu Province (2022SJZD059), Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX21_1840), Key Topics of Jiangsu Provincial Social Science Application Research Excellence Project (22SYA-016), Nanjing Social Science Research Project (22YB04).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *Am. Econ. Rev.* 102, 131–166. doi:10.1257/aer.102.1.131

Andryeyeva, N., Nikishyna, O., Burkinskyi, B., Khumarova, N., Laiko, O., and Tiutiunnyk, H. (2021). Methodology of analysis of the influence of the economic policy of the state on the environment. *Insights into regional Dev.* 3 (2), 198–212. doi:10.9770/IRD.2021.3.2

Bai, J., Wang, Y., Jiang, F., and Jing, L. (2017). R&D factor mobility, spatial knowledge spillovers and economic growth. *Econ. Res.* 52, 109–123. CNKI:SUN:JJYJ.0.2017-07-009.

Bosseboeuf, D., and Richard, C. (1997). The need to link energy efficiency indicators to related policies: A practical experience based on 20 years of facts and trends in France (1973–1993). *Energ Policy* 25, 813–823. doi:10.1016/s0301-4215(97)00071-2

Bukht, R., and Heeks, R. (2017). *Defining, conceptualising and measuring the digital economy*. Manchester, United Kingdom: Development Informatics working paper. doi:10.2139/ssrn.3431732

Chen, S., and Chen, D. (2018). Haze pollution, government governance and high quality economic development. *Econ. Res.* 53, 20–34.

Chen, Y., and Tang, X. (2018). Study on the spillover effect of manufacturing agglomeration on green total factor productivity in cities - based on city rank perspective. *Finance Trade Res.* 29, 1–15. doi:10.19337/j.cnki.34-1093/f.2018.01.001

Chen, Z., Kahn, M. E., Liu, Y., and Wang, Z. (2018). The consequences of spatially differentiated water pollution regulation in China. *J. Environ. Econ. Manag.* 88, 468–485. doi:10.3386/w22507

Ding, Q. S. (2019). *Statistical measurements and spatial characteristics of regional environmental management performance in China*. Dalian, China: M.S., Northeast University of Finance and Economics. doi:10.27006/d.cnki.gdbcu.2019.000013

Feng, X-M., and Zhang, R-J. (2021). Industrial structure change, green eco-efficiency and regional economic growth. *Statistics Decis. Mak.* 37, 104–108. doi:10.13546/j.cnki.tjyjc.2021.21.021

Grosskopf, S., Lovell, A., and Pasurka, C. (1989). *Multilateral productivity comparisons when some outputs undesirable: A distance function approach*.

He, W., Wen, J., and Zhang, M. (2022). A study on the impact of digital economy development on green eco-efficiency in China - based on a two-way fixed effects model. *Econ. Issues* 1, 1–8. doi:10.16011/j.cnki.jjwt.2022.01.002

Hu, X., and Yang, L. (2011). Regional green total factor productivity growth differences and convergence analysis in China. *Finance Econ. Res.* 37, 123–134. doi:10.16538/j.cnki.jfe.2011.04.010

Huang, X., and Pan, O. (2021). The origin, development and future of "digital China. *J. Beijing Univ. Aeronautics Astronautics Soc. Sci. Ed.* 34, 99–106. doi:10.13766/j.bhsk.1008-2204.2021.0073

Ji, Y., Koo, Z., and Xue, J. (2022). Porter effect of environmental regulation on industrial green total factor productivity. *Statistics Decis. Mak.* 7, 82–86. doi:10.13546/j.cnki.tjyjc.2022.07.016

Jing, W., and Zhang, L. (2014). Environmental regulation, openness and green technological progress of Chinese industry. *Econ. Res.* 49, 34–47.

Klimas, E. (2020). Sustainable development and urban planning regulations in the context of climate change management measures. *Entrepreneursh. Sustain. Issues* 8 (1), 24–37. doi:10.9770/jesi.2020.8.1(2

Knickrehm, M., Berthon, B., and Daugherty, P. (2016). *Digital disruption: The growth multiplier*. Boston, United States: Accenture Strategy.

Lei, M., and Yu, X. W. (2013). Local fiscal spending, environmental regulation and China's low carbon economic transition. *Econ. Sci.* 5, 47–61. doi:10.19523/j.jjkx.2013.05.005

Li, C., and Bi, C. (2012). Analysis of total factor productivity changes in western region industries under environmental regulations. *J. Xi'an Jiaot. Univ. Soc. Sci. Ed.* 32, 18–22. doi:10.15896/j.xjtuskxb.2012.01.002

Li, J., Tan, Q., and Bai, J. H. (2010). Spatial econometric analysis of regional innovation production in China - an empirical study based on static and dynamic spatial panel models. *Manag. World* 7, 43–55. doi:10.19744/j.cnki.11-1235/f.2010.07.006

Li, B., Peng, X., and Ouyang, M. K. (2013). Environmental regulation, green total factor productivity and change of industrial development mode in China: An empirical study based on data from 36 industrial sectors. *China Ind. Econ.* 4, 56–68. doi:10.19581/j.cnki.ciejournal.2013.04.005

Liu, W-S., Tian, Y-H., and Luo, Y. (2018). Industrial structure upgrading, energy efficiency and green total factor productivity. *Theory Pract. Finance Econ.* 39, 118–126. doi:10.16339/j.cnki.hdxbcjb.2018.01.018

Liu, J., Yang, Y., and Zhang, S. (2020). A study on the measurement and drivers of China's digital economy. *Shanghai Econ. Res.* 6, 81–96. doi:10.19626/j.cnki.cn31-1163/f.2020.06.008

Liu, P., Liu, F., Wang, X., Yin, Z., Cao, H., and Li, C. (2021). Theory and technology system of green manufacturing and its new framework. *J. Mech. Eng.* 57, 165–179. doi:10.3901/jme.2021.19.016

Liu, Q., Ma, Y., Xu, S., Hidru, T. H., Yang, Y., Wang, S., et al. (2022). Atrial cardiomyopathy markers and new-onset atrial fibrillation risk in patients with acute myocardial infarction. *China Popul. - Resour. Environ.* 32, 72–79. doi:10.1016/j.ejim.2022.04.019

Luo, N., and Wang, Y. (2017). Fiscal decentralization, environmental regulation and regional eco-efficiency: An empirical study based on dynamic spatial Durbin model. *China Population-Resources Environ.* 27, 110–118. doi:10.12062/cpre.20170327

Mao, J., Zeng, R., Du, Y., and Jiang, B. (2010). Eco-efficiency of industry sectors for China. *Environ. Sci.* 31, 2788–2794. doi:10.27006/d.cnki.gdbcu.2019.000013

Mesenbourg, T. L. (2001). *Measuring the digital economy*, 1. Cambridge, MA, United States: US Bureau of the Census, 1–19. doi:10.7551/mitpress/6986.003.0003

Michelsen, O., Fet, A. M., and Dahlsrud, A. (2006). Eco-efficiency in extended supply chains: A case study of furniture production. *J. Environ. Manage* 79, 290–297. doi:10.1016/j.jenvman.2005.07.007

Pan, M., and Xie, R. S. (2019). Exploring the spatial differentiation of green eco-efficiency driven by science and technology innovation - based on the perspective of regional market segmentation. *Soft Sci.* 33, 20–25. doi:10.13956/j.ss.1001-8409.2019.10.04

Pei, C-H., Ni, J-F., and Li, Y. (2018). Analysis of the political economy of the digital economy. *Finance Trade Econ.* 39, 5–22. doi:10.19795/j.cnki.cn11-1166/f.2018.09.001

Peng, H., Zhang, J., Han, Y., Tang, G., and Zhang, Y. (2017). SBM-DEA model and empirical analysis of eco-efficiency measurement of tourism sites. *J. Ecol.* 37, 628–638. doi:10.5846/stxb201507311616

Rybalkin, O., Lavrinenko, O., Ignatjeva, S., and Danilevica, A. (2021). Introduction of EEPSE green economy index for the analysis of regional trends. *Entrepreneursh. Sustain. Issues* 9, 415–435. doi:10.9770/jesi.2021.9.1(26

Schaltegger, S., and Sturm, A. (1990). Ökologische rationalität: Ansatzpunkte zur ausgestaltung von ökologieorientierten managementinstrumenten. *Unternehm.* 44, 273–290.

Schmidheiny, S., and Timberlake, L. (1992). *Changing course: A global business perspective on development and the environment*. Cambridge, U.S.: MIT press, 11–17. doi:10.2307/20045337

Sneideriene, A., Viederyte, R., and Abele, L. (2020). Green growth assessment discourse on evaluation indices in the European Union. *Entrepreneursh. Sustain. Issues* 8 (2), 360–369. doi:10.9770/jesi.2020.8.2(21

Su, Y., Li, Z., and Yang, C. (2021). Spatial interaction spillover effects between digital financial technology and urban ecological efficiency in China: An empirical study based on spatial simultaneous equations. *Int. J. Environ. Res. Public Health* 18, 8535. doi:10.3390/ijerph18168535

Wang, J., and Sheng, P. (2015). Has environmental management reduced total factor growth in Chinese industry? --A study based on a modified directional distance function. *Industrial Econ. Res.* 5, 31–39. doi:10.13269/j.cnki.ier.2015.05.004

Wang, J., Zhu, J., Luo, X., Huang, L., Chen, C., Wang, L., et al. (2021). Lich-gregoir vesico-ureteral reimplantation for duplex kidney anomalies in the pediatric population: A retrospective cohort study between laparoscopic and open surgery. *Res. Quantitative Econ. Technol. Econ.* 38, 26–32. doi:10.21037/tp-20-163

Yang, Y., and Deng, X. Z. (2019). Regional differences in the spatial and temporal evolution of urban eco-efficiency and influencing factors in China. *Geoscience* 39, 1111–1118. doi:10.13249/j.cnki.sgs.2019.07.009

Yin, K., Wang, R., Zhou, C., and Liang, J. (2012). A review of domestic and international eco-efficiency accounting methods and their applications. *J. Ecol.* 32, 3595–3605. doi:10.5846/stxb201104280564

Zhao, T., Zhang, Z., and Liang, S. (2020). Digital economy, entrepreneurial activity and high quality development - empirical evidence from Chinese cities. *Manag. World* 36, 65–76. doi:10.19744/j.cnki.11-1235/f.2020.0154

Zhao, L., Jia, J., Cao, N-G., and Wu, D-T. (2021). Spatial patterns and influencing factors of inclusive green efficiency in Chinese cities. *Statistics Decis. Mak.* 37, 57–60. doi:10.13546/j.cnki.tjyjc.2021.19.012

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 24 January 2023
DOI 10.3389/fenvs.2023.1134882

Check for updates

OPEN ACCESS

EDITED BY
Grigorios L. Kyriakopoulos,
National Technical University of Athens,
Greece

REVIEWED BY
Guangqin Li,
Anhui University of Finance and
Economics, China
Xinghua Cui,
Jiangxi University of Finance and
Economics, China
Ruonan Fang,
Jimei University, China

*CORRESPONDENCE
Yanfang Lyu,
yanfang902@sina.com
Dong Wang,
wangrichard72@sina.com

SPECIALTY SECTION
This article was submitted to
Environmental Economics
and Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 31 December 2022
ACCEPTED 16 January 2023
PUBLISHED 24 January 2023

CITATION
Lyu Y, Zhang L and Wang D (2023), The impact of digital transformation on low-carbon development of manufacturing.
Front. Environ. Sci. 11:1134882.
doi: 10.3389/fenvs.2023.1134882

The impact of digital transformation on low-carbon development of manufacturing

Yanfang Lyu[1]*, Leifeng Zhang[1] and Dong Wang[2]*

[1]School of Statistics, Institute of Quantitative Economics, Huaqiao University, Xiamen, China, [2]School of Business, Minnan Normal University, Zhangzhou, China

Objective: To measure the low-carbon development level and digital transformation degree of China's manufacturing industry, and to examine the impact of digital transformation on low-carbon development.

Methods: This paper uses Super Slack Based Measure (SBM) model and multi-regional input-output model to measure the low-carbon development level and digital transformation degree of 17 manufacturing industries in 30 provinces of China from 2012 to 2018, and uses high-dimensional fixed effect model and mediation model to study the impact of digital transformation on low-carbon development.

Results: 1) During the study period, China's manufacturing industry showed an upward trend in terms of low-carbon development level and digital transformation, but there were significant regional and industrial disparities. 2) Digital transformation can significantly promote the low-carbon development of manufacturing industry, which is still valid in the robustness test. 3) For sub-indicators, digital industrialization has the most obvious effect on the low-carbon development of manufacturing industry, and the improvement of digital development environment also has a positive impact on low-carbon development. 4) The heterogeneity analysis indicate that digital transformation has a greater impact on promoting low-carbon development of manufacturing in underdeveloped regions, and the positive effect is obvious in medium-low-energy-consuming industries, but not in high-energy-consuming industries. 5) The mechanism test shows that technological innovation is a channel for digital transformation to promote low-carbon development.

Value: This paper provides empirical evidence for the environmental impact of digital transformation, and offers a scientific basis for relevant departments to formulate low-carbon development policies from the perspective of digital transformation.

KEYWORDS

digital transformation, manufacturing, low-carbon development, multi-regional input-output model, high-dimensional fixed effects model

1 Introduction

After more than 40 years of reform and opening up, China's manufacturing industry has achieved leapfrog development. However, due to the long-term extensive production mode oriented by high energy consumption and high pollution in China's traditional manufacturing industry, environmental problems have also expanded rapidly with the development of traditional manufacturing industry (Peng et al., 2022). According to data from CEADs, the energy consumption of 30 manufacturing industries in China increased from 0.61 billion tons of standard coal in 2000 to 2.3 billion tons of standard coal in 2019, an increase of nearly

2.8 times in 20 years; at the same time, carbon emissions increased from 1.12 billion tons to 3.51 billion tons, an increase of 2.1 times in 20 years. The continuous increase in energy consumption and carbon emissions not only has a negative impact on the sustainable development of China's economy, but also seriously hinders China's progress towards its peak carbon and carbon neutrality goals (Ge et al., 2022). Therefore, it is an urgent and practical issue to be studied how to break the crude development mode of some industries and realize the low-carbon development of China's manufacturing industry.

At present, digital technologies represented by the Internet, artificial intelligence and big data are deeply integrated with various fields of economic and social development, gradually becoming a strong engine for the transformation of new and old kinetic energy in China (Zhang C et al., 2022). According to the "China Digital Economy Development Report (2022)" released by the China Academy of Information and Communications Technology, the scale of China's digital economy reached 7.1 trillion US dollars in 2021, accounting for 39.8% of Gross Domestic Product (GDP), which shows that the digital economy has changed from an important component of China's economy to a key leading force for economic development. In the critical period of China's economic transformation, the application of digital technology will undoubtedly affect the mode of industrial production, and will also have a profound impact on the industry's energy demand and carbon emissions (Ren et al., 2021; Wang J et al., 2022). From existing literature, most scholars focus on the economic effects of digital transformation, both exploring its important impact on the economic development of countries or regions (Mićić, 2017; Pan et al., 2022; Wu and Yang, 2022) and its key role in corporate development (Bhimani, 2015; Ballestar et al., 2021; Gaglio et al., 2022; Zhang J et al., 2022). With the development of digital economy and the tightening of resource and environmental constraints, the environmental effects of digital transformation have attracted the attention of scholars. Relevant studies show that the development of regional digital economy has a positive effect on reducing energy consumption (Ren et al., 2021), improving green total factor productivity (Li and Liao, 2022; Lyu et al., 2023), promoting clean energy development (Chen, 2022), and promoting green development efficiency (Luo et al., 2022). Some scholars have studied the impact of digital transformation on energy efficiency (Zhang L et al., 2022), green technology innovation (El-Kassar and Singh, 2019; Ning et al., 2022) and environmental management (Xia et al., 2022) from the enterprise level. Their research also confirms that digital transformation can promote green development. However, the relationship between digital transformation and carbon emissions remains controversial in academia. Most scholars (Ge et al., 2022; Yu et al., 2022; Zha et al., 2022) believe that digital transformation can help reduce carbon emissions. Zhang W et al. (2022) found that the development of digital industries has squeezed out carbon-intensive industries, optimized the industrial structure, and reduced carbon emissions. Yu et al. (2022) believes that the application of digital technology has greatly improved production conditions, optimized factors other than energy input, and helped to reduce carbon emissions. However, some scholars (Salahuddin and Alam, 2015; Avom et al., 2020) believe that digital transformation will increase the demand for energy sources such as electricity, which will lead to an increase in carbon emissions.

Although scholars have conducted extensive research on the economic and environmental effects of digital transformation from a regional or corporate perspective, few studies have explored the relationship between digital transformation and environmental performance from a combined regional and industry perspective, which hinders a comprehensive understanding of the impacts of digital transformation. Therefore, this paper extends the existing research as follows: 1) This paper explores the impact of digital transformation on low-carbon development of manufacturing industry from the perspective of sub-region and sub-industry. 2) Using matching data to measure the low-carbon development level of manufacturing industry in China's provincial-level. This avoids measurement errors caused by ignoring the heterogeneity of regions or industries. 3) By combining the multi-regional input-output model with the evaluation system of digital economy development level, the measurement framework of the digital transformation of manufacturing industry in various provinces of China is constructed, which enriches the measurement research of digital transformation.

2 Theoretical analysis

Digital transformation refers to the process by which enterprises apply digital technologies such as networks, communications, and computing to transform organizational structures and business models to achieve workflow optimization, organizational efficiency improvement, and value creation (Vial, 2019). As a revolution, digital transformation may fundamentally change the structure and trading mode of production factors, which will have an important impact on production efficiency and ecological environment (Goldfarb et al., 2015; Verhoef et al., 2019).

2.1 Direct mechanism

The deep integration of digital technologies such as big data and traditional manufacturing industry can promote the low-carbon development of manufacturing industry by eliminating the information gap, achieving accurate matching of supply and demand, and adapting to the market environment (Wu et al., 2022). The acceleration of the digitization process has spawned a variety of information service platforms, which have profoundly changed the information search mode and resource allocation mode of market participants. The digital platform gradually reduces the information asymmetry in the field of resource allocation by aggregating massive resource demand information, which is conducive to the supply and demand sides to grasp each other‘s real needs in an instant and efficient manner, thereby improving resource utilization efficiency (Kaija et al., 2022). Producers use data mining technology to analyze consumer demand preferences, carry out targeted production activities, and form a dynamic and accurate matching mechanism between supply and demand, thereby reducing unnecessary waste in production.

Although the scale effect of digital transformation will lead to an increase in energy demand (Moyer and Hughes, 2012; Lange et al., 2020), the rapid penetration of digital technology profoundly affects the supply-demand structure and utilization efficiency of energy (Goldbach et al., 2018). The carbon reduction caused by the adjustment of energy consumption structure, the matching of energy supply-demand, and the improvement of energy efficiency is greater than the carbon increase caused by the expansion of production scale, which makes the "net" impact of digital transformation on carbon emissions show an inhibitory effect (Zhang Z et al., 2022). From the perspective of structural adjustment, the application of digital technology can strengthen the substitution role of clean energy for fossil energy, reduce the dependence of the industry on fossil energy. In addition, the application of digital technology has laid a technical foundation for the research and development and promotion of clean energy, which is conducive to changing the production mode of the industry based on fossil energy consumption. From the perspective of supply-demand matching, digital transformation is conducive to improving the coordinated and matching of energy supply side and demand side (Kaija et al., 2022). The application of digital technology makes it easy to collect and process information. Producers can use the information they have to judge the supply and demand of energy to match supply and demand (Goldbach et al., 2018). Improving energy efficiency is another effective way to achieve carbon emission reduction (Yi et al., 2022). On the one hand, the application of digital technology and data resources has spawned new technologies and formats related to energy production, helping to improve industrial energy efficiency. On the other hand, digital transformation can promote the penetration of digital technology into the enterprise's energy scheduling system, which will help realize the efficient operation of procurement, storage and management of energy, and then promote the low-carbon development of industry (Zhang et al., 2023). Based on the above analysis, this paper proposes the research hypothesis.

H1: The digital transformation has a positive effect on low-carbon development in manufacturing.

2.2 Indirect mechanism

Technological innovation is an effective way to achieve economic growth and protect the environment (Daron et al., 2012). The improvement of technology is conducive to cleaner production for enterprises, which has a positive effect on achieving carbon emission reduction (Leung et al., 2014; Xu et al., 2021). In theory, using digital technologies to improve production and management processes can have a positive impact on innovation (Nambisan et al., 2019; Ning et al., 2022). From Schumpeter's explanation of innovation (Schumpeter, 1934), the essence of innovation lies in the recombination of elements. Digitization accelerates the construction of modern information communication networks. Data, knowledge and information, as the key innovation elements, are rapidly spread and applied through communication network technology. It is more convenient for enterprises to obtain heterogeneous innovation elements and realize knowledge linkage than before. In addition, the widespread application of digital technology facilitates the flow of knowledge and information between internal and external enterprises, which is conducive to breaking down invisible barriers to innovation (Niu et al., 2023). Digital transformation not only promotes the diffusion of innovation elements, but also gives birth to more innovation elements. The application of digital technologies such as big data and cloud computing enables the storage and analysis of data, knowledge and information. The accumulation of innovative resources provides favorable conditions for low-carbon technology innovation. Based on the above analysis, this paper proposes the research hypothesis.

H2: Digital transformation improves the low-carbon development level of manufacturing industry by promoting the mechanism of technological innovation.

3 Measurement of core variable

3.1 Low-carbon development level

The existing literature points out that the low-carbon production efficiency calculated by taking carbon emissions as undesired output, regional GDP as expected output, labor, capital and energy as production factors can not only reflect the efficiency of economic output, but also take into account the problem of carbon emissions, which can better measure the extent to which the development model meets the dual goals of economic growth and energy conservation and emission reduction (Chen and Golley, 2014).

3.1.1 Method

The traditional Data Envelopment Analysis (DEA) calculation method does not consider the slack variables, and most of them are angle and radial models. There are problems such as the incomparability of decision making units on the efficiency Frontier (Andersen and Petersen, 1993) and the same proportion of input or output changes (Tone, 2001). Therefore, this paper selects the Super-SBM model, which is improved by Tone on the basis of its non-radial and non-angle SBM model (Tone, 2002), and fully takes into account the scale reward problem, selecting the more realistic variable returns to scale (VRS). In addition, the carbon emission constraint is treated as undesirable output, and the Super-SBM model considering undesirable output is constructed. The model relaxes the constraints of the same proportion change of each factor and the effective decision-making unit efficiency value $\leqslant 1$, so that the effective decision-making unit can be comparable in time.

Specifically, assuming that there are n effective decision making units (DMU), each DMU has m input factors, and each DMU will produce r_1 expected output and r_2 undesirable output. The corresponding input factors, expected output and undesirable output are expressed as: x_{ik}, y_{qk} and b_{tk}, respectively. The calculation model of the efficiency value ρ is expressed as follows:

$$\rho = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{c_i^-}{x_{ik}}}{1 - \frac{1}{r_1+r_2}\left(\sum_{q=1}^{r_1}\frac{c_q^+}{y_{qk}} + \sum_{t=1}^{r_2}\frac{c_t^-}{b_{tk}}\right)}$$

$$s.t. \begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - c_i^- \leqslant x_{ik} & i = 1, \cdots, m \\ \sum_{j=1, j\neq k}^{n} y_{qj}\lambda_j + c_q^+ \geqslant y_{qk} & q = 1, \cdots, r_1 \\ \sum_{j=1, j\neq k}^{n} b_{tj}\lambda_j - c_t^- \leqslant b_{tk} & t = 1, \cdots, r_2 \\ \sum_{j=1, j\neq k}^{n} \lambda_j = 1, \ \lambda \geqslant 0 & j = 1, \cdots, n \\ c_i^-, c_q^+, c_t^- \geqslant 0 \end{cases}$$

In the formula, c_i^-, c_q^+, c_t^- are the slack vectors of input factors, expected output and undesirable output respectively; λ is the index weight, when $\sum_{j=1, j\neq k}^{n}\lambda_j = 1$ and $\lambda \geqslant 0$, it is variable returns to scale; ρ is low-carbon development level.

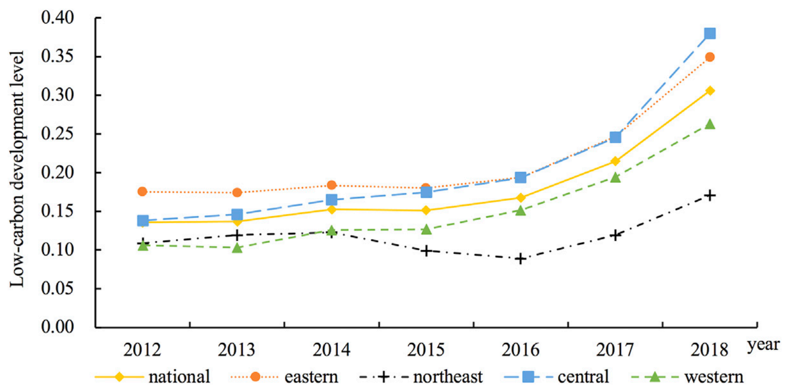


FIGURE 1
The evolution trend of the average value of low-carbon development of manufacturing industry in china and its four regions.

3.1.2 Indicators and data

This paper uses gross industrial output as the expected output index, carbon emissions as the unexpected output index; input indicators are general, including capital, labor and energy consumption. To estimate the total industrial output value data from 2012 to 2018, the industrial sales output value, the current year inventory and the previous year inventory are taken into account. Then, according to the producer price index of industrial products divided by provinces and industries in each year, the data was deflated to the comparable industrial output value based on 2012 as the base year. Capital investment is measured by the capital stock of the manufacturing industry in each province. This year's capital stock is calculated according to the perpetual inventory method. The composition of energy consumption includes 20 energy types such as coal, oil, natural gas and electricity. Because the average low calorific value of each type of energy is not the same, it can not be directly added. Therefore, the reference coefficients of various types of energy converted into standard coal provided by the "China Energy Consumption Statistical Yearbook" are used to convert units of different energy types into 10,000 tons of standard coal and add them.

The original data of expected output, capital input and labor input required for the measurement of low-carbon development level of manufacturing industry are from the "China Industrial Statistical Yearbook". The original data of unexpected output and energy consumption are from the CEADs database. The price deflator data is from the "China Price Statistical Yearbook".

3.1.3 Results and analysis

This paper uses Matlab 2020b software to calculate the low-carbon development level of 17 manufacturing industries in 30 provinces of China from 2012 to 2018, and analyzes its evolution characteristics from the national level, regional level and industry level. As shown in Figure 1, from 2012 to 2018, the low-carbon development level of manufacturing industry in China and its regions showed an upward trend. According to the changing characteristics of low-carbon development level of manufacturing industry, the research interval can be divided into two stages. During the first stage from 2012 to 2015, the low-carbon development level of the manufacturing industry increased at a relatively low rate, and the growth trend was not obvious. The second stage is from 2016 to 2018. During this period, the low-carbon development level of China's manufacturing industry showed a rapid upward trend, and the increase was obvious. The reason for this change trend may be that 2012–2015 is the early stage of China's low-carbon transformation and development. Because the economic development model has a certain path dependence effect, the effect of low-carbon development in the short term is not significant. In addition, China's digital transformation during this period is still in its infancy, and the digital economy and the real economy have not achieved deep integration, which makes the low-carbon development level of manufacturing industry grow more slowly. With the deepening of the concept of low-carbon development and the deep integration of digital economy and real economy, the low-carbon transformation kinetic energy accumulated in the early stage has been released, and the low-carbon development level of manufacturing industry has been rapidly improved.

From the perspective of regional differences, the low-carbon development level of manufacturing industry in the eastern and central regions is relatively close, which is higher than the national average; the level of low-carbon development in the western region has greatly improved, but there is still a big gap with the eastern and central regions. The low-carbon development level of manufacturing in northeast is not only lower than the eastern and central regions, but also gradually lags behind the western region, and the gap with other regions gradually widened. This regional difference is highly correlated with China's economic development, industrial layout and spatial distribution of resources.

Further, analyze the changes in the level of low-carbon development of China's manufacturing industry from an industry perspective. Table 1 lists the calculation results for 2012, 2015, and 2018. On the whole, the low-carbon development level of each manufacturing industry is on the rise. From the perspective of industry differences, food and tobacco, communications electronic equipment and electrical machinery and equipment in the three industries of low-carbon development level in each year ranked high, and Paper printing cultural education sports, metal smelting and non-metallic products low-carbon development level ranked low. It can be found that industries with high levels of low-carbon development are mostly low-energy-consuming industries. These industries for energy dependence is not strong, low-carbon development action less resistance. Most of the industries with low low-carbon development levels belong to traditional manufacturing industries with high energy consumption and high pollution. Such

TABLE 1 Measurement results of low-carbon development level of manufacturing industry.

Industry code	Abbreviation	2012	Rank	2015	Rank	2018	Rank
6	Food and tobacco	0.1960	3	0.2585	1	0.4549	1
7	Textile industry	0.0906	13	0.1121	12	0.3311	8
8	Manufacture of leather, fur, feather and related products	0.1040	11	0.1417	8	0.3237	9
9	Processing of timber and furniture	0.1215	9	0.1672	5	0.4353	2
10	Paper printing cultural education sports	0.0700	17	0.0953	17	0.1872	16
11	Petroleum processing	0.2913	1	0.1080	14	0.2093	14
12	Chemical products	0.1242	8	0.1381	10	0.2372	12
13	Non-metallic products	0.0861	15	0.1031	15	0.2091	15
14	Metal smelting	0.1572	6	0.0967	16	0.1866	17
15	Metal products	0.1269	7	0.1566	6	0.2766	10
16	General purpose machinery	0.1020	12	0.1238	11	0.2229	13
17	Special purpose machinery	0.1158	10	0.1386	9	0.2433	11
18	Transportation equipment	0.1596	4	0.2205	3	0.3694	6
19	Electrical machinery and equipment	0.2332	2	0.2094	4	0.3964	4
20	Communication electronic equipment	0.1581	5	0.2484	2	0.3985	3
21	Instrumentation	0.0843	16	0.1449	7	0.3851	5
22	Other manufactured goods	0.0880	14	0.1095	13	0.3379	7

industries have high demand for energy and many have overcapacity problems, so the level of low-carbon development is low. This industry difference shows that the traditional high-pollution and high-energy-consuming manufacturing industry is still the key industry of China's low-carbon reform, and improving the low-carbon development level of such industries plays a key role in achieving the "dual-carbon goals" and promoting the high-quality development of the manufacturing industry.

3.2 Digital transformation

From the literature on digital economy measurement, most studies measure the level of digital economy development at the national and regional levels or the degree of digital transformation at the enterprise level. Scholars usually use input-output tables or macroeconomic indicators to measure the level of digital economic development including national, provincial and urban dimensions (Balcerzak and Pietrzak, 2017; Liu et al., 2022; Zhang C et al., 2022). Or use text analysis to measure the degree of digital transformation at the enterprise level (Feng et al., 2022), and a small number of studies have measured the degree of digital transformation at the industry level. These studies can reflect the development of digital economy or digital transformation in China to some extent. However, measuring the degree of digital transformation from the regional level or the industry level alone will lead to deviations in the measurement of digital transformation. Out of self-interest motivation, enterprises exaggerate the disclosure of digital related words, which will lead to distortion of digital measurement at the enterprise level. In view of this, this paper constructs a new measurement model of digital transformation degree.

3.2.1 Measurement model and data

The degree of digital transformation of manufacturing in different regions depends not only on the intensity of industry digital input, but also on the development of regional digital economy. Therefore, drawing on the research ideas of Arnold et al. (Arnold et al., 2016), using China's multi-regional input-output model, combined with the measurement system of digital economy development level of each province, this paper constructs a framework for measuring the digital transformation degree of manufacturing industry in different provinces in China. The benchmark calculation formula is:

$$\boldsymbol{digital_{ijt} = Idigital_{ijt} \times Rdigital_{it}}$$

In the formula, $digital_{ijt}$ represents the degree of digital transformation of i province and j industry in the t year; $Idigital_{ijt}$ represents the digital input intensity of i province and j industry in the t year; $Rdigital_{it}$ represents the level of digital economy development in province i in year t.

This paper uses input-output method to measure the digital input intensity of manufacturing industry. Industry digital input intensity is the proportion of industry digital intermediate input in total input. Among them, the digital intermediate input part includes direct digital intermediate input and complete digital intermediate input. In the case of only considering direct digital intermediate input, the calculation expression of digital input intensity is:

$$\boldsymbol{Idigital_{cj}^{direct} = Z_{cj} \big/ X_j}$$

TABLE 2 Measurement system of digital economy development level.

First grade indexes	Second index	Measurement index	Unit	Attribute
Digital industrialization	Computer communications and other electronic equipment manufacturing	Main business income	CNY100 million	+
		Number of employees	10,000	+
	Telecommunications broadcast television and satellite transmission services	Total telecommunications business *per capita*	CNY 10,000	+
		Long-distance optical cable line length	10,000 km	+
		Mobile phone penetration rate	%	+
	Internet and related services	Internet penetration rate	%	+
		Number of Internet broadband access ports	Unit	+
		Number of websites *per capita*	Unit	+
	Software and information technology services	Per capita software business income	CNY 10,000	+
		Information technology service income *per capita*	CNY 10,000	+
Industrial digitalization	Digital application	The proportion of enterprises with e-commerce transactions	%	+
		E-commerce sales	CNY100 million	+
		Per capita express business volume	Piece	+
		Number of websites per 100 enterprises	Unit	+
		Digital inclusive financial index	—	+
Digital economy development environment	Innovation environment	R&D expenditure intensity	%	+
		Number of patent applications	10,000 piece	+
	Market circumstances	Whether to issue policies in support of the 'digital economy'	—	+
		Marketization index	—	+

where $Idigital_{cj}^{direct}$ represents the direct digital input intensity of industry j; Z_{cj} represents the intermediate input of digital industry c to industry j; X_j represents the total input of industry j. The calculation expression of complete digital input intensity is:

$$\boldsymbol{Idigital_{cj}^{complete} = Idigital_{cj}^{direct} + \sum_{k=1}^{n} Idigital_{ck}^{direct} Idigital_{kj}^{direct} + \sum_{s=1}^{n}\sum_{k=1}^{n} Idigital_{cs}^{direct} Idigital_{sk}^{direct} Idigital_{kj}^{direct} + \cdots}$$

Where $Idigital_{cj}^{complete}$ represents the full digital input intensity of industry j; the first item on the right side of the equal sign is the direct digital input intensity, and the subsequent items are the forward indirect digital input intensity, that is, the n+1th item is the nth indirect digital input intensity, which adds up to the complete digital input intensity. Considering that complete digital intermediate input can accurately measure the real situation of industry digitization, this paper uses the digital input intensity under the measurement of complete digital intermediate input to calculate the degree of industry digital transformation, and uses the degree of digital transformation obtained under the measurement of direct digital intermediate input as a substitution variable for subsequent robustness tests.

The data of digital input intensity are derived from China's multi-regional input-output table in 2012, 2015, and 2017 released by CEADs database. China's multi-regional input-output table contains 31 provinces and 42 economic sectors. Some sectors related to the digital economy only have some digital content, so this paper constructs the digital industry stripping coefficient to separate the digital content part. The digital industry stripping coefficient is the proportion of digital output in the total output of the industry containing digital content. The formula is expressed as:

$$\boldsymbol{\delta_{it} = X_{it}^{d} / X_{it}}$$

Among them, δ_{it} is the digital industry divestiture coefficient of industry i in year t, X_{it}^{d} is the digital output part of industry i in year t, and X_{it} is the total output of industry i in year t. Constrained by data constraints, this paper uses industry operating income to characterize total output to determine the digital industry stripping coefficient. Considering the change of digital output and total output in the time dimension, this paper determines the stripping coefficient of digital industry in different years. Since the China multi-regional input-output table is not continuous, this paper uses the digital industry divestiture coefficient to obtain digital intermediate input data for consecutive years from 2012 to 2018.

According to the definition of the core industries of the digital economy in the "Statistical Classification of Digital Economy and Its Core Industries (2021)", this paper constructs a measurement system for the development level of digital economy from three dimensions: digital industrialization, industrial digitization and digital economic development environment (Zhang J et al., 2022; Lyu et al., 2023), as shown in Table 2. The marketization index data in the sample are derived from the "China Provincial Marketization Index Report

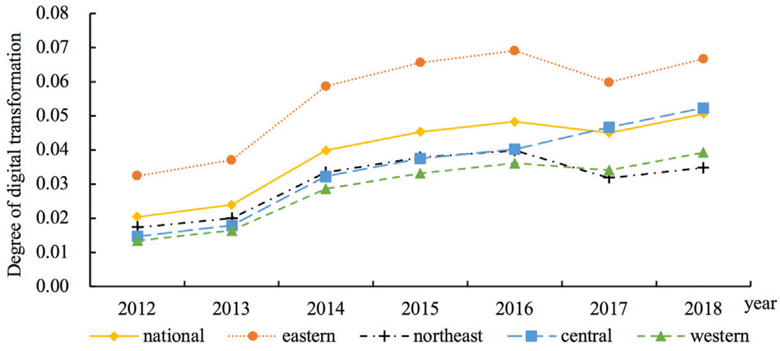


FIGURE 2
Evolution trend of average degree of digital transformation of manufacturing industry in china and four regions.

(2021)", the Digital Inclusive Finance Index is derived from the "Peking University Digital Inclusive Finance Index (2011–2020)", and other data are derived from the "China Statistical Yearbook", "China Information Yearbook" and the CSMAR digital economy database. In order to avoid the subjectivity of the evaluation results and fully reflect the original information of the data, the entropy method is used to measure the level of digital economy development at the provincial level.

3.2.2 Results and analysis

According to the measurement model constructed above, the degree of digital transformation of manufacturing industry in China's provinces from 2012 to 2018 is measured. Figure 2 shows the changes in the degree of digital transformation of manufacturing industry in the whole country and its four major regions. Overall, from 2012 to 2018, the degree of digital transformation of manufacturing in various regions of the country is on the rise. In terms of time nodes, 2012–2015 is a period of rapid growth of digital transformation of manufacturing industry in various regions. This period is a period of rapid integration of digital technology and real economy. The demand for digital input in manufacturing industry is strong, and the degree of digital transformation shows rapid growth. From 2016 to 2018, it was a stage of fluctuating growth. During this period, the growth rate of digital transformation of manufacturing industry slowed down, and it decreased slightly in 2017. The reason for this trend may be that the scale dividend in the early stage of digital transformation of manufacturing industry gradually disappeared, the transformation entered a mature stage of development, and the demand for digital input was relatively stable.

From the perspective of regional differences, the eastern region has the highest degree of digital transformation of manufacturing industry, which has remained above the national average. The degree of digital transformation of manufacturing industry in the central, western and northeastern regions is similar and lower than the national average. It is worth noting that the digital transformation gap between the eastern and central regions and the western and northeastern regions has been expanding year by year, which to some extent reflects the "digital divide" phenomenon caused by unbalanced regional development in the digital era.

Table 3 shows the average degree of digital transformation at the two-digit industry level in 2012, 2015, and 2018. On the whole, from 2012 to 2018, the degree of digital transformation in China's manufacturing industries is on the rise. From the perspective of industry differences, communication electronic equipment, instrumentation and electrical machinery and equipment are the industries with the highest degree of digital transformation, which are mostly high-end manufacturing industries with low energy consumption and obvious technical characteristics. Petroleum processing, metal smelting, food and tobacco are industries with low degree of digital transformation. Most of these industries are traditional manufacturing industries. The traditional production mode is relatively solid, the pace of digital transformation is relatively slow, and the degree of transformation is low. This industry difference shows that it is urgent to promote the digital transformation of traditional manufacturing industry.

4 Empirical design

4.1 Empirical model

This paper uses high-dimensional panel data at the provincial and industry levels in China from 2012 to 2018 to empirically study the impact of digital transformation on low-carbon development of manufacturing. The high-dimensional fixed effect model is constructed as follows:

$$\boldsymbol{Lcp_{ijt}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 Digital_{ijt}} + \boldsymbol{\beta Control_{ijt}} + \boldsymbol{\mu_i} + \boldsymbol{\mu_j} + \boldsymbol{\mu_t} + \boldsymbol{\varepsilon_{ijt}}$$

Among them, Lcp_{ijt} is the level of low-carbon development, $Digital_{ijt}$ is the degree of digital transformation, and $Control_{ijt}$ represents the collection of control variables; μ_i、 μ_j and μ_t are province effect, industry effect and time fixed effect respectively; ε_{ijt} is random error term; subscripts i, j and t represent province, industry, and year, respectively. The model mainly focuses on the symbol, size and significance level of the coefficient α_1.

4.2 Variables

The explanatory variable is the level of low-carbon development in manufacturing (Lcp). The core explanatory variable is the degree of digital transformation in manufacturing ($Digital$). The mechanism variable is the level of technological innovation (*Innov*), which is measured by the proportion of industry patents in national patents.

TABLE 3 Measurement results of digital transformation degree of manufacturing industry.

Industry code	Abbreviation	2012	Rank	2015	Rank	2018	Rank
6	Food and tobacco	0.0086	17	0.0197	17	0.0230	16
7	Textile industry	0.0090	16	0.0215	16	0.0269	14
8	Manufacture of leather, fur, feather and related products	0.0132	9	0.0262	13	0.0330	9
9	Processing of timber and furniture	0.0105	13	0.0239	15	0.0301	12
10	Paper printing cultural education sports	0.0120	12	0.0304	11	0.0318	11
11	Petroleum processing	0.0102	15	0.0250	14	0.0205	17
12	Chemical products	0.0134	8	0.0333	9	0.0340	8
13	Non-metallic products	0.0130	10	0.0344	8	0.0327	10
14	Metal smelting	0.0103	14	0.0301	12	0.0230	15
15	Metal products	0.0129	11	0.0327	10	0.0296	13
16	General purpose machinery	0.0199	4	0.0479	4	0.0469	5
17	Special purpose machinery	0.0182	6	0.0435	5	0.0471	4
18	Transportation equipment	0.0169	7	0.0380	7	0.0409	6
19	Electrical machinery and equipment	0.0234	3	0.0553	3	0.0607	3
20	Communication electronic equipment	0.0932	1	0.1761	1	0.2394	1
21	Instrumentation	0.0431	2	0.0926	2	0.1021	2
22	Other manufactured goods	0.0184	5	0.0390	6	0.0380	7

According to the existing research conclusions, this paper selects the following control variables: Energy consumption structure (Es). The energy consumption structure is measured using the proportion of coal energy consumption in the manufacturing industry's total energy consumption. Production factor structure (Fe). Capital and labor are the two most basic production factors in production activities. Therefore, the ratio of capital stock to labor force is used to measure production factor structure. R&D investment intensity ($Lnrd$). R&D investment intensity is represented by the logarithm of internal expenditure of research and experimental development funds of industrial enterprises above designated size. It is generally believed that green technology innovation is the basis for achieving low-carbon production, and R&D investment, as an important source of green technology innovation, should have a positive impact on achieving low-carbon development. Environmental regulation intensity ($Ereg$). The environmental regulation intensity index was constructed by using the industrial wastewater discharge compliance rate, industrial sulfur dioxide removal rate, industrial smoke (powder) dust removal rate and solid waste comprehensive utilization rate. Level of openness ($Lnfdi$). The opening level is measured by the logarithmic form of the total amount of foreign capital actually utilized. Government intervention (Gov). Considering that local fiscal expenditure is an important index to reflect‘s participation in economic activities, this paper uses the ratio of fiscal expenditure deducting education expenditure to regional GDP as the proxy variable of government intervention (Li and Lin, 2017).

TABLE 4 Descriptive statistics of main variables.

Variables	Obs	Mean	Std.Dev.	Min	Max
Lcp	3570	0.181	0.205	0.001	5.742
$Digtial$	3570	0.039	0.049	0.001	0.537
Es	3570	0.220	0.221	0.000	0.992
Fe	3570	0.020	0.082	0.000	1.861
$Lnrd$	3570	5.087	1.331	1.872	7.653
$Ereg$	3570	0.510	0.534	0.000	2.585
$Lnfdi$	3570	5.366	1.944	−2.345	7.722
Gov	3570	0.224	0.103	0.096	0.672

4.3 Data sources

The sample period of this paper is 2012–2018, and 17 two-digit manufacturing industries in 30 provinces in China are selected for the study. The control variable data comes from "China Statistical Yearbook", "China Industrial Statistical Yearbook", "China Economic Census Yearbook", "China Science and Technology Statistical Yearbook", provincial statistical yearbooks and CEADs database. Variable data are provided in the Supplementary Table S1. The descriptive statistics of the main variables are shown in Table 4.

TABLE 5 Results of benchmark regression and further analysis[a].

Variables	(1)	(2)	(3)	(4)	(5)
Digital	0.2382**	0.3084***			
	(2.2640)	(2.9262)			
Digital_id			0.4001*** (3.2560)		
Digital_di				0.2067*** (2.6033)	
Digital_de					0.2079** (2.2106)
Es		−0.0626***	−0.0629***	−0.0618***	−0.0617***
		(−3.4748)	(−3.4922)	(−3.4336)	(−3.4219)
Fe		0.1891***	0.1907***	0.1860***	0.1868***
		(4.9833)	(5.0271)	(4.9105)	(4.9174)
Lnrd		0.0685***	0.0686***	0.0693***	0.0678***
		(3.3168)	(3.3217)	(3.3535)	(3.2784)
Ereg		−0.0538***	−0.0536***	−0.0533***	−0.0545***
		(−2.8338)	(−2.8289)	(−2.8085)	(−2.8710)
Lnfdi		−0.0033	−0.0031	−0.0035	−0.0033
		(−1.0209)	(−0.9605)	(−1.0796)	(−1.0009)
Gov		−0.5435***	−0.5460***	−0.5401***	−0.5517***
		(-3.0520)	(-3.0676)	(-3.0308)	(-3.0976)
Constant	0.1715***	−0.0027	−0.0040	−0.0055	0.0063
	(34.0161)	(−0.0238)	(−0.0356)	(−0.0487)	(0.0558)
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect Year effect	*YES* *YES*	*YES* *YES*	*YES* *YES*	*YES* *YES*	*YES* *YES*
$Adj.R^2$	0.2819	0.2954	0.2958	0.2950	0.2946
Obs	3570	3570	3570	3570	3570

[a]The ***, **, and * in the table represent the significant levels of 1%, 5%, and 10%, respectively. The t statistic is in parentheses. The following table has the same meaning.

5 Empirical results and analysis

5.1 Benchmark regression results

Considering that industry differences, regional differences and time factors may have an impact on the estimation results, this paper uses high-dimensional fixed effects model for parameter estimation. The benchmark regression results are shown in Table 5. Among them, column 1) is the estimation result without control variables, and the estimation coefficient of the core explanatory variable is significantly positive at the 5% level. Column 2) is the estimated result of adding control variables. The estimated coefficient of digital transformation is still significantly positive and can reject the null hypothesis at the 1% level. The above results show that digital transformation can significantly promote the low-carbon development level of manufacturing industry. H1 of this paper is verified. Digital transformation can strengthen the synergy between the upstream and downstream of the industrial chain and reduce unnecessary losses in the production process, which has a positive impact on promoting low-carbon development.

The control variable symbol is consistent with expectations. The impact coefficient of energy consumption structure on low-carbon development was significantly negative at the level of 1%, indicating that the excessive proportion of coal energy consumption was not conducive to the improvement of low-carbon development level of the manufacturing industry. The structure of production factors has a significant role in promoting the low-carbon development of manufacturing industry. The regression coefficient of R&D investment is positive, indicating that increasing R&D investment in manufacturing can help its low-carbon development. The impact of government intervention on low-carbon development is negative, which may be because excessive government intervention in the market harms the level playing field. The regression coefficient of environmental regulation is positive, indicating that environmental regulation can promote the low-carbon development of manufacturing industry. The regression coefficient of openness is negative, but the result is not significant, indicating that foreign investment has not effectively promoted the low-carbon development level of manufacturing industry.

TABLE 6 Results of stability test.

Variables	(1)	(2)	(3)	(4)	(5)
	Lcp_sbm	*Lcp*	*Lcp_cp*	*Lcp_ct*	*Lcp*
Digital	0.2632***		0.7034***	−0.8312***	0.3084***
	(3.1872)		(5.2535)	(−4.2942)	(2.9262)
$Digital^{direct}$		0.5154***			
		(2.6856)			
Control variables	*YES*	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect	*YES*	*YES*	*YES*	*YES*	*YES*
Year effect	*YES*	*YES*	*YES*	*YES*	*YES*
$Adj.R^2$	0.3952	0.2951	0.1892	0.0921	0.2954
Obs	3570	3570	3570	3570	3570

5.2 Further analysis

Exploring the impact of sub-indicators of digital transformation on the low-carbon development of manufacturing industry is of great significance for optimizing the digital transformation strategy to give full play to its low-carbon effect. This paper divides the development level of regional digital economy into three dimensions: digital industrialization ($Digital\_id$), industrial digitization ($Digital\_di$) and digital development environment ($Digital\_de$), and constructs sub-indicators of digital transformation based on this. The sub-indicators of digital transformation were used as the explanatory variables for regression, and the results were shown in columns (3)–(5) in Table 5. It can be found that all sub-indicators of digital transformation have a significant positive impact on the low-carbon development of the manufacturing industry, but their impact is different. Among them, the effect of digital industrialization on the low-carbon development of manufacturing industry is the most obvious. The promoting effect of industrial digitalization and digital development environment on low-carbon development of manufacturing industry is weaker than that of digital industrialization. As the foundation of the development of the digital economy, digital industrialization plays a supporting role in the digital transformation of the manufacturing industry. At the current stage, digital industrialization is developing faster and the most mature, so its positive effect on promoting the low-carbon development of manufacturing industry is strong. Industrial digitalization also plays a positive role in promoting the low-carbon development of the manufacturing industry, but due to cost and technology constraints, the process of industrial digitalization lags behind digital industrialization. The digital development environment mainly affects the low-carbon development of the manufacturing industry by promoting digital transformation, so its impact effect is weaker than that of digital industrialization. Further analysis shows that in order to give full play to the role of digital transformation in the low-carbon development of the manufacturing industry, it is necessary to accelerate the process of digital industrialization and industrial digitization, and the importance of the digital development environment cannot be ignored.

5.3 Robustness test

5.3.1 Replace the key variable measurement method

First, the SBM model is used to recalculate the low-carbon development level of manufacturing industry. Second, the measurement method of replacing the core explanatory variables. The degree of digital transformation ($Digital^{direct}$) measured by the direct digital intermediate input method is used as the core explanatory variable. The estimation results after replacing the main variables are shown in columns (1)–(2) of Table 6.

5.3.2 Replace the measurement indicators of low-carbon development level

The connotation of low-carbon development of manufacturing industry is rich, and excessive reliance on single indicators will inevitably make the research conclusion one-sided. Therefore, drawing on the measurement of low-carbon development level in existing literature, single-factor low-carbon production efficiency (i.e., output per unit of carbon emissions) and carbon emission intensity are used as indicators of low-carbon development level of manufacturing industry to re-estimate the benchmark model (Kaya and Yokobori, 1997). The results are shown in columns (3)–(4) of Table 6.

5.3.3 Processing extreme values

OLS estimation method is susceptible to extreme values. If there are extreme values in the data set, it will cause the regression curve to shift in the direction of extreme values, making the estimated results deviate from the real situation. Therefore, the bilateral extreme values of all variables are indented according to the 5% and 95% quantiles, respectively, and the parameters are re-estimated. The estimation results are shown in column (5) of Table 6.

TABLE 7 Results of endogenous treatment.

Variables	IV-2SLS				SYS-GMM
	(1)	(2)	(3)	(4)	(5)
$L1.Lcp$[a]					0.7511***
					(11.8342)
Digital	0.2611**	0.3840**	0.4557*	0.3474**	0.2112***
	(2.0060)	(2.1287)	(1.8962)	(2.4371)	(3.2498)
Control variables	*YES*	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect	*YES*	*YES*	*YES*	*YES*	*YES*
Year effect	*YES*	*YES*	*YES*	*YES*	*YES*
Anderson test	2392.0370***	1358.9540***	874.6510***	1951.0610***	—
Cragg-Donald test	11000 {16.38}[b]	2844.4530 {16.38}	1489.089 {16.38}	4231.2750 {16.38}	—
AR (1) test	—	—	—	—	0.029
AR (2) test	—	—	—	—	0.361
Hansen test	—	—	—	—	0.115
$Adj.R^2$	0.0184	0.0173	0.0132	0.0202	—
Obs	3060	2550	2040	3570	3060

[a]*L1.* represents one period lagged variable.
[b]The critical value of the Stock-Yogo test at the 10% level is within {}.

The above robustness test results show that the positive impact of digital transformation on low-carbon development is still significant, indicating that the core conclusions of this paper are robust.

5.4 Endogenous treatment

Effectively controlling endogeneity is key to accurately identifying the causal relationship between digital transformation and low-carbon development. First of all, this paper attempts to use digital transformation lag phase I, lag phase II and lag phase III as the instrumental variables of the current digital transformation. China's industrial digital transformation often has the characteristics of top-down and step-by-step, so the current digital process is rooted in the previous accumulation. At the same time, the current low-carbon development level will not interfere with the previous digital process. This satisfies the exogeneity and relevance criteria for instrumental variable selection. Columns (1)–(3) in Table 7 show the estimation results of two-stage least squares (2SLS). Anderson test and Cragg-Donald test show that the model does not have the problem of unidentifiable and weak instrumental variables, indicating that the instrumental variables are effective. The regression coefficients of digital transformation are significantly positive, indicating that digital transformation can still effectively promote the low-carbon development of manufacturing industry after dealing with potential endogenous problems.

In addition, the instrumental variable construction method proposed by Lewbel has been widely used in existing research (Lewbel, 1997). Miruna (2022) used this idea to construct the instrumental variables of Industry 4.0. Wang Q et al. (2022) used this method to construct instrumental variables of the degree of digitization at the provincial level in China. The above research verifies the effectiveness of this instrumental variable construction method. Therefore, this paper refers to Lewbel's idea, using the digital transformation variable and the corresponding industry digital transformation mean difference of three power as the instrumental variable of digital transformation (Lewbel_IV). The 2SLS estimation results are shown in column (4) of Table 7. The Anderson test and the Cragg-Donald test show that the instrumental variables are valid. The estimated coefficients of the core explanatory variables are in good agreement with the benchmark regression results, which again shows that the digital transformation of the manufacturing industry has a promoting effect on low-carbon development.

Further, this paper uses the generalized moment estimation method (GMM) to alleviate the endogenous bias caused by problems such as two-way causality and missing variables. Considering that the difference generalized moment estimation method (DIF-GMM) still has the problem of weak instrumental variables, and the two-step estimation is more effective than the one-step estimation, this paper uses the two-step system generalized moment estimation method (SYS-GMM) to deal with endogeneity. The estimation results of the two-step SYS-GMM are shown in column (5) of Table 7. Among them, the Arellano-Bond test and the Hansen test show that the instrumental variables are valid and that the model does not have over-identification problems and satisfies the two-step SYS-GMM usage conditions (Arellano and Bover, 1995; Blundell and Bond, 1998). From the estimation results, the coefficient of the core explanatory variable is significantly positive at the 5% level.

10.3389/fenvs.2023.1134882

TABLE 8 Results of heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)
	Developed regions	Underdeveloped regions	High-energy-consuming industry	Medium-low-energy-consuming industry
Digital	0.2827*	0.3298**	0.5272	0.2747**
	(1.6688)	(2.1533)	(1.1357)	(2.2727)
Control variables	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*
Industry effect Year effect	*YES* *YES*	*YES* *YES*	*YES* *YES*	*YES* *YES*
$Adj.R^2$	0.2815	0.3408	0.4893	0.2880
Obs	1564	2006	1050	2520

The two-step SYS-GMM regression results are basically consistent with the benchmark regression results, which verifies the robustness of the basic conclusions of this paper.

5.5 Heterogeneity analysis

5.5.1 Heterogeneity of regional economic development level

Heterogeneity analysis based on regional economic development level. In order to explore the impact of digital transformation on the low-carbon development of manufacturing industry in different economic development levels. In this paper, the average *per capita* GDP of each region is used as the standard, and the whole sample is divided into developed regions and underdeveloped regions and makes regression respectively. From the regression results in Table 8, digital transformation has a significant positive impact on the low-carbon development of the manufacturing industry, whether in developed regions or underdeveloped regions, but the magnitude of the impact is different. The impact of digital transformation in underdeveloped areas on the low-carbon development of manufacturing industry is higher than that in developed areas. This may be due to the fact that the manufacturing industry in developed regions is in a higher stage of development, the low-carbon production level itself is high, and the role of digital empowerment in its low-carbon development is relatively limited, while the low-carbon production capacity in underdeveloped regions is relatively weak, with greater room for improvement, and the effect of digital empowerment is higher than that in developed regions.

5.5.2 Heterogeneity of industrial energy consumption level

Heterogeneity analysis based on industry energy consumption types. There are great differences in energy consumption among different manufacturing industries. Therefore, according to the "2010 National Economic and Social Development Statistical Report", this paper divides 17 manufacturing industries into high-energy-consuming industry groups and medium-low-energy-consuming industries groups for heterogeneity analysis. From the results of Table 8, it can be found that digital transformation has a positive impact on low-carbon development in both high-energy-consuming industries and medium-low-energy-consuming industries, but the regression results of high-energy-consuming industries are not significant. There may be two reasons: First, the degree of digital transformation of high-energy-consuming industries is relatively low, and the energy-saving effect, technological innovation effect and resource allocation optimization effect of digital transformation have not yet been formed. Second, high-energy-consuming industries are often traditional manufacturing sectors, many factors restricting green development, may lead to the promotion of digital transformation is offset.

TABLE 9 Results of mechanism test.

Variables	(1)	(2)
	Innov	***Lcp***
Digital	0.021***	0.2845***
	(7.7192)	(2.6775)
Innov	—	1.112* (1.74)
Control variables	*YES*	*YES*
Province effect	*YES*	*YES*
Industry effect Year effect	*YES* *YES*	*YES* *YES*
$Adj.R^2$	0.9924	0.2960
Obs	3570	3570

5.6 Mechanism test

According to theoretical analysis, digital transformation promotes low-carbon development of manufacturing industry through technological innovation effect. This paper constructs a mediation model to test this mechanism. The model is constructed as follows:

$$Innov_{ijt} = \rho_0 + \rho_1 Digital_{ijt} + \delta Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$
$$Lcp_{ijt} = \alpha_0 + \alpha_1 Digital_{ijt} + \beta Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$
$$Lcp_{ijt} = \sigma_0 + \sigma_1 Digital_{ijt} + \gamma Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$

Among them, $Innov_{ijt}$ represents the mechanism variable, and the other variables mean the same as the benchmark model. The mechanism test is divided into three steps: First, the core explanatory variables and mechanism variables are regressed, and the regression coefficient represents the impact of digital transformation on technological innovation. Secondly, we will return to digital transformation and low-carbon development. Finally, digital transformation and technological innovation are included in the regression equation to verify whether the digital economy has an impact on low-carbon development through technological innovation.

The mechanism test results are shown in Table 9, where column 1 shows that digital transformation has a significant role in promoting technological innovation and passes the 1% significance test. Column 2 shows that both digital transformation and technological innovation have significantly promoted low-carbon development and passed the 10% significance test. The above results show that digital transformation promotes low-carbon development of manufacturing industry through technological innovation effect. H2 of this paper is verified. Low-carbon development is closely related to technological innovation. Digital transformation can promote low-carbon technology innovation by diffusing innovation elements, which in turn can promote low-carbon development.

6 Conclusion

Using the matching data of China Industrial Economy Database, CEADs Database and China‘s multi-regional input-output table, this paper constructs a measurement framework for the low-carbon development level and digital transformation degree of 17 manufacturing industries in 30 provinces in China, and conducts an empirical study on the relationship between digital transformation and low-carbon development from the perspective of sub-regions and sub-industries. The results show that:

(1) The low-carbon development level of China‘s manufacturing industry is increasing year by year, but the development gap between regions and industries is large. At the regional level, the development level of the eastern and central regions is higher, and the development level of the western and northeastern regions is lower. At the industry level, the development level of medium-low-energy-consuming industries is higher, while that of high-energy-consuming industries is lower.
(2) The degree of digital transformation of China‘s manufacturing industry is on the rise, but there is an imbalance between regions and industries. At the regional level, the eastern region has a higher degree of transformation, while the central, western and northeastern regions have lagged behind. At the industry level, the high-end manufacturing industry has a higher degree of transformation, while the traditional manufacturing industry has a lower degree of transformation.
(3) The digital transformation of the manufacturing industry has a significant role in promoting its low-carbon development, and this conclusion still holds after the robustness tests such as changing the measurement method of variables, replacing core variables, dealing with extreme values and considering endogeneity.
(4) For sub-indicators, digital industrialization, industrial digitization and digital development environment can significantly promote the low-carbon development of manufacturing industry. Among them, the impact of digital industrialization is the most obvious.
(5) The impact of digital transformation of manufacturing on its low-carbon development is heterogeneous across regions and industries. The low-carbon effect of digital transformation in underdeveloped areas is higher than that in developed areas. The low-carbon effect of digital transformation in medium-low-energy-consuming industries is obvious, but the low-carbon effect of digital transformation in high-energy-consuming industries has not appeared.
(6) The mechanism test results show that technological innovation is an important channel for digital transformation to promote the low-carbon development of the manufacturing industry.

The policy orientation of the research conclusion is clear. The government should actively affirm the environmental performance of digital transformation and create a good external environment for the digital transformation of manufacturing industry. On the one hand, the government should continue to increase investment in digital infrastructure to provide support for the digital transformation of the manufacturing industry. On the other hand, the government should actively promote cooperation between enterprises and universities, scientific research institutions and other institutions, establish a technology exchange platform, open up digital technology application channels, and accelerate the application of digital technology. In addition, the differences in digital transformation in different regions and industries should be taken seriously to avoid further widening the gap. By formulating differentiated support policies, providing policy support for backward areas can narrow the development gap. At the same time, the construction of big data platform can provide more adequate data resource services for traditional manufacturing enterprises, which is conducive to the digital transformation of enterprises.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

YL: Conceptualization, methodology, resources, validation. LZ: Data curation, Software, writing-original draft preparation, visualization. DW: Writing-reviewing and editing, supervision.

Funding

This work was supported by the National Social Science Foundation of China (Grant No. 18BJY006) and Fujian Social Science Foundation Project (Grant No. FJ2022B081).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1134882/full#supplementary-material

References

Andersen, P., and Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Manage. Sci.* 39, 1261–1264. doi:10.1287/mnsc.39.10.1261

Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68, 29–51. doi:10.1016/0304-4076(94)01642-D

Arnold, J. M., Javorcik, B., Lipscomb, M., and Mattoo, A. (2016). Services reform and manufacturing performance: Evidence from India. *Econ. J.* 126, 1–39. doi:10.1111/ecoj.12206

Avom, D., Nkengfack, H., Fotio, H. K., and Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technol. Forecast. Soc.* 155, 120028. doi:10.1016/j.techfore.2020.120028

Balcerzak, A. P., and Pietrzak, M. B. (2017). Digital economy in Polish regions. Proposal of measurement via TOPSIS with generalized distance measure GDM. Working Papers.

Ballestar, M. T., Camiña, E., Díaz-Chao, Á., and Torrent-Sellens, J. (2021). Productivity and employment effects of digital complementarities. *J. Innov. Knowl.* 6, 177–190. doi:10.1016/j.jik.2020.10.006

Bhimani, A. (2015). Exploring big data's strategic consequences. *J. Inf. Technol.* 30, 66–69. doi:10.1057/jit.2014.29

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econom.* 87, 115–143. doi:10.1016/S0304-4076(98)00009-8

Chen, P. (2022). Is the digital economy driving clean energy development? New evidence from 276 cities in China. *J. Clean. Prod.* 372, 133783. doi:10.1016/j.jclepro.2022.133783

Chen, S., and Golley, J. (2014). Green' productivity growth in China's industrial economy. *Energy Econ.* 44, 89–98. doi:10.1016/j.eneco.2014.04.002

Daron, A., Philippe, A., Leonardo, B., and David, H. (2012). The environment and directed technical change. *Am. Econ. Rev.* 102, 131–166. doi:10.1257/aer.102.1.131

El-Kassar, A., and Singh, S. K. (2019). Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc.* 144, 483–498. doi:10.1016/j.techfore.2017.12.016

Feng, H., Wang, F., Song, G., and Liu, L. (2022). Digital transformation on enterprise green innovation: Effect and transmission mechanism. *Int. J. Environ. Res. Public Health* 19, 10614. doi:10.3390/IJERPH191710614

Gaglio, C., Kraemer-Mbula, E., and Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technol. Forecast. Soc.* 182, 121785. doi:10.1016/j.techfore.2022.121785

Ge, W., Xu, Y., Liu, G., Shen, B., Su, X., Liu, L., et al. (2022). Exploring the impact of the digital economy on carbon emission efficiency under factor misallocation constraints: New insights from China. *Front. Environ. Sci.* 10, 953070. doi:10.3389/FENVS.2022.953070

Goldbach, K., Rotaru, A. M., Reichert, S., Stiff, G., and Gölz, S. (2018). Which digital energy services improve energy efficiency? A multi-criteria investigation with European experts. *Energy Policy* 115, 239–248. doi:10.1016/j.enpol.2017.12.036

Goldfarb, A., Greenstein, S. M., and Tucker, C. E. (2015). *Economic analysis of the digital economy*. Chicago, America: University of Chicago Press.

Kaija, V., Ralf-Martin, S., and Einari, K. (2022). Implications of digitalization in facilitating socio-technical energy transitions in Europe. *Energy Res. Soc. Sci.* 91, 102720. doi:10.1016/J.ERSS.2022.102720

Kaya, Y., and Yokobori, K. (1997). *Environment, energy and economy: Strategies for sustainability*. Tokyo, Japan: United Nations University Press.

Lange, S., Pohl, J., and Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecol. Econ.* 176, 106760. doi:10.1016/j.ecolecon.2020.106760

Leung, D. Y. C., Caramanna, G., and Maroto-Valer, M. M. (2014). An overview of current status of carbon dioxide capture and storage technologies. *Renew. Sustain. Energy. Rev.* 39, 426–443. doi:10.1016/j.rser.2014.07.093

Lewbel, A. (1997). Constructing instruments for regressions with measurement error when no additional data are available, with an application to patents and R&D. *Econometrica* 65, 1201. doi:10.2307/2171884

Li, G., and Liao, F. (2022). Input digitalization and green total factor productivity under the constraint of carbon emissions. *J. Clean. Prod.* 377, 134403. doi:10.1016/j.jclepro.2022.134403

Li, J., and Lin, B. (2017). Does energy and CO2 emissions performance of China benefit from regional integration? *Energy Policy* 101, 366–378. doi:10.1016/j.enpol.2016.10.036

Liu, Y., Yang, Y., Li, H., and Zhong, K. (2022). Digital economy development, industrial structure upgrading and green total factor productivity: Empirical evidence from China's cities. *Int. J. Environ. Res. Public Health* 19, 2414. doi:10.3390/IJERPH19042414

Luo, K., Liu, Y., Chen, P., and Zeng, M. (2022). Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. *Energy Econ.* 112, 106127. doi:10.1016/j.eneco.2022.106127

Lyu, Y., Wang, W., Wu, Y., and Zhang, J. (2023). How does digital economy affect green total factor productivity? Evidence from China. *Sci. Total Environ.* 857, 159428. doi:10.1016/j.scitotenv.2022.159428

Mićić, L. (2017). Digital transformation and its influence on GDP. *Economics* 5, 135–147. doi:10.1515/eoik-2017-0028

Miruna, S. (2022). The impact of industry 4.0 on innovation performance: Insights from German manufacturing and service firms. *Technovation* 113, 102415. doi:10.1016/j.technovation.2021.102415

Moyer, J. D., and Hughes, B. B. (2012). ICTs: Do they contribute to increased carbon emissions? *Technol. Forecast. Soc.* 79, 919–931. doi:10.1016/j.techfore.2011.12.005

Nambisan, S., Wright, M., and Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Res. Policy* 48, 103773. doi:10.1016/j.respol.2019.03.018

Ning, J., Yin, Q., and Yan, A. (2022). How does the digital economy promote green technology innovation by manufacturing enterprises? Evidence from China. *Front. Environ. Sci.* 10, 967588. doi:10.3389/FENVS.2022.967588

Niu, Y., Wen, W., Wang, S., and Li, S. (2023). Breaking barriers to innovation: The power of digital transformation. *Financ. Res. Lett.* 51, 103457. doi:10.1016/J.FRL.2022.103457

Pan, W., Xie, T., Wang, Z., and Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *J. Bus. Res.* 139, 303–311. doi:10.1016/j.jbusres.2021.09.061

Peng, C., Jia, X., and Zou, Y. (2022). Does digitalization drive corporate green transformation? based on evidence from Chinese listed companies. *Front. Environ. Sci.* 10, 963878. doi:10.3389/FENVS.2022.963878

Ren, S., Hao, Y., Xu, L., Wu, H., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

Salahuddin, M., and Alam, K. (2015). Internet usage, electricity consumption and economic growth in Australia: A time series evidence. *Telemat. Inf.* 32, 862–878. doi:10.1016/j.tele.2015.04.011

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle cambridge, britain*. Cambridge, Mass: Harvard University Press.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi:10.1016/S0377-2217(99)00407-5

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 143, 32–41. doi:10.1016/S0377-2217(01)00324-1

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., et al. (2019). Digital transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* 122, 889–901. doi:10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *J. Strateg. Inf. Syst.* 28, 118–144. doi:10.1016/j.jsis.2019.01.003

Wang, J., Dong, K., Sha, Y., and Yan, C. (2022). Envisaging the carbon emissions efficiency of digitalization: The case of the internet economy for China. *Technol. Forecast. Soc.* 184, 121965. doi:10.1016/j.techfore.2022.121965

Wang, Q., Hu, A., and Tian, Z. (2022). Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. *Energy Econ.* 115, 106346. doi:10.1016/j.eneco.2022.106346

Wu, B., and Yang, W. (2022). Empirical test of the impact of the digital economy on China's employment structure. *Financ. Res. Lett.* 49, 103047. doi:10.1016/j.frl.2022.103047

Wu, L., Sun, L., Chang, Q., Zhang, D., and Qi, P. (2022). How do digitalization capabilities enable open innovation in manufacturing enterprises? A multiple case study based on resource integration perspective. *Technol. Forecast. Soc.* 184, 122019. doi:10.1016/j.techfore.2022.122019

Xia, J., Wu, Z., and Chen, B. (2022). How digital transformation improves corporate environmental management: A review and research agenda. *Front. Environ. Sci.* 10. doi:10.3389/FENVS.2022.943843

Xu, L., Fan, M., Yang, L., and Shao, S. (2021). Heterogeneous green innovations and carbon emission performance: Evidence at China's city level. *Energy Econ.* 99, 105269. doi:10.1016/J.ENECO.2021.105269

Yi, M., Liu, Y., Sheng, M. S., and Wen, L. (2022). Effects of digital economy on carbon emission reduction: New evidence from China. *Energy Policy* 171, 113271. doi:10.1016/j.enpol.2022.113271

Yu, Z., Liu, S., and Zhu, Z. (2022). Has the digital economy reduced carbon emissions? Analysis based on panel data of 278 cities in China. *Int. J. Environ. Res. Public Health* 19, 11814. doi:10.3390/IJERPH191811814

Zha, Q., Huang, C., and Kumari, S. (2022). The impact of digital economy development on carbon emissions - based on the Yangtze River Delta urban agglomeration. *Front. Environ. Sci.* 10, 750. doi:10.3389/FENVS.2022.1028750

Zhang, C., Chen, P., and Hao, Y. (2022). The impact of digital transformation on corporate sustainability-new evidence from Chinese listed companies. *Front. Environ. Sci.* 10, 418. doi:10.3389/FENVS.2022.1047418

Zhang, J., Lyu, Y., Li, Y., and Geng, Y. (2022). Digital economy: An innovation driving factor for low-carbon development. *Environ. Impact Assess. Rev.* 96, 106821. doi:10.1016/j.eiar.2022.106821

Zhang, L., Mu, R., Zhan, Y., Yu, J., Liu, L., Yu, Y., et al. (2022). Digital economy, energy efficiency, and carbon emissions: Evidence from provincial panel data in China. *Sci. Total Environ.* 852, 158403. doi:10.1016/j.scitotenv.2022.158403

Zhang, W., Liu, X., Wang, D., and Zhou, J. (2022). Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* 165, 112927. doi:10.1016/J.ENPOL.2022.112927

Zhang, Z., Fu, W. K., and Ma, L. (2022). The impact of digital economy on green development in China. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.991278

Zhang, H., Gao, S., and Zhou, P. (2023). Role of digitalization in energy storage technological innovation: Evidence from China. *Renew. Sustain. Energy. Rev.* 171, 113014. doi:10.1016/j.rser.2022.113014

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 03 February 2023
DOI 10.3389/fenvs.2023.1099008

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Ganeshkumar Chandirasekaran,
Indian Institute of Plantation Management, India
Vera Yurak,
Ural State Mining University, Russia
Anton Eitzinger,
International Center for Tropical Agriculture (CIAT), Colombia
Pouria Ataei,
Tarbiat Modares University, Iran

*CORRESPONDENCE
Longbao Wei,
lbwei@zju.edu.cn
Jingyuan Chen,
11320047@zju.edu.cn

†These authors have contributed equally to this work

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management, a section of the journal Frontiers in Environmental Science

RECEIVED 15 November 2022
ACCEPTED 23 January 2023
PUBLISHED 03 February 2023

CITATION
Manzoor F, Wei L and Chen J (2023), Empirical evaluation of ethical practices and digitalization of agricultural system with the mediation of user behavior: A case study of Pakistan.
Front. Environ. Sci. 11:1099008.
doi: 10.3389/fenvs.2023.1099008

Empirical evaluation of ethical practices and digitalization of agricultural system with the mediation of user behavior: A case study of Pakistan

Faiza Manzoor[1†], Longbao Wei[1*†] and Jingyuan Chen[2*†]

[1]Department of Agricultural Economics and Management, School of Public Affairs, Zhejiang University, Hangzhou, China, [2]School of Management, Zhejiang University, Zhejiang, China

Pakistan is one developing country and 70% of the population is depending on Agriculture and faces a lack of innovation in the agriculture sector overall. the main objectives of our study were to i) identify ethical practices (knowledge-sharing, trustworthiness in loan providing, loyalty in professionalism, responsibility of actions, and accountability) of the agriculture departments and institutions or government towards improving digital technology in the agriculture sector. ii) Quantify the user behavior in the digitalization of the agricultural system. iii) Identify the intervening role of user behavior in the relation to ethical practices and agricultural technology development. The study examined 490 users of farming technologies who work in the agriculture sector in two provinces of Pakistan. Using the Baron and Kenny framework, this research confirmed the prediction that user behavior mediated the relationship between ethical practices and agricultural technology in a four-step process. The main outcomes of the study have revealed a positive and significant impact of ethical practices on the development of the digitalization of the agricultural system. Specifically, the study indicated that "user behavior" significantly mediates the association between ethical practices and agricultural technology development. Furthermore, this study proposes that it is essential for Pakistan's agriculture sector to nurture circumstances dedicated to better practices as it will not only attract more residents to agricultural growth but also help the agriculture sector achieve its eventual goal of increased productivity. Implications of this research study are deliberated and provide directions for future research in the area.

KEYWORDS

ethical practices, digitalization, user behavior, development, agricultural system, Pakistan

1 Introduction

Digitalization, the socio-technical process of implementing digital innovations is a pervasive trend. Big data, the Internet of Things (IoT), augmented reality, robotics, sensors, 3D printing, system integration, ubiquitous connectivity, artificial intelligence, machine learning, digital twins and blockchain are examples of digitalization phenomena and technologies (Klerkx et al., 2019; Lo et al., 2021; Mihai et al., 2022). Digital agriculture, also known as smart farming or e-agriculture, is a tool that digitally collects, store, analyze, and share electronic data and/or information in the agriculture (Le Roux, 2022). These technologies can give the agricultural business the tools and data it needs to make better decisions and increase productivity (Saiz-Rubio and Rovira-Más, 2020). Agricultural products hold an inimitable place in human life and an inevitable requirement of livelihoods across the world. Advanced technologies to improve multiple aspects of agriculture have been developed in recent years (Pallathadka et al., 2021).

The global economy has entered a new phase due to the digitalization (Lorberg and Janusch, 2021). Sensors, drones, weather satellites, intelligent software algorithms, and robots are just a few examples of the technologies that make farming 'smart'. Drones and robots make time-consuming tasks more effective and efficient, such as irrigation, monitoring the health and location of a herd or driving it in a specific direction, sowing crops, and milking cows (Mohamed et al., 2021). Smart agriculture technology based on the Internet of Things (IoT) technologies has many advantages related to all agricultural processes and practices in real-time, which include irrigation and plant protection, improving product quality, fertilization process control, and disease prediction (Mohamed et al., 2021). Weather satellites and sensors provide information that can be used to tailor irrigation, fertilizer, and pesticides to the needs of plants, or to determine the best time to seed. Pesticides are sprayed over cropping areas in open-air or greenhouse settings to improve yield. Farmers can also use ML as part of precision agriculture management, in which agrichemicals are applied based on time, place, and affected crops. Farmers must accurately detect and classify crop quality features to increase product prices and reduce waste. Machines can use data to detect and reveal new traits that contribute significantly to crop quality. Agriculture's water management significantly impacts the agronomic, climatological, and hydrological balance. ML-based applications can estimate evapotranspiration daily weekly, or monthly, allowing irrigation systems to be used more effectively (Javaid et al., 2022).

Furthermore, all of these technologies provide data that can be aggregated and evaluated across farms in the region, providing farmers with even better insights (based on more data) and assisting them in reducing their environmental effects (Van der Burg et al., 2019). However, challenges persist in the development of digital agricultural and food technology, particularly in developing countries (Schelenz and Schopp, 2018). The developing nations have many challenges in implementing smart systems regarding the availability of infrastructure owned by the state and other capabilities possessed by individuals (Raza et al., 2022). Therefore, the barriers to the implementation of smart agricultural technology in developing countries can be explained simply: *a*) the availability of a suitable fourth or fifth-generation network is the most important factor in data transmission between sensors *via* the Internet. *b*) The availability of sensors as they are responsible for measuring the various phenomena and characteristics on the farm. *c*) Availability of devices and equipment capable of carrying out agricultural operations; *d*) trained experts based on smart farms. However, several factors also affect many farmers' adoption of smart farming technology, including weak socio-economic backgrounds and face many challenges due increasing cost of cultivation. These challenges need concrete strategies at different levels, from local to national. Many technological and natural science aspects of agricultural digitalization have a large quantity of literature (Kurbatova et al., 2019; Ukolova et al., 2020). Artificial intelligence, blockchain, big data, robotics, the IoT, system design, and other topics related to the technical optimization of farm production and food systems have gotten the most interest in this area. International research in this emerging field of agricultural technology has also concentrated on ethical innovation issues and principles (Eastwood et al., 2019; Lajoie-O'Malley et al., 2020). Therefore, an assessment of the existing literature has helped to recognize a significant gap that needs to be filled in this field. Empirical studies in this area are absent in the previous literature. However, there is a growing need for empirical evaluation of responsible and ethical activities to determine their protracted effect. To meet this aim, this research focuses on the empirical valuation to test the influence of ethical practices on the digitalization of the agricultural system of one developing country, Pakistan. We have developed a framework that allows gaining insight into the relations between ethical practices and the digitalization of the agriculture system.

People such as farmers, agripreneurs/agri-businesspersons/agri-entrepreneurs, as well as all others who work in the agriculture sector and use farming technology are users of agricultural technologies. User behavior refers to how individuals (users) engage with a product (Johansson, 2016). Mohamed and Hassan (2008) define "user behavior" as the way that people think, perceive, behave, and feel about information retrieval systems when they interact with a software interface. Furthermore, this study also focuses on the role of user behavior (users of agricultural technologies such as farmers, agripreneurs/agri-businesspersons/agri-entrepreneurs, etc.) as an intervening factor. Therefore, we can say that in this study, we also identify user behavior toward digital technologies in the context of the agriculture sector in Pakistan. Most importantly, we examine user behavior as a mediator role in the relationship between ethical practices and agricultural technology development. This approach provides a better understanding of the unknown impact. This is the first comprehensive research of its kind in Pakistan. The study's precise research questions are.

1. Do ethical practices (such as fairness in providing loans, respect for others, knowledge-sharing methods, honesty, loyalty, the responsibility of actions, and accountability of agricultural departments and institutions) affect the digitalization of the agricultural system in Pakistan?
2. Does user behavior play a mediating role in the relationship between ethical practices and agricultural technology development in Pakistan?

The study creates noteworthy contributions to the existing research by observing the interrelationship between ethical practices, digitalization of the agricultural system (agricultural technology development), and user behavior. Through the addition of the diffusion of innovation theory (Shang et al., 2021), we identify how ethical practices are associated with the digitalization of agricultural systems and user behavior in the agricultural sector, prolonging the inadequate research on the linkage between ethical practices and agricultural technology development. Furthermore, with limited research on ethical practices in Pakistan and the vast majority lacking clarity on ethical practices and the digitalization of the agricultural system in Pakistan, the study will benefit the Pakistani agricultural sector and help evaluate the role of ethical practices in digital agriculture on a global scale. Henceforth, the study attempts to recognize the gap and discourse in the arena of ethical practices in the agriculture sector by displaying how ethical practices increase agricultural technology development. The methodological contribution contains the usage of a mediation approach that will show how user behavior mediates the association between ethical practices and agricultural technology development.

The next sections make up the remainder of the research. The second step is to generate reviews and hypotheses from the acceptable literature. The third section discusses research methodologies. The fourth section goes with the study findings and discussion. In addition, section five contains a conclusion, limitations of the study, and future research directions.

2 Hypotheses development and research framework

Ethics theory is a theory or system that deals with human behavior values, such as the rightness and wrongness of specific activities, as well as the goodness and badness of the motives and ends of those actions (Frederiksen and Nielsen, 2013). Agricultural technology is becoming increasingly important, and development in technology has increased the scale, speed, and productivity of agricultural equipment, resulting in land more efficient cultivation. Seed, irrigation, and fertilizers have also considerably improved, assisting farmers in increasing harvests (Lopez, 2014). Ethical practices support the development of agricultural technology by dealing with the responsibility of actions in a professional manner while confirming the ethics theory (Madden and Thompson, 1987; Mahroof et al., 2021). Moreover, the ethical practices of agriculture departments also influence and motivate the users with the facilitation of the preeminent opportunities and services in digital technology (Kijsanayotin et al., 2009).

Farm management chores and upstream supply chain interactions are informed by gathered data, improved by setting and condition awareness, and triggered by real-time occurrences in the digital farming strategy (Wolfert et al., 2017). These data are collected using a variety of sensors to monitor animals, soil, water, and plants. The information is used to evaluate the past and forecasts the future to make more fast and more accurate decisions on the farm and in the supply chain, where the collection of data from various farms enables the so-called big data analysis (Carbonell, 2016). Policymakers and researchers are progressively moving to smart farming as a technological solution to address social issues related to agriculture, such as provenance and food traceability (Dawkins, 2016), animal welfare in livestock industries (Yeates, 2017), and the environmental impact of various farming practices (Busse et al., 2015). Most of the literature on digital farming focuses on its potential to improve agricultural practices and productivity (Rutten et al., 2013), although some researchers have looked at the socio-ethical consequences (Driessen and Heutinck, 2015; Carbonell, 2016). At the farm, the wider agricultural community, and society levels, these socio-ethical difficulties in digital farming have been recognized by Bos and Munnichs (2016). The practice of farming will be transformed by smart farming, with less 'hands-on management and a more data-driven approach (Eastwood et al., 2012). Different abilities and skills will be required across the agricultural team to apply and adapt smart farming technologies (Higgins et al., 2017), as well as customized advisory structures, potentially leading to displaced farm personnel and service suppliers. Therefore, all suppliers and agricultural departments, and institutions that are responsible for sharing knowledge about farming technology with farmers and agripreneurs, must deal with the responsibility of actions in a professional and qualified manner. Furthermore, the ethical practices of concerned departments or institutions affect the user behavior towards the adoption and use of digital agriculture.

The agricultural technology system in Pakistan as an underdeveloped country is still in the developing stage as compared to developed regions like the USA, Finland, and Europe (Bilsborrow, 1987; Lewandowski et al., 2003). Likewise, developed countries like (European Union, Canada, and the USA) acknowledged the significance of responsible ethical practices in the digitalization (Francer et al., 2014) and mostly took great initiatives to stimulate and opt for ethical practices in the agricultural technology (Madden and Thompson, 1987; Mahroof et al., 2021). Nevertheless, a developing country such as Pakistan is still in the early stage of development (Khan et al., 2020; Ikram et al., 2021). In addition, the implementation of ethical practices in the agricultural technology system in Pakistan is still weak. The behavior of users when using technologies has been generally addressed in the existing literature (Hsiao, 2018). The more innovations that are introduced, the more study is required to understand how users adopt and engage with them. This study also focused on testing user behavior towards ethical practices of agricultural departments and the adoption of farming technology. User behavior as it relates to data acquired from device users when they utilize the device's services (Keith et al., 2013). To describe user behavior, two basic theories were employed extensively; the Theory of Reasoned Action (Madden et al., 1992) and the Theory of Planned Behavior (Ajzen, 1991).

To manage land, livestock, and farm personnel more efficiently, digital technology is becoming very crucial. Agricultural specialties and organizations that are responsible for loan providing and knowledge sharing about farming technology to cultivators and agripreneurs need to deal with the responsibility of actions professionally. Farmers and agripreneurs (users) can be motivated to learn if the personnel in these departments are loyal and honest in their duties and perform respectfully. Alternatively, their attitude toward using farming technology will be positive, and they will be interested in learning how to use farming technology, resulting in increased agricultural technology development.

The following hypotheses are proposed based on the literature:

H1: The development of the agricultural technology system was positively influenced by ethical practices.

H2: Ethical Practices have a significant and positive effect on user behavior.

H3: User behavior has a positive effect on the development of agricultural technologies.

2.1 Equifinality hypothesis

Equifinality is the concept that a particular end state can be attained in a variety of possible ways. Hans Driesch invented the term and notion, which was eventually adopted by Ludwig von Bertalanffy (Drack, 2015). In this study, the focus is on achieving enhanced agricultural technology development, and the study expects to achieve this result through a diverse arrangement of ethical practices and user behavior. The hypothesized relations propose a causative chain leading from ethical practices and user behavior to agricultural technology development. Research also shows that both the digital agricultural development (Dahlberg, 1988) and ethical practices are complex concepts (de Rooij et al., 2010). Hence, the relationship between ethical practices and user behavior, which leads to improved agricultural technology development, cannot be straightforward as recognized in the majority of ethical practices literature. This recommends that the presence of multifaceted

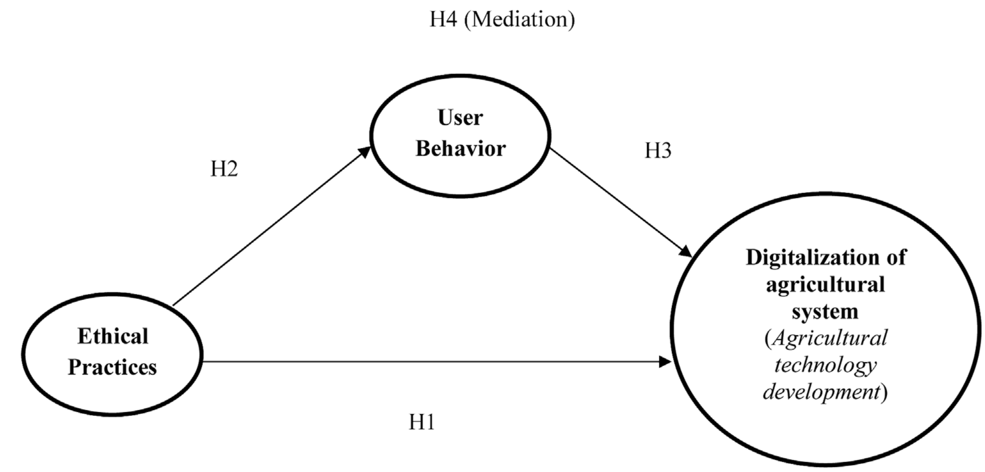


FIGURE 1
Conceptual framework.

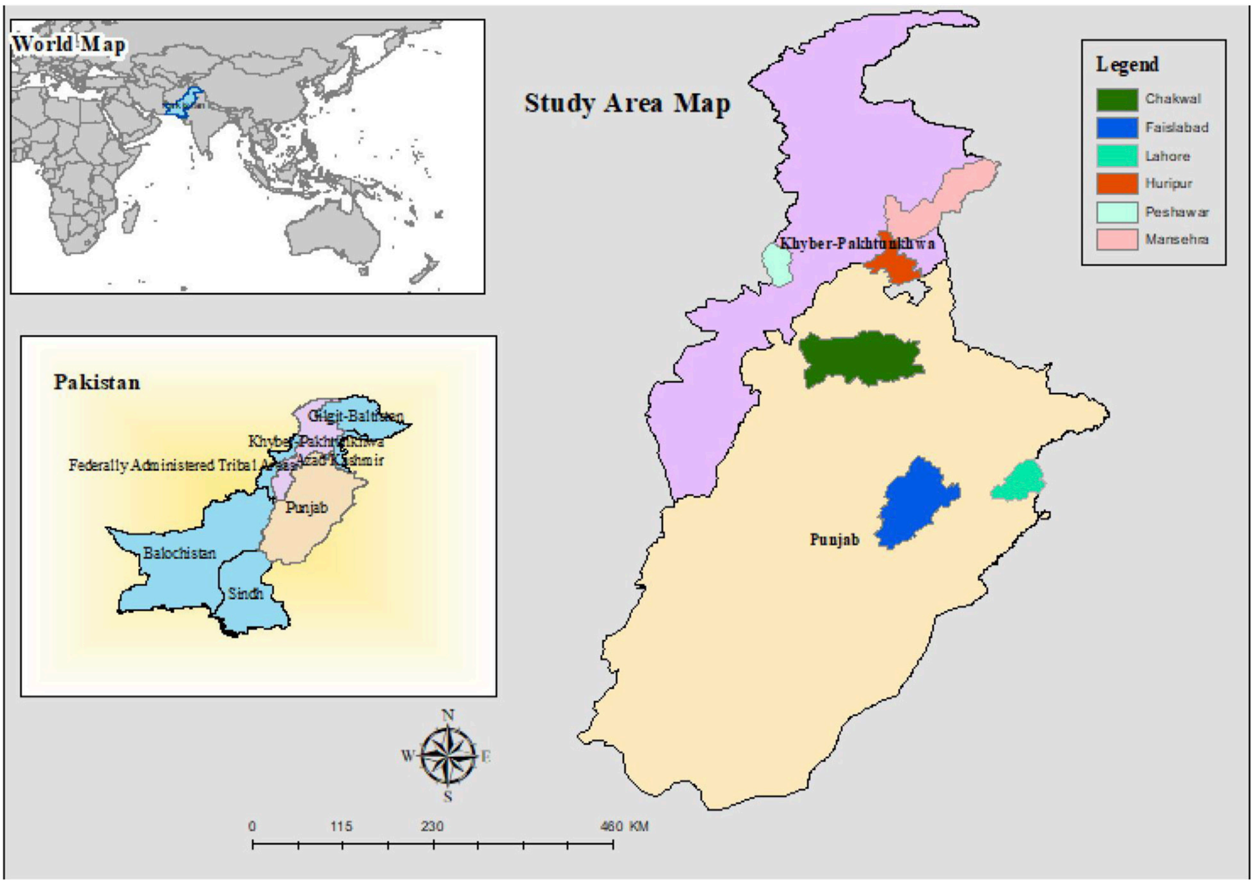


FIGURE 2
Map of the study area (ArcGIS 10.7).

configurations of ethical practices and user behavior are related to agricultural technology development. In keeping with this view, this study assumes the following hypothesis:

H4: User behavior mediates the relationship between "ethical practices" and "agricultural technology development" (Figure 1).

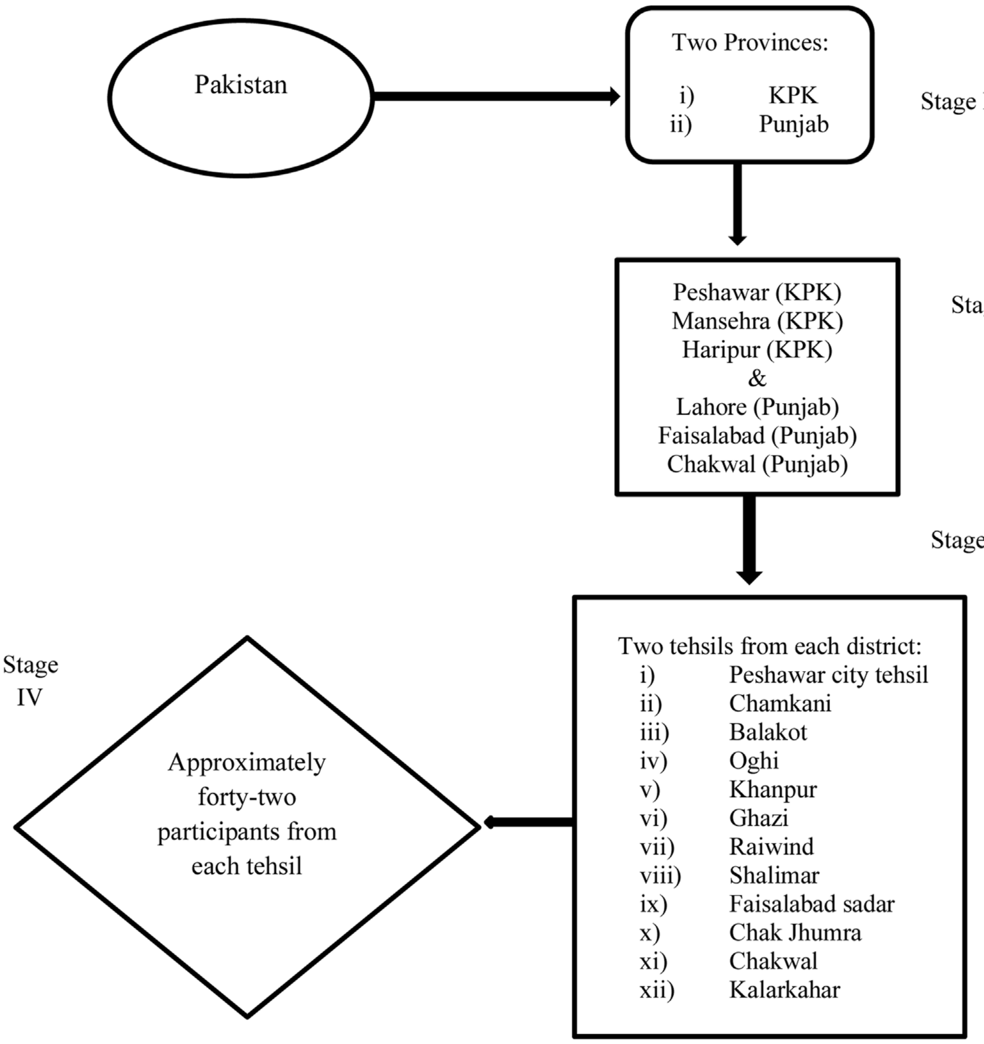


FIGURE 3
Stages of sampling to select sample.

3 Methods of the study

3.1 Study site, population sample, and data collection

This study is carried out in two provinces of Pakistan, namely the Khyber Pakhtunkhwa (abbreviated as KPK) province and Punjab. We have selected three districts from each province, namely Peshawar, Mansehra, and Haripur from KPK and Lahore, Faisalabad, and Chakwal from Punjab which is shown in Figure 2. The sample universe includes farmers, agripreneurs/agri-businesspersons/agri-entrepreneurs, and the residents of the study area who were directly and keenly involved in the agriculture sector and are users of digital technology. A multi-stage stratified random sampling technique (Figure 3) was used to choose settings for the study (Manzoor et al., 2021). In the first phase, the choice of the study area is two provinces of Pakistan; in the second stage, three districts of each province, because these districts have many residents and departments working in the agricultural sector. In the third stage, two tehsils are randomly chosen from each district. Tehsil is a name used to explain the administrative divisions of a district (Manzoor et al., 2021). In the fourth and last stage, approximately forty-two participants were randomly selected from each Tehsil.

To achieve the study objective, data has been collected through the questionnaire survey method from the users of the digital agricultural technologies of Pakistan. The study participants are users of digital farming technologies such as farmers, Agri-preneurs, agri-businesspeople, agri-entrepreneurs, etc., and all others who work in the agriculture sector and users of agricultural technology. We first prepared the questionnaire in the English language and then translated it into Urdu with the help of multilingual specialists to confirm content quality and clarity. With the help of a senior researcher, we identified and distributed the questionnaire to those interested in contributing to the study. All respondents were requested to self-administer their answers fairly and then return them to the person in charge. A total of 500 questionnaires have been distributed to the target population from June 2021 to October 2021 (the selection of participants was according to Figure 3). Total 490 responses were received out of 500 disseminated questionnaires, resulting in a 98 percent response rate. The remaining questionnaires that were fragmented or inaccurate were discarded.

3.2 Measurement of variables and explanations

Three main variables are used in this study, i.e., ethical practices, user behavior, and agricultural technology development. In the study, the explanatory variable is ethical practices that are based on agricultural department's and institutions' responsibilities towards the upgrade of all workers related to agricultural digital technologies. Such as all agricultural departments and institutions' current policies and practices for those who are recently working for the modification of agricultural workers regarding the usage and provision of digital technologies in the agriculture sector. In this study, we tested knowledge-sharing methods, fairness in providing loans, respect for others, honesty, loyalty in professionalism, responsibility of actions, and accountability of agricultural departments, and institutions (as a proxy for ethical practices). The proposed study referred to the existing research and picked 16 measurement items. However, the phrasing of the items was slightly changed to accommodate them in a study setting (Holton et al., 2009). The ethical practices variable is measured by five items scale. Moreover, the structure of the concept of ethical practice is allied with the instruction of Hood (2003) and Ladany et al. (1999). Example questions for ethical practices are "all agricultural departments are dedicated to their work and do their best to provide us services such as knowledge sharing about the adoption/use of digital technology respectfully" and "I am truly satisfied with agricultural institutes' equitable loan distribution".

User behavior is used as a mediator construct in this study. A mediator is a way for a predictor variable to influence an outcome variable. It is part of the causal pathway of an effect, and it explains how or why an effect occurs. A mediator is something that is caused by the predictor variables. It affects the dependent variable (MacKinnon, 2012). Users in our study are all those persons who are currently using digital farming technologies, and we tested their behavior to ethical practices (such as knowledge-sharing methods, fairness in providing loans, respect for others, honesty, loyalty in professionalism, responsibility, and accountability of agricultural departments, institutions, and the government). The items of user behavior have been adopted from the study of Nusairat et al. (2021), with four items measured on a scale. Sample elements for 'user behavior' are 'I am pleased with the assistance of the agricultural department in the use of farming technology and 'Agricultural institution personnel are loyal, honest, and competent in knowledge sharing about the use of farming technology.

Likewise, in the present study, we measure 'agricultural technology development' as a predicted variable which is measured through a proxy of digital technology provision, as well as awareness of the use of that technology, and the example question is 'I have used and knowledge of all sophisticated technologies such as robots, temperature and moisture sensors, aerial images, and GPS technology. Six items scale measured agricultural technology development. Furthermore, the survey questionnaire used a five-point Likert scale with "1" denoting "strongly disagree" and "5" denoting "strongly agree." Appendix A contains items of the variables (questionnaires).

3.3 Data analytic strategy

The main uses of regression analysis are forecasting and finding the cause-and-effect relationship between variables. The regression model was used for quantitative analysis to investigate the empirical relationship between two variables and the hypothesis testing (Manzoor et al., 2019a; Manzoor et al., 2019b). The mediation approach is an extension of the regression model (Preacher and Hayes, 2004). In this study, the data were evaluated by using the conceptual and statistical recommendations of Baron and Kenny (1986) and Holmbeck (1997) for determining the presence of a mediator effect. Baron and Kenny (1986) 's four-step mediation approach has been employed for analyses in which regression analyses are used and the significance of coefficients is estimated (Baron and Kenny, 1986). An ANOVA delivers a limited test of a mediational hypothesis as extensively discussed in Fiske et al. (1982). Rather, as recommended by Judd and Kenny (1981), a series of regression models should be measured. The three regression equations below should be assessed to test for mediation. First, the agricultural technology development measure was regressed on the ethical practice measure to see if there was a mediating impact (Path C in Figure 4A).

The regression model can be expressed as:

$$Y_i = \beta_0 + \beta_i X_i + \cdots + \varepsilon$$

where Y_i = dependent variable, X_i = independent variable, ß$_0$ = intercept, ßi = coefficient to be estimated, and e = error term.

The proposed modified regression model is represented by the following equation, which is the regression line for evaluating the effect of ethical practices on agricultural technology development:

$$Agtd = a_0 + a_1 EP + a_2 Edu + a_3 Gd + a_4 Ag + e \tag{1}$$

Where Agtd is a predicted or explained variable which refers to Agricultural technology development; and EP is an independent or explanatory variable that denotes ethical practices. Education (Edu), Gander (Gd), and Age (Ag) are control variables. According to Baron and Kenny (1986), if the measured coefficient α_1 is significantly positive or if there is an association between the underlying variables, then the following test would be continued.

Second, the measure of user behavior was regressed on the measure of the ethical practice to create Path a (see Figure 4B) in the mediational chain. To accomplish this purpose, simple regression analysis was employed, with the mediator predicting the outcome, and the following regression line was created:

$$UB = a_0 + a_1 EP + a_2 Edu + a_3 Gd + a_4 Ag + e \tag{2}$$

Here, UB denotes user behavior. It is simply a mediator or the intermediary variable. It is also a predictor variable here. Ethical practices (EP) are an independent or explanatory variable; others are control variables. If the assessed coefficient α_1 is significantly positive, demonstrating that the independent variable accurately predicts the predicted variable, then the next step would be expected.

In the third equation, the agricultural technology development measure was regressed in both ethical practices and user behavior measures. This allowed for a test of whether user behavior was linked to agricultural technology development (Path b) and an estimation of the relationship between the ethical practices and the agricultural technology development controlling for user behavior (Path c').

The user behavior was then tested as an intermediary variable using regression analysis. Mediation analysis has been performed to determine whether UB mediates between EP and Agtd or not. The

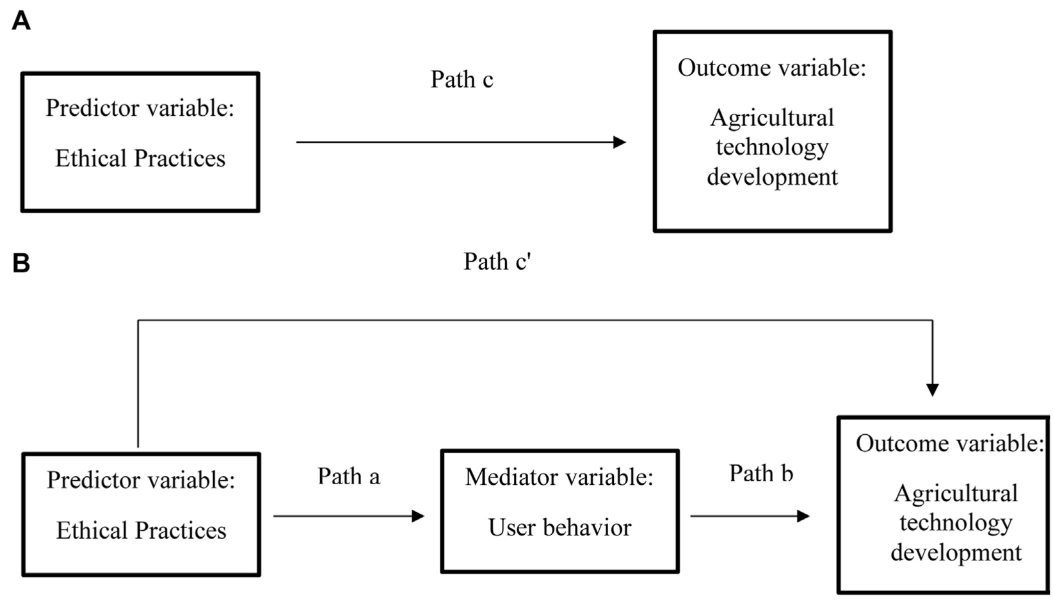


FIGURE 4
Diagrams of paths in the hypothesized mediational model.

development of agricultural technology (outcome variable), ethical practices (explanatory variable), and user behavior (intermediary or mediator variable) are all included in the model to create a new equation.

$$Agtd = a_0 + a_1EP + a_2UB + a_3Edu + a_4Gd + a_5Ag + e \quad (3)$$

In models 1 through 3, α_0 is a constant term, α_1, α_2 are the coefficients to be tested and ε is the error term. Control variables are used to improve a study's internal validity by minimizing the incidence of confounding and other extraneous variables (Christ, 2007). According to Baron and Kenny (1986) separate coefficients for each equation should be computed. There is no requirement to perform hierarchical or stepwise regression, or partial or semi-partial correlations. These three regression equations provide the assessments of the link of the mediational model.

4 Empirical results and discussion

A total 490 people (394 males, 96 females) from two provinces of Pakistan participated in the study. The highest age range of the respondents was 40–49 (34.1%). Most of the respondents (254: 51.8%) were from the KPK province and the rest (236: 48.2%) were from the Punjab province. Most of them (171: 34.9%) have higher secondary school certificates; others (169: 34.5%) were secondary school certificates holders; a few of them (42: 8.6%) were above higher secondary school certificates holders; remaining participants (108: 22%) were had Primary education and were illiterate. Most of the nature/type of participants (217: 44.3%) were farmers; agripreneurs/agribusinessmen/Agri entrepreneurs (187: 38.2%); and the rest of them (86: 17.5%) were other professionals working in the agriculture sector and were users of digital technology in the study area. The demographic information of the respondents was presented in Table 1.

TABLE 1 Demographic figures for participants.

Category	Frequency	Percentage
Gender		
Male	394	80.4
Female	96	19.6
Region		
KPK Province	254	51.8
Punjab Province	236	48.2
Age		
Below 29 years	56	11.4
30–39	91	18.6
40–49	167	34.1
50–59	128	26.1
60 above	48	9.8
Education		
Illiterate/Primary	108	22.0
Secondary school	169	34.5
Higher secondary school	171	34.9
Above higher secondary	42	8.6
Type		
Farmers	217	44.3
Agripreneurs/agribusinessmen/agri-entrepreneur	187	38.2
Other	86	17.5

TABLE 2 Means, standard deviations, reliability estimates, and correlations for study variables.

Variables	Mean	Std. Div	α	1	2	3
1. Ethical Practices	3.340	1.084	0.91	—	0.233**	0.167**
2. User behavior	3.381	1.054	0.85	—	—	0.128**
3. Agricultural technology development	3.245	1.190	0.94	—	—	—

**$p < 0.01$, and Cronbach's coefficient α.

TABLE 3 Testing for User behavior as a mediator using multiple regression.

Steps in testing for mediation	Estimated coefficient (T-values)	B	SE B	95% CI	R-square
Model 1) Testing step 1 (Path c) Outcome: Agricultural technology development Predictor: ethical practices Control: other variables	0.125** (2.792)	0.135	0.048	0.040, 0.230	0.025
Model 2) Testing step 2 (Path a) Outcome: User behavior Predictor: ethical practices Control: other variables	0.226** (5.226)	0.205	0.039	0.128, 0.282	0.311
Model 3) Testing step 3 (Path b and c') Outcome: Agricultural technology development Mediator: User behavior (Part b) Predictor: ethical practices Control: other variables	0.145** (3.103) 0.093* (2.024)	0.173 0.100	0.056 0.049	0.063, 0.282 0.003, 0.197	0.044

Note. CI, confidence interval. *$p < 0.05$; **$p < 0.01$.

All the current study variables' means, standard deviations, reliability evaluations, and intercorrelations are listed in Table 2. Ethical practices significantly correlated with both user behavior and agricultural technology development in the expected direction: ethical practices were positively associated with both user behavior (r = 0.233, $p < 0.01$) and agricultural technology development (r = 0.167, $p < 0.01$). User behavior is also positively connected with agricultural technology development (r = 0.128, $p < 0.01$) as expected. The results of the correlation matrix were consistent with those of the previous study (Manzoor et al., 2021; Manzoor et al., 2022). Multicollinearity was generally low and did not pose a serious problem.

Table 3 comprises the analyses essential to investigate the mediational hypothesis. Following the steps defined before for estimating mediation, first, we confirmed that the predictor (ethical practices) is linked to the predicted variable (agricultural technology development) by regressing agricultural technology development on ethical practices (Step 1). Ethical practices were significantly associated with the development of agricultural technology (H1: B = 0.135, estimated coefficient = 0.125, $p < 0.01$), path c was significant and the mediation requirement in Step 1 was met. This finding suggests that ethical practices influence the development of agricultural technologies. The coefficient for the variable is positive and significant at the level of 1%. This empirical evidence confirms that the ethical practices of agricultural departments/institutions have a positive effect on farming technology development. This means that farmers, agri-preneurs, and others can easily obtain services and assistance from the agricultural department. These findings are consistent with previous studies by Veisi et al. (2016) and (Driessen and Heutinck, 2015).

Next, to find that ethical practices are linked to the hypothesized mediator (user behavior) we regressed user behavior on ethical practices (Step 2). Ethical practices were also significantly related to user behavior (H2: B = 0.205, estimated coefficient = 0.226, $p < 0.01$), and consequently the condition for Step 2 was met (Path a was significant). These results showed that ethical practices have a positive effect on user behavior. The p-value (<0.01) indicated the significant effect of ethical practices on user behavior which is less than the cutoff point. In other words, ethical practices of agricultural departments/institutions (such as their loyalty to professionalism, honesty, fairness in loan provision, respect for learners, the responsibility of actions, and accountability) increase the positive behavior of users of farming technology, which in turn increases development in the use of agricultural technologies. This could be attributed to the notion that ethical practices of the agricultural institutions and departments advance individual adaptability and individual learning pledges that are expected to improve individual capabilities and further lead to individual contentment and positive user behavior (Hansen, 1996). Adoption of digital technologies and learning and gaining knowledge about the usage of the technologies from the agricultural departments promote optimistic user behavior, which in turn is helpful in the development of digital technologies in the agricultural sector of the country.

Likewise, to examine whether the hypothesized mediator (user behavior) is associated with the predicted (agricultural technology development) we regressed agricultural technology development simultaneously on both ethical practices and user behavior (Step 3). User behavior was significantly linked with agricultural technology development controlling for ethical practices (H3: B = 0.173, coefficient estimated = 0.145, $p < 0.01$). Path b was significant and the requirement for Step 3 was met. This third regression equation also offered an estimation of path c', the relationship between ethical practices and agricultural technology development, controlling for user behavior. We have evidence for complete mediation when path c' is zero. Nevertheless, path c' was still significant (B = 0.100, estimated coefficient = 0.093, $p < 0.05$), though it is less than path c (B = 0.135, estimated coefficient = 0.125, $p < 0.01$), and this proposes partial mediation (H4). Therefore, the outcomes of the present study endorse the significant effect of user behavior on agricultural technology development. The results specify that user behavior significantly and positively affects digital technology development, which successively increases the productivity of the agricultural sector. These outcomes support the claims put forth by the scholars' (Hong et al., 2006; Liao et al., 2009). User behavior helps people in knowledge-intensive settings in developing a shared understanding and deriving value from knowledge. More specifically, positive user behavior towards the use of digital technology improves internal satisfaction because it is an interest to develop access, share, and use of knowledge, that develops efficiency in carrying out one's tasks, which can be important to improve technology adoption. This demonstrates that ethical practices can help user behavior and thus promote high agricultural technology development.

Equifinality presence, rapidly increasing in the literature (Barrett, 2019), and can be found in our case in the context of ethical practices and user behavior combinations that can lead to development in agricultural technology, which has not yet been measured in the literature. The mediation analysis thus shows that ethical practices considerably contribute to the high productivity in the agricultural sector through digital technology development.

However, the following conditions must be held to find the mediation (Baron and Kenny, 1986): First, the predictor variable must affect the outcome variable in the first equation; secondly, in the second equation the predictor variable must be proven to affect the mediator variable; and third, the mediator must influence the outcome variable in the third equation. If all these criteria hold in the predicted direction, the effect of the predictor variable on the outcome variable in the third equation must be smaller than in the first. Perfect mediation occurs when the independent variable has no influence when the mediator is controlled. These two variables should be connected because the explanatory variable is supposed to cause the mediator. When the independent variable predicts the dependent variable alone, it can have a smaller coefficient than when it predicts the outcome variable with the mediator, but the greater coefficient is not significant and the less one is (Manzoor et al., 2019c; Manzoor et al., 2021). On the other hand, the results are partial mediation, as such present study shows partial mediation. As a result, H4 is proven due to evidence of a partial mediation mechanism.

5 Conclusion, and implications

5.1 Conclusion

The current study observed whether the relations between ethical practices and agricultural technology development could be accounted for by user behavior. In addition, this work demonstrated how to apply multiple regression analyses to assessment for mediation in the study in a step-by-step way. User behavior partially mediated the association between ethical practices and agricultural technology development. Moreover, the results of this study establish a significant influence of ethical practices on agricultural technology development. This shows that ethical practices (knowledge-sharing methods, fairness in providing loans, respect for others, honesty, loyalty in professionalism, responsibility of actions, and accountability of agricultural departments, and institutions) can help in the development of digital technology. Furthermore, the outcomes prove that agricultural technology can improve and be modified through a combination of ethical practices and user behavior.

The study's findings indicate that ethical practices of agricultural institutions and departments in terms of organizing some programs and policies to knowledge sharing, providing loans, and being responsible for actions in the development of digital technology; these initiatives not only can help improve the interest of concerned people, but they can also significantly improve the productivity of agricultural sector in Pakistan. The research suggests that it is vital for the agriculture sector in Pakistan to foster a situation that focused on better practices as it will tend not merely to increase people's interest in agricultural development but will also help the agriculture sector achieve its goal of increased productivity.

5.2 Theoretical and methodological contributions

This study tried to unify the fragmented literature on ethical practices into a holistic approach and build a framework for ethical practice that may enhance user behavior and agricultural technology development. According to theoretical criteria, the interrelationships between ethical practices and user behavior are more intricate than encouraged by literature on agricultural technology development. Henceforth, the study with mediation found that specific combinations of ethical practices and user behavior of the digital technologies trigger higher development in agricultural technology rather than a direct effect of the ethical practices on digitalization in earlier studies. The present study stated that ethical practices and user behavior pave the way for higher development in digital technology. From a methodological perspective, this study's contribution comprises the use of a mediation approach that shows how user behavior mediates the association between ethical practices and agricultural technology development.

5.3 Implications, limitations, and future research directions

Both academics and practitioners will reap the benefit of this investigation. Apart from adding to the limited research on ethical practices and digitalization, the study supports the need to create an environment in the agricultural sector that fosters ethical practices and responsibilities. This would result in improved digital technology development and raise improved agricultural productivity in the country. The study assesses ethical practice in terms of knowledge sharing and knowledge utilization, the responsibility of actions, develop loan provision policies as critical processes that could help the development of agricultural technology to attain improved productivity. The combination of ethical practices with user behavior would further help develop agricultural technology that can ultimately help the agricultural sector attain higher productivity to reduce poverty in the country.

There are certain limitations to the study that should be acknowledged. First, while this study focuses on two provinces in Pakistan, more research should be done in the remaining areas. Second, the present study is from one country's perspective; we recommend that more qualitative research be carried out in other underdeveloped nations to boost the generalizability of the findings. Third, the present study applied survey data gathered from the farmers, agripreneurs, agri-businesspersons, and users of digital technology, for the crosschecking of results future research can be performed over secondary data. Finally, while we considered the demographics of several participants, it may be claimed that such elements can moderate and mediate the links between ethical practices and the development of digital technology. Hence, we also call for more research into such consequences.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by Ethics Committee of Zhejiang University China. The patients/participants provided their written informed consent to participate in this study.

Author contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by LW, FM, and JC. The first draft of the manuscript Was written by FM and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding

This study is supported by National Natural Science Foundation of China [71972123] and the National Social Science Foundation of China [22&ZD081].

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Ajzen, I. (1991). The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* 50, 179–211. doi:10.1016/0749-5978(91)90020-t

Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. personality Soc. Psychol.* 51, 1173–1182. doi:10.1037/0022-3514.51.6.1173

Barrett, B. J. (2019). Equifinality in empirical studies of cultural transmission. *Behav. Process.* 161, 129–138. doi:10.1016/j.beproc.2018.01.011

Bilsborrow, R. E. (1987). Population pressures and agricultural development in developing countries: A conceptual framework and recent evidence. *World Dev.* 15, 183–203. doi:10.1016/0305-750x(87)90077-5

Bos, J., and Munnichs, G. (2016). *Digitalisering van dieren: Verkenning precision livestock farming*.Netherlands: Rathenau Instituut.

Busse, M., Schwerdtner, W., Siebert, R., Doernberg, A., Kuntosch, A., König, B., et al. (2015). Analysis of animal monitoring technologies in Germany from an innovation system perspective. *Agric. Syst.* 138, 55–65. doi:10.1016/j.agsy.2015.05.009

Carbonell, I. (2016). The ethics of big data in big agriculture. *Internet Policy Rev.* 5 (1). doi:10.14763/2016.1.405

Christ, T. J. (2007). Experimental control and threats to internal validity of concurrent and nonconcurrent multiple baseline designs. *Psychol. Sch.* 44, 451–459. doi:10.1002/pits.20237

Dahlberg, K. A. (1988). Ethical and value issues in international agricultural research. *Agric. Hum. Values* 5, 101–111. doi:10.1007/bf02217181

Dawkins, M. S. (2016). Animal welfare and efficient farming: Is conflict inevitable? *Animal Prod. Sci.* 57, 201–208. doi:10.1071/an15383

De Rooij, S. J., De Lauwere, C., and Van Der Ploeg, J. D. (2010). Entrapped in group solidarity? Animal welfare, the ethical positions of farmers and the difficult search for alternatives. *J. Environ. Policy & Plan.* 12, 341–361. doi:10.1080/1523908x.2010.528882

Drack, M. (2015). Ludwig von Bertalanffy's organismic view on the theory of evolution. *J. Exp. Zoology Part B Mol. Dev. Evol.* 324, 77–90. doi:10.1002/jez.b.22611

Driessen, C., and Heutinck, L. F. (2015). Cows desiring to be milked? Milking robots and the co-evolution of ethics and technology on Dutch dairy farms. *Agric. Hum. Values* 32, 3–20. doi:10.1007/s10460-014-9515-5

Eastwood, C., Chapman, D., and Paine, M. (2012). Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. *Agric. Syst.* 108, 10–18. doi:10.1016/j.agsy.2011.12.005

Eastwood, C., Klerkx, L., Ayre, M., and Rue, B. D. (2019). Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. *J. Agric. Environ. Ethics* 32, 741–768. doi:10.1007/s10806-017-9704-5

Fiske, S. T., Kenny, D. A., and Taylor, S. E. (1982). Structural models for the mediation of salience effects on attribution. *J. Exp. Soc. Psychol.* 18, 105–127. doi:10.1016/0022-1031(82)90046-4

Francer, J., Izquierdo, J. Z., Music, T., Narsai, K., Nikidis, C., Simmonds, H., et al. (2014). Ethical pharmaceutical promotion and communications worldwide: Codes and regulations. *Philosophy, Ethics, Humanit. Med.* 9, 7–17. doi:10.1186/1747-5341-9-7

Frederiksen, C. S., and Nielsen, M. E. J. (2013). The ethical foundations for CSR. *Corporate social responsibility*. Germany: Springer.

Hansen, J. W. (1996). Is agricultural sustainability a useful concept? *Agric. Syst.* 50, 117–143. doi:10.1016/0308-521x(95)00011-s

Higgins, V., Bryant, M., Howell, A., and Battersby, J. (2017). Ordering adoption: Materiality, knowledge and farmer engagement with precision agriculture technologies. *J. Rural Stud.* 55, 193–202. doi:10.1016/j.jrurstud.2017.08.011

Holmbeck, G. N. (1997). Toward terminological, conceptual, and statistical clarity in the study of mediators and moderators: Examples from the child-clinical and pediatric psychology literatures. *J. Consult. Clin. Psychol.* 65, 599–610. doi:10.1037/0022-006x.65.4.599

Holton, E. F., III, Wilson, L. S., and Bates, R. A. (2009). Toward development of a generalized instrument to measure andragogy. *Hum. Resour. Dev. Q.* 20, 169–193. doi:10.1002/hrdq.20014

Hong, S., Thong, J. Y., and Tam, K. Y. (2006). Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet. *Decis. support Syst.* 42, 1819–1834. doi:10.1016/j.dss.2006.03.009

Hood, J. N. (2003). The relationship of leadership style and CEO values to ethical practices in organizations. *J. Bus. ethics* 43, 263–273. doi:10.1023/a:1023085713600

Hsiao, M.-H. (2018). A conceptual framework for technology-enabled and technology-dependent user behavior toward device mesh and mesh app. *Future Bus. J.* 4, 130–138. doi:10.1016/j.fbj.2018.03.003

Ikram, M., Ferasso, M., Sroufe, R., and Zhang, Q. (2021). Assessing green technology indicators for cleaner production and sustainable investments in a developing country context. *J. Clean. Prod.* 322, 129090. doi:10.1016/j.jclepro.2021.129090

Javaid, M., Haleem, A., Khan, I. H., and Suman, R. (2022). Understanding the potential applications of artificial intelligence in agriculture sector. *Adv. Agrochem.* doi:10.1016/j.aac.2022.10.001

Johansson, A. (2016). *Clustering user-behavior in a collaborative online social network: A case study on quantitative user-behavior classification*. Digitala Vetenskapliga Arkivet.

Judd, C. M., and Kenny, D. A. (1981). Process analysis: Estimating mediation in treatment evaluations. *Eval. Rev.* 5, 602–619. doi:10.1177/0193841x8100500502

Keith, M. J., Thompson, S. C., Hale, J., Lowry, P. B., and Greer, C. (2013). Information disclosure on mobile devices: Re-Examining privacy calculus with actual user behavior. *Int. J. human-computer Stud.* 71, 1163–1173. doi:10.1016/j.ijhcs.2013.08.016

Khan, N. A., Gao, Q., Ali, S., Shahbaz, B., Khan, P., and Abid, M. (2020). Analyzing ICT-enabled agricultural advisory services in Pakistan: Evidence from a marginalized region of Punjab province. *Electron. Commer. Res.* 22, 1107–1129. doi:10.1007/s10660-020-09442-z

Kijsanayotin, B., Pannarunothai, S., and Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *Int. J. Med. Inf.* 78, 404–416. doi:10.1016/j.ijmedinf.2008.12.005

Klerkx, L., Jakku, E., and Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS-Wageningen J. Life Sci.* 90, 1–16. doi:10.1016/j.njas.2019.100315

Kurbatova, S. M., Aisner, L. Y., and Naumkina, V. (2019). Some aspects of the essence and legal regulation of agriculture digitalization as one of the priorities of modern state policy of agriculture development. *IOP Conf. Ser. Earth Environ. Sci.* 315, 032021. doi:10.1088/1755-1315/315/3/032021

Ladany, N., Lehrman-Waterman, D., Molinaro, M., and Wolgast, B. (1999). Psychotherapy supervisor ethical practices: Adherence to guidelines, the supervisory working alliance, and supervisee satisfaction. *Couns. Psychol.* 27, 443–475. doi:10.1177/0011000099273008

Lajoie-O'Malley, A., Bronson, K., Van Der Burg, S., and Klerkx, L. (2020). The future (s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. *Ecosyst. Serv.* 45, 101183. doi:10.1016/j.ecoser.2020.101183

Le Roux, S. (2022). *Achieving net zero—the small island developing states (SIDS) initiative: An exploratory investment decision support framework to help address uncertainty uncertainty deconstructed*. Germany: Springer.

Lewandowski, I., Scurlock, J. M., Lindvall, E., and Christou, M. (2003). The development and current status of perennial rhizomatous grasses as energy crops in the US and Europe. *Biomass bioenergy* 25, 335–361. doi:10.1016/s0961-9534(03)00030-8

Liao, C., Palvia, P., and Chen, J.-L. (2009). Information technology adoption behavior life cycle: Toward a Technology Continuance Theory (TCT). *Int. J. Inf. Manag.* 29, 309–320. doi:10.1016/j.ijinfomgt.2009.03.004

Lo, C., Chen, C., and Zhong, R. Y. (2021). A review of digital twin in product design and development. *Adv. Eng. Inf.* 48, 101297. doi:10.1016/j.aei.2021.101297

Lopez, A. (2014). Social work, technology, and ethical practices: A review and evaluation of the national association of social workers' technology standards. *Soc. work health care* 53, 815–833. doi:10.1080/00981389.2014.943454

Lorberg, D., and Janusch, H. (2021). *Transnational corporations and fordism in the digital era: A theoretical explanation and prediction*. Germany: Springer.

Mackinnon, D. P. (2012). *Introduction to statistical mediation analysis*. Milton Park: Routledge.

Madden, P., and Thompson, P. B. (1987). Ethical perspectives on changing agricultural technology in the United States. *Notre Dame JL Ethics & Pub. Pol'y* 3, 85.

Madden, T. J., Ellen, P. S., and Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality Soc. Psychol. Bull.* 18, 3–9. doi:10.1177/0146167292181001

Mahroof, K., Omar, A., Rana, N. P., Sivarajah, U., and Weerakkody, V. (2021). Drone as a service (DaaS) in promoting cleaner agricultural production and circular economy for ethical sustainable supply chain development. *J. Clean. Prod.* 287, 125522. doi:10.1016/j.jclepro.2020.125522

Manzoor, F., Wei, L., Asif, M., Haq, M. Z. U., and Rehman, H. U. (2019a). The contribution of sustainable tourism to economic growth and employment in Pakistan. *Int. J. Environ. Res. public health* 16, 3785. doi:10.3390/ijerph16193785

Manzoor, F., Wei, L., Nurunnabi, M., and Abdul Subhan, Q. (2019b). Role of SME in poverty alleviation in SAARC region via panel data analysis. *Sustainability* 11, 6480. doi:10.3390/su11226480

Manzoor, F., Wei, L., Nurunnabi, M., Subhan, Q. A., Shah, S. I. A., and Fallatah, S. (2019c). The impact of transformational leadership on job performance and CSR as mediator in SMEs. *Sustainability* 11, 436. doi:10.3390/su11020436

Manzoor, F., Wei, L., and Sahito, N. (2021). The role of SMEs in rural development: Access of SMEs to finance as a mediator. *Plos one* 16, e0247598. doi:10.1371/journal.pone.0247598

Manzoor, F., Wei, L., Ul Haq, M. Z., and Ur Rehman, H. (2022). Assessment of mental health of medical personnel during COVID-19: Insights from Pakistan. *Heliyon* 8, e11824. doi:10.1016/j.heliyon.2022.e11824

Mihai, S., Yaqoob, M., Hung, D. V., Davis, W., Towakel, P., Raza, M., et al. (2022). Digital twins: A survey on enabling technologies, challenges, trends and future prospects. *IEEE Commun. Surv. Tutorials* 24, 2255–2291. doi:10.1109/comst.2022.3208773

Mohamed, E. S., Belal, A., Abd-Elmabod, S. K., El-Shirbeny, M. A., Gad, A., and Zahran, M. B. (2021). Smart farming for improving agricultural management. *Egypt. J. Remote Sens. Space Sci.* 24, 971–981. doi:10.1016/j.ejrs.2021.08.007

Mohamed, K. A., and Hassan, A. (2008). Web usage mining analysis of federated search tools for Egyptian scholars. *Program Electron. Libr. Inf. Syst.* 42, 418. doi:10.1108/00330330810912098

Nusairat, N., Al-Gasawneh, J., Aloqool, A., Alzubi, K., Akhorshaideh, A., Joudeh, J., et al. (2021). The relationship between Internet of things and search engine optimization in Jordanian Tele-Communication Companies: The mediating role of user behavior. *Int. J. Data Netw. Sci.* 5, 163–172. doi:10.5267/j.ijdns.2021.6.016

Pallathadka, H., Mustafa, M., Sanchez, D. T., Sajja, G. S., Gour, S., and Naved, M. (2021). Impact of machine learning on management, healthcare and agriculture. *Mater. Today Proc.*, doi:10.1016/j.matpr.2021.07.042

Preacher, K. J., and Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behav. Res. methods, Instrum. Comput.* 36, 717–731. doi:10.3758/bf03206553

Raza, M. A., Aman, M. M., Abro, A. G., Tunio, M. A., Khatri, K. L., and Shahid, M. (2022). Challenges and potentials of implementing a smart grid for Pakistan's Electric Network. *Energy Strategy Rev.* 43, 100941. doi:10.1016/j.esr.2022.100941

Rutten, C. J., Velthuis, A., Steeneveld, W., and Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *J. dairy Sci.* 96, 1928–1952. doi:10.3168/jds.2012-6107

Saiz-Rubio, V., and Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy* 10, 207. doi:10.3390/agronomy10020207

Schelenz, L., and Schopp, K. (2018). Digitalization in Africa: Interdisciplinary perspectives on technology, development, and justice. *Int. J. Digital Soc.* 9, 1412–1420. doi:10.20533/ijds.2040.2570.2018.0175

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., and Rasch, S. (2021). Adoption and diffusion of digital farming technologies-integrating farm-level evidence and system interaction. *Agric. Syst.* 190, 103074. doi:10.1016/j.agsy.2021.103074

Ukolova, N., Monakhov, S., Shikhanova, J., Pototskaya, L., and Novikova, N. (2020). Improving the technology transfer and digitalization of the agricultural economy. *Rev. Inclusiones*, 641–651.

Van Der Burg, S., Bogaardt, M.-J., and Wolfert, S. (2019). Ethics of smart farming: Current questions and directions for responsible innovation towards the future. *NJAS-Wageningen J. Life Sci.* 90, 1–10. doi:10.1016/j.njas.2019.01.001

Veisi, H., Liaghati, H., and Alipour, A. (2016). Developing an ethics-based approach to indicators of sustainable agriculture using analytic hierarchy process (AHP). *Ecol. Indic.* 60, 644–654. doi:10.1016/j.ecolind.2015.08.012

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.-J. (2017). Big data in smart farming–a review. *Agric. Syst.* 153, 69–80. doi:10.1016/j.agsy.2017.01.023

Yeates, J. W. (2017). How good? Ethical criteria for a 'good life'for farm animals. *J. Agric. Environ. Ethics* 30, 23–35. doi:10.1007/s10806-017-9650-2

APPENDIX A: (Questionnaires)

Ethical Practices.

1. All agricultural departments are dedicated to their work and strive to provide us with the best services possible.
2. Agriculture departments are enthusiastic about sharing techniques and knowledge about the adoption and use of digital technology in a respectful manner.
3. I am truly satisfied with agricultural institutes' equitable loan distribution.
4. The supervisor ensures adequate communication between the (Agriculture department) supervisor and farmers to provide appropriate supervisory backup.
5. There is no favoritism based on racial, ethnic, cultural, sexual orientation or gender issues toward us (farmers), and services are for all.

User Behavior.

1. I am pleased with the agricultural department's assistance in the utilization of farming technology.
2. Personnel at agricultural institutions are loyal, honest, and knowledgeable about how to apply farming technology.
3. I am at ease using the agricultural department's services.
4. After using their services, I feel more confident in my abilities.

Agricultural Technology Development.

1. I am using few farming technologies in my fields.
2. I have knowledge of all sophisticated technologies.
3. The usage of robots, temperature and moisture sensors, aerial images, and GPS technology is common in my area.
4. Online farming services are available in my area.
5. All agricultural technologies contribute to increased productivity.
6. In my area, farming technologies are cost-effective.

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 09 February 2023
DOI 10.3389/fenvs.2023.1124680

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Luigi Aldieri,
University of Salerno, Italy
Natalia Dneprovskaya,
National Research University Higher School of Economics, Russia
Liudmila Kabir,
Financial Research Institute of the Ministry of Finance of the Russian Federation, Russia
Pekka Neittaanmäki,
University of Jyväskylä, Finland

*CORRESPONDENCE
Yue Xiao,
xy_economy@163.com
Zai Qi Liu,
lzq1911@126.com

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management,
a section of the journal Frontiers in Environmental Science

RECEIVED 15 December 2022
ACCEPTED 30 January 2023
PUBLISHED 09 February 2023

CITATION
Xiao Y, Wu S, Liu ZQ and Lin HJ (2023), Digital economy and green development: Empirical evidence from China's cities. *Front. Environ. Sci.* 11:1124680.
doi: 10.3389/fenvs.2023.1124680

Digital economy and green development: Empirical evidence from China's cities

Yue Xiao*, Si Wu, Zai Qi Liu* and Hai Ji Lin

School of Economics and Management, Wuhan University, Wuhan, China

With prominent environmental pollution and depleted resources, how to coordinate economic growth and eco-environmental protection to guide green development represented by green total factor productivity (GTFP) is an urgent issue. This study aims to empirically evaluate the direct effect, indirect effect, spatial spillover effect and non-linear effect of the digital economy on green development using the data of 284 prefecture-level cities in China. The empirical results indicate that: (1) the digital economy significantly improves GTFP, which is still valid after testing for robustness, including introducing instrumental variables, taking the "broadband China" pilot policy as a quasi-natural experiment, changing core explanatory variables and dependent variables, and changing the sample size; (2) the influence of the digital economy on GTFP is characterized by significant heterogeneity among resource dependence, geographical location, financial development level and openness level; (3) the mechanism analysis shows that the digital economy promotes GTFP by green technological innovation, industrial structure upgrading and energy conservation; (4) the spatial econometric models indicate that the digital economy significantly enhances GTFP of neighboring cities; (5) there is a non-linear relationship between the digital economy and GTFP using the threshold model. The findings could provide references for policymakers to promote urban green development.

KEYWORDS

digital economy, green total factor productivity, innovation, industrial structure, energy conservation

1 Introduction

Under the background of the increasingly prominent environmental pollution and resource shortages, how to coordinate economic growth and eco-environmental protection is an urgent issue (Wang and Feng, 2021). Cities are the area where the deterioration of ecological environment is relatively serious, which is mainly due to the concentration of human energy consumption and carbon dioxide emissions. According to the statistics of UN Habitat, cities consume 78% of the world's primary energy and account for more than 50% of the global total greenhouse gas emissions. Especially, as the largest emerging country and carbon emitter in the world, China bears the pressure of energy consumption and ecological destruction during its rapid urbanization. China's urban energy consumption accounts for 85% of China's carbon emissions, far exceeding the world average of 67%. To combat global warming caused by carbon emissions, the Chinese government proposed to achieve a carbon peak by 2030 and carbon neutrality by 2060 at the 75th United Nations General Assembly in 2020. The 20th National Congress of the Communist Party of China once again proposed to promote green development and harmonious coexistence between human beings and nature, which emphasize the coordinated development of socio-economy and eco-environment. Cities are the main battleground for carbon emissions reduction and national economic growth to achieve the "dual carbon" target. At this stage, the key to achieving this target lies in guiding green development in cities by promoting the green transformation of traditional industries and the development of low-carbon intelligent industries (Yang et al., 2019).

The digital economy may be a feasible option for China to achieve green development by promoting green transformation of traditional industries and facilitate forming sustainable green productivity (Tao et al., 2023). The digital economy refers to a serious of economic activities that take data as the key production factor, information network as the main carrier, and digital technology application as the driving force to improve the level of digitalization, networking and intelligence of the economy and society (G20, 2016; Zhang et al., 2022). China's digital economy ranked second in the world in 2021, with a share of 39.8% of China's GDP[1]. With the characteristics of permeability and sharing, the digital economy is conducive to the transformation of production and governance modes, which obviously provides the opportunities for the green development. On the one hand, the digital economy deeply integrates digital technology such as artificial intelligence, big data, the Internet of Things, cloud computing and blockchain with the real economy, favorable to achieve the green transformation of traditional industries (Li and Wang, 2022; Yi et al., 2022). On the other hand, the digital economy can extend the scale of environmentally friendly and intelligent digital industry. What cannot be ignored is that the digital economy may exacerbate pollution emissions through scale expansion owing to the energy rebound effect. Therefore, whether the digital economy can be a desirable way to achieve green development remains to be further explored.

Many scholars have studied the economic effect of the digital economy at macro, meso and micro levels and confirmed that the digital economy significantly improves production efficiency hence accelerating economic growth. At the macro level, Tranos et al. (2021) proved that the digital economy exerts a positive and lasting impact on subsequent regional productivity. Kim et al. (2021) empirically analyzed that information and communication technology (ICT), the basis of the digital economy, can both directly contribute to output growth and generates economic spillover effects to other industries using the country-level data from 15 European countries. Yabo and Jie (2022) demonstrated that the digital economy significantly improves the quality of exports. At the meso-regional level, Pan et al. (2022) proposed that the digital economy is an innovation driver for the development of provincial total factor productivity. At the micro level, the studies found that the digital economy is beneficial to firm productivity and performance (He and Liu, 2019; Li and Wang, 2021). The core of digital economy, digital technologies contributes to competition advantages of enterprises (Teece, 2018). It seems that there is a consensus that the digital economy has positive economic effects.

There is no agreed conclusion about the environmental effect of the digital economy with similar duality of ICT in both developed and developing countries. Extensive research has confirmed that the digital economy can mitigate climate change and exerts a positive impact on sustainable environment (Balogun et al., 2020). Schulte et al. (2016) showed that ICT significantly decreases energy demand using the panel data from OECD countries. Emerging countries have greatly reduced carbon emissions by increasing Internet access (Ozcan and Apergis, 2018). Danish (2019) proposed that ICT reduces the carbon dioxide emissions of countries along the Belt and Road. Wang et al. (2021) based on the data of OECD countries found that digital technology reduces the domestic carbon emission intensity since the carbon emissions reduction through cross-industry technology spillover exceeds the emission increased by technology innovation in the information industry. Yi et al. (2022) and Zhang et al. (2022) respectively demonstrated that the digital economy is conducive to the reduction of carbon emissions at the provincial and urban levels in China. On the contrary, some scholars believe that the digital economy exerts a negative impact on the environment due to the energy rebound effect (Lange et al., 2020). The application of digital technologies requires energy and resources inputs, such as the manufacture, processing, operation and distribution of electronic equipment, which greatly increases energy consumption and damages to the environment for European Union (EU) countries (Park et al., 2018). Specifically, the use of large global data centers and mobile data traffic may generate manufacturing-related electronic waste (Lennerfors et al., 2015). The studies on OECD countries and emerging economies found that the application of ICT significantly increases the electricity consumption in both the short and long term (Sadorsky, 2012; Salahuddin and Alam, 2016). Ren et al., 2021 proved that Internet development significantly improves the energy consumption scale by boosting economic growth using the provincial panel data of China. Xue et al. (2022) pointed out that digital economy development increases the energy consumption based on the urban panel data of China. Furthermore, Higón et al. (2017) claimed that there is an inverted U-shaped relationship between ICT and carbon emissions using the data from 142 countries, and many developed countries have already passed the turning point and gained the environmental dividend brought by ICT, while the developing countries have not yet reached the turning point. Li and Wang (2022) proved the inverted U-shaped relationship between digital economy and carbon emissions based on the city-level data of China. Stefanie and David (2021) discussed that whether digitalization can become part of the "solution" for environmental sustainability depends on the comprehensive effect of various mechanisms, like political and economic system. These controversial findings on the environmental effects of the digital economy provides room for further study on the impact of the digital economy on green development.

Research on the digital economy and green development is in its infancy, requiring more abundant data and empirical proofs (Hao et al., 2022; Hu and Guo, 2022; Ma and Zhu, 2022). Green total factor productivity (GTFP), which comprehensively seeks the coordination of economic growth and eco-environmental protection, is widely employed to measure green development (Qiu et al., 2021; Wang et al., 2021; Hao et al., 2022; Ma and Zhu, 2022). This indicator incorporates environmental factors into the economic efficiency analysis framework and covers both expected output and undesired output like industrial wastewater emissions, which can effectively reflect the sustainable growth of economy (Emrouznejad and Yang, 2018; Liu and Xin, 2019; Zhang and Vigne, 2021; Li et al., 2022). Hao et al. (2022) demonstrated that the digital economy improves the manufacturing GTFP of China. Hu and Guo (2022) confirmed that the digital economy positively impacts the GTFP of the Yangtze River Economic Belt in China. Ma and Zhu (2022) confirmed that the digital economy drives the high-quality green development of emerging economies by enhancing industrial restructuring and green technological innovation. However, the theoretical explanations and

1 The data are obtained from the "Development of China's Digital Economy" white paper (2022).

mechanisms of the digital economy's impact on green development are inadequately studied. The spatial spillover effects of the digital economy and the regional heterogeneity of the impact of the digital economy on green development in China need further validation analysis. Whether the digital economy has played a critical role in promoting green development urgently need further empirical verification, which has vital theoretical and policy implication for emerging countries to achieve green development.

The aims of this paper are as follows. 1) Figure out whether the digital economy can promote green development represented by green total factor productivity and decompose the GTFP into green technology progress index (GTP) and green technology efficiency index (GTE) to evaluate its specific impact path. 2) Analyze the intrinsic mechanism of digital economy to impact the green total factor productivity. 3) Explore the spatial spillover effect of the digital economy on green total factor productivity using the spatial econometric models. 4) Ascertain whether there is a non-linear relationship between the digital economy and green total factor productivity by adopting the threshold model. 5) Further investigate the heterogenous effect of digital economy on green total factor productivity in terms of cities characteristics. This study uses the data of 284 prefecture-level cities in China from 2011 to 2019 to examine the effect of the digital economy on green development and its transmission mechanism, which is momentous to verify whether digital economy can become an efficient channel for emerging countries to achieve green development. The super-efficient SBM-DDF with pollution emission as undesirable output is employed to estimate the urban GTFP and the composite indicator of digital economy is constructed using principal component analysis at the city level (Huang et al., 2019; Zhao et al., 2020).

The contributions of this study can be reflected in the following aspects. First, it enriches the research on the impact and transmission mechanisms of the digital economy on green development taking the coordinated development of economy and environment into account at the urban level in emerging countries. The current literature mainly concentrates on the economic and environmental effect of the digital economy separately and draws controversial conclusions about environmental effects. Different from the most literature that utilizes the development level of ICT to represent the digital economy, which is not completely scientific and may lead to biased empirical results, a comprehensive indicator is constructed to measure the digital economy. This paper proves the impact and intrinsic mechanisms of the digital economy on GTFP from the aspects of green technological innovation, industrial structure upgrading and energy conservation at the urban level. Second, this paper investigates the heterogeneous effects of the digital economy on GTFP in terms of resource dependence, geographical location, financial development level and openness for cities. Finally, the appropriate spatial econometric method is adopted to analyze the spatial spillover effect of the digital economy on GTFP. The research conclusion has considerable application value for promoting urban green development.

2 Theoretical mechanism and research hypothesis

2.1 The direct impact of the digital economy on GTFP

With digital technologies as the driving force, the digital economy provides opportunities for achieving green development that emphasizes the coordination of economic growth and environmental protection. The digital economy breaks the bottleneck of factor supply for the development of emerging industries and innovates the business models, which in turn guarantee green production, green lifestyle and environmental governance (Xu et al., 2019). First, the deep integration of digital technologies with the real economy is conducive to the green transformation of production mode. The digital technology optimizes production processes and operation modes, replaces clean energy and promotes waste management processes, so as to improve energy efficiency and energy conservation. Simultaneously, the digital economy builds a digital platform for information sharing and exchange between the supply and the demand sides, thereby saving business costs (Hao et al., 2022). In terms of green lifestyle, the digital economy drives the green transformation of residents' consumption pattern in digital application scenarios. The digital technology gives birth to digital consumption platforms such as online shopping, online meetings, remote learning, non-inductive payment and paperless office system, which reduce travel and cultivate a green lifestyle (Martin et al., 2018). The application of digital technologies in vehicles like shared-bikes can also contribute to the reduction of energy consumption and carbon emission by increasing vehicle usage and sharing rates. In terms of social governance, the digital technology optimizes the environmental governance mode and broaden the governance channels to achieve energy conservation and pollution emission reduction (Roscia et al., 2013). For one thing, the application of digital technologies in government departments could improve the efficiency of governmental affairs by enhancing the ability of pollution emission prediction, supervision, management, and emergency response. Digital government could obtain and track data from regional energy suppliers and consumers to better monitor and address corporate environmental pollution behavior (Li et al., 2022). It can also prevent corruption such as data forgery and collusion between government and enterprises through enhancing information transparence (Zhang et al., 2022). For another, digital economy encourages the public participation in supervising environmental governance by creating diversified communication platforms. The residents can perceive environmental changes and then give timely feedbacks through the digital media platform like TikTok, WeChat, Weibo and governmental websites. Moreover, the dramatic advancement of ICT has stimulated a free culture providing its consumer with utility and happiness, in which case, the consumers gradually tends to pursue social, cultural and emotional values rather than just economic value of the products (Watanabe et al., 2015). The current GDP statistics fails to capture the excess over the economic value owing to the digital contents' characteristics of freebies, mass standardization and easy replication (Watanabe et al., 2018). Therefore, this paper proposes:

Hypothesis 1: The digital economy promotes urban green total factor productivity.

2.2 The indirect impact mechanism of the digital economy on GTFP

2.2.1 The digital economy affects GTFP by advancing green technological innovation

With data as the key production factor and digital technologies as the driving force, the digital economy has realized the transformation from factor-driven to innovation-driven forms. The digital economy stimulates green technological innovation that innovates products and processes just as energy saving, pollution prevention and control, waste recycling and green product design (Luo et al., 2022), thus improving GTFP.

With the characteristics of fairness and real-time interactivity, the digital technology breaks the boundaries of time and space, reducing information asymmetry and transaction costs (Chung, 2018). In addition, digital technology triggers a learning and imitation effect by facilitating knowledge spillover and innovation resources exchange (Proeger and Runst, 2020). These make it possible to match human-centered information on innovation factors with individual skills in a timely manner, which greatly stimulate the green technological innovation. From the production side, green technological innovation optimizes the production process and augments the input of renewable resources (Danish and Ulucak, 2021), thus controlling pollution emissions at the source and in the production process. On the governance side, green technological innovation is conducive to updating the terminal treatment equipment or process to reduce pollution emissions at the end of production (Cai and Li, 2018). These could greatly reduce unnecessary production and operation costs (Wang et al., 2021), pollution emissions (Yi et al., 2020; Obobisa et al., 2022), and improving energy efficiency (Miao et al., 2017), thus improving urban GTFP. Therefore, the digital economy contributes to the GTFP by boosting green technological innovation.

2.2.2 The digital economy affects GTFP by promoting industrial structure upgrading

Relying on the digital technology, the digital economy eliminates time and space barriers to the flow of production factors between industries, hence accelerating emerging industries and upgrading traditional industries. For one thing, the digital economy fuels new business models and new business forms of industries by means of digital technology services and digital platform construction. It establishes a green and intelligence industrial chain for promoting the development of emerging industries with high added value and low pollution. For another thing, the digital economy guides the digital transformation of traditional industries such as agriculture, industry and tertiary industry to green and intelligent directions. With strong permeability and coordination of new production factors, the digital economy realizes the efficient matching of data elements and traditional production factors. For instance, digital technologies like artificial intelligence, big data, the Internet of Things and cloud computing enhances the technological innovation capability and production efficiency of manufacturing firms, and correspondingly increase the added value of manufacturing industries (Cardona et al., 2013; Li et al., 2014). Therefore, the digital economy drives the upgrade of industrial structure by promoting the development of emerging industries and increasing the added value of traditional industries, thus enhancing GTFP.

2.2.3 The digital economy affects GTFP by boosting energy conservation

The digital economy decreases energy consumption *via* changing production efficiency and energy efficiency, thus improving GTFP. Digital technologies optimize energy utilization technologies and production technologies, significantly reducing energy consumption in the production process of companies (Ramirez et al., 2019). On the one hand, the deep combination of digital technologies and green manufacturing technologies has given birth to green intelligent manufacturing platforms, including product design systems, process planning systems and manufacturing decision systems. These optimize power systems and realize intelligent production and industry chain reorganization, which improves the energy utilization efficiency of enterprises and directly reduces the energy consumption (Li and Du, 2021). On the other hand, enterprises rely on digital platforms to build their own energy management systems to achieve self-control and optimization of energy systems (Ren et al., 2021). The digital command platform can realize the interconnection and orderly coordination among numerous energy systems to facilitate the allocation of energy resources and improve the overall efficiency of energy systems (Iqbal et al., 2018; Pan and Dong, 2022).

Based on the above analysis, this paper proposes:

Hypothesis 2: The digital economy enhances urban green total factor productivity by promoting green technological innovation, upgrading industrial structure and energy conservation.

2.3 The spatial spillover effects of the digital economy on GTFP

Relying on its networking features and digital technologies, the digital economy breaks through the restrictions of time, space and industrial boundaries, promoting information flow and interdepartmental connections between cities and regions, hence generating spatial spillover effect. For one thing, the digital technology accelerates the diffusion of information and various resource elements and guide the cross-regional labor division and cooperation. Accordingly, it enhances the economic ties between cities and achieves the coordinated progress of related areas. For another, digital platforms effectively match users and producers and improve resources utilization efficiency by reducing information asymmetry between supply and demand sides. Moreover, developed cities form regional growth poles through the “polarization effect” due to the output of advanced technologies and management methods. This process stimulates the diffusion of information technology to the surrounding developing cities and form a learning and imitation effect, thus improving the green total factor productivity in the neighboring areas. Therefore, this paper proposes:

Hypothesis 3: The digital economy exerts spatial spillover effect on urban green total factor productivity of neighboring cities.

2.4 The non-linear effects of the digital economy on GTFP

On the basis of the network effect, the value of the network depends upon the size of its other users. This means that if the product or service provided by a firm can gain a certain number of users or suppliers faster, then it forms a network value advantage over the firm’s competitors, thus generating a positive feedback mechanism and vice versa a negative feedback mechanism (Li, 2019). According to the Metcalfe’s law, the value of the network is equal to the square of the number of network nodes and the value of the network explodes when the size of users exceeds a critical point (Pei et al., 2018). Digital economy possesses the attributes of network since its core is digital technological innovation and expeditious network (Ma and Zhu, 2022). As the broadband usage, digital infrastructure construction and Internet access continuously increase until the scale of connections reaches a critical value, the digital economy will generate incremental scale effects and positive network externalities. Therefore, digital economy development may exert a non-linear impact on urban green total factor productivity. In view of the above analysis, this paper proposes:

Hypothesis 4: The digital economy has a non-linear impact on urban green total factor productivity.

3 Methodology

3.1 Model

The following fixed effects model are constructed to verify the above proposed theoretical hypothesis of the impact of the digital economy on urban green development:

$$\boldsymbol{GTFP_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_c X_{it} + \sigma_i + \delta_t + \varepsilon_{it}} \tag{1}$$

where i and t represent cities and years, respectively. $GTFP_{it}$ and DE_{it} denote the development level of green total factor productivity and digital economy of city i in year t, respectively. The $GTFP_{it}$ is evaluated by the GML-SBM-DDF model and decomposed into green technological progress index (GTP_{it}) and green technological efficiency index (GTE_{it}). X_{it} represents a set of control variables to reflect the influence of macro factors on urban green total factor productivity. σ_i and δ_t refer to individual fixed effect and year fixed effect, respectively. ε_{it} denotes the random error term. The core coefficient α_1 indicates the impact of digital economy on green total factor productivity. If digital economy significantly promotes urban GTFP, the variable α_1 should be statistically significant positive. According to the decomposition index of the explanatory variables, this study replaces $GTFP_{it}$ in Equation 1 with GTE_{it} and GTP_{it}, respectively.

3.2 Description of variables and data

3.2.1 Relevant indicators for GTFP measurement

This paper applies the super-efficient slack-based measure (SBM) directional distance function (DDF) and Global Malmquist - Luenberger (GML) index to measure GTFP at the urban level (Fukuyama and Weber, 2009; Yang et al., 2019). The GML index and its corresponding decomposition of the green technical efficiency index (GTE) and the green technical progress index (GTP) of cities are calculated by using the MaxDEA software. The green technical efficiency (GTE) index measures the changes of technical efficiency due to resource allocation efficiency and management system while the green technical progress (GTP) index reflects the changes of the technical progress likes improvement of production technological capability and manufacturing process. The GML index reflects the growth rate of urban GTFP, where GML = GTE × GTP. Drawing on the methods of Qiu et al. (2008) and Yuan and Xie (2015), the growth rate of GTFP is converted into the corresponding absolute values, and the GTFP of 2011 is set as the base period with the corresponding value of 1. The GML indices of GTFP, GTE, and GTP are cumulatively multiplied year by year in turn to obtain the corresponding levels of GTFP, GTE, and GTP of each city from 2011 to 2019 respectively. The specific indicators of GTFP are set as in Table 1.

3.2.1.1 Input index

The employees of the whole society represent labor input, the sum of employees in urban units, private employees and individual employees. Capital inputs is expressed by capital stock of each city at constant prices after estimating a base year based on the perpetual inventory method referring to Zhang et al. (2004). Given the available data, the energy input is measured by the total social electricity consumption (million kilowatt-hours) of each city in that year, with a uniform caliber for the whole city.

3.2.1.2 Output index

The expected output is represented by the urban actual GDP at constant prices in 2011. The undesired output consists of industrial wastewater discharge, sulfur dioxide discharge and soot discharge which are called "three waste emissions". In the robustness test, this paper adds CO_2 emissions as the undesired output on the basis of "three waste emissions" and construct a new index using CO_2 emissions alone as the undesired output. Drawing on the calculation method of Wu and Guo (2016) and the report of the United Nations Intergovernmental Panel on Climate Change (IPCC), the carbon emissions from gas, electrical heat and LPG consumption are summed to obtain the CO_2 emissions, with the data base of the primary energy consumption of coal, crude oil and natural gas.

3.2.2 The digital economy index

Due to the limited methodology and statistical data, there is no commonly accepted index to directly measure the digital economy (DE). This paper constructs the digital economy development index in terms of both digital finance and Internet development level (Huang et al., 2019; Zhao et al., 2020). The former is represented by the overall digital inclusive finance index jointly compiled by the Digital Finance Research Center of Peking University and Ant Finance Group. The latter is evaluated from four aspects: telecommunication business revenue, the number of employees in computer services and software industry, the number of mobile phone users and the number of Internet broadband access subscribers at the end of the year. The specific calculation methods of each index are per capita telecommunication business volume, the proportion of employees in computer and software industry to the total number of employees in the city, the number of mobile phone users per 100 people and the number of Internet access subscribers per 100 people, respectively. The comprehensive index of the digital economy at the urban level is calculated using principal component analysis (PCA) using the software stata15.0 based on the above five dimensions.

3.2.3 Control variables

Drawing on existing studies, the control variables in this paper are as follows: (1) Actual utilization of foreign capital (Fdi) is defined as the ratio of actual utilization foreign capital of each city to GDP in that year. (2) Human capital (Hum) promotes the growth of GTFP (Hu and Guo, 2022), indicated by the proportion of the number of students enrolled in general colleges and universities to the total population at the end of the year (Wu et al., 2021; Hao et al., 2022; Hu et al., 2022; Ren et al., 2022). This may be because the enhancement of human capital through education improves energy efficiency and renewable energy consumption through skilled labor, knowledge sharing and technological progress to reduce energy consumption and pollution emissions (Bano et al., 2018). Besides, it brings additional benefits such as compliance with government rules, reduction of unfairness and

TABLE 1 Urban GTFP index system.

Target layer	First-level indicators		Second-level indicators
Green Total Factor Productivity (GTFP)	Input index	Labor input	Total number of employees in the whole society (person)
		Capital input	Investment in fixed assets (million yuan)
		Energy input	Total annual electricity consumption (million kilowatt-hours)
	Output index	Expected output	Gross domestic product (GDP) (million yuan)
		Undesired output	Industrial wastewater (million tons)
			Industrial sulfur dioxide (tons)
			Industrial soot (tons)

TABLE 2 Descriptive statistics.

Variable types	Variable	Observation	Mean	Std. Dev.	Min	Max
Explained variable	GTFP	2556	1.016	0.300	0.247	4.088
Explanatory variable	DE	2556	0.000243	1.045	−1.546	8.490
Control variables	lnPgdp	2556	10.721	0.590	8.773	15.671
	Pgdp2	2556	115.298	12.797	76.964	245.606
	Envir	2556	0.855	1.067	0.005	12.380
	Fdi	2556	0.017	0.017	0.000	0.119
	Indu	2556	46.981	10.667	11.700	89.340
	Hum	2556	0.019	0.024	0.000	0.131
	Gover	2556	0.200	0.101	0.044	0.872

crime rates, which are conducive to economic growth (Mehrara et al., 2015). (3) Fiscal intervention (Gover) is proxied by the proportion of fiscal expenditure to GDP. (4) Industrial structure (Indu) is given by the ratio of the added value of the secondary industry to GDP. (5) Environmental regulation (Envir) is expressed as the number of employees in the water, environment and public facilities management industry that reflects the governmental environmental protection. (6) Economic development (lnPgdp) is represented by the logarithm of GDP per capita and its squared term (Pgdp2) to reflect the change of economic scale and its non-linear impact on GTFP. The environmental Kuznets curve hypothesis (EKC) suggests that the impact of economic growth on the environment rises and then declines (Dinda, 2004). It is assumed that the relationship between regional output per capita and GTFP may be U-shaped.

3.2.4 Data source and descriptive statistics

In view of the missing data and administrative area adjustment, a total of 284 Chinese prefecture-level cities from 2011–2019 are used as the research sample. The data is mainly derived from: (1) Digital Inclusive Finance Index jointly published by Digital Finance Research Center of Peking University and Ant Financial Services Group; (2) relevant statistical yearbooks including China Statistical Yearbook, China Regional Economic Statistical Yearbook, China City Statistical Yearbook, statistical yearbooks of provinces and cities and statistical bulletins of prefecture-level cities; (3) China Research Data Service Platform (CNRDS) Innovation Patent Research Database. Table 2 summarizes the descriptive statistics of the main variables in this paper.

4 Empirical analysis

4.1 Benchmark regression results

Table 3 presents the estimated results of the impact of digital economy on GTFP. The coefficient of *DE* is always significantly positive regardless of gradually adding fixed effects and control variables. The finding in column (6) suggests that the coefficient of *DE* is 0.0681 at the significant level of 1%, revealing that the digital economy has significantly promoted GTFP. Hypothesis H1 has been well verified. As a key driver of innovation and technology diffusion, the digital economy stimulates to innovate products and processes just as energy saving, pollution prevention and control, waste recycling and green product design (Luo et al., 2022), thus contributing to GTFP of Chinese cities. Next, the coefficient of the control variable basically conforms to the expectation.

To be specific, we distinguish the positive impact path on GTFP. The GTFP can be decomposed into green technology progress index (GTP) and green technology efficiency index (GTE) (Jiang et al., 2021). The specific regression results are reported in Table 4. The

TABLE 3 Benchmark regression results.

Variables	GTFP					
	(1)	(2)	(3)	(4)	(5)	(6)
DE	0.115*** (0.00742)	0.0887*** (0.00890)	0.0849*** (0.0031)	0.0704*** (0.0129)	0.0700*** (0.0130)	0.0681*** (0.0130)
lnpgdp				−2.092*** (0.215)	2.091*** (0.216)	−2.209*** (0.218)
Pgdp2				0.0851*** (0.00929)	0.0850*** (0.00929)	0.0893*** (0.00937)
Envir				0.0431*** (0.0164)	0.0432*** (0.0164)	0.0401*** (0.0164)
Fdi				−0.253 (0.500)	−0.247 (0.500)	−0.0978 (0.501)
Indu				0.00403*** (0.00117)	0.00404*** (0.00117)	0.00365*** (0.00118)
Hum					0.712 (1.126)	0.565 (1.125)
Gover						−0.479*** (0.152)
_cons	1.016*** (0.0113)	1.051*** (0.0171)	1.049*** (0.0146)	13.33*** (1.224)	13.31*** (1.225)	14.18*** (1.253)
City fixed effects	NO	NO	YES	YES	YES	YES
Year fixed effects	NO	YES	YES	YES	YES	YES
N	2556	2556	2556	2556	2556	2556
R^2	0.120	0.155	0.155	0.200	0.200	0.203

Note: ** and *** denote significant at the level of 5% and 1%, respectively._cons represents a constant term, N represents the number of samples.

TABLE 4 Decomposition results.

Variables	GTP		GTE	
	(1)	(2)	(3)	(4)
DE	0.0494*** (0.0102)	0.0251*** (0.00972)	0.0135 (0.0155)	0.0198 (0.0156)
lnpgdp		−2.243*** (0.164)		0.0551 (0.263)
Pgdp2		0.0922*** (0.00703)		−0.00329 (0.0113)
Envir		0.0871*** (0.0123)		−0.0243 (0.0198)
Fdi		−0.406 (0.376)		−0.231 (0.605)
Indu		0.00449*** (0.000883)		0.000964 (0.00142)
Hum		4.266*** (0.845)		−1.675 (1.357)
Gover		−0.818*** (0.114)		0.712*** (0.184)
_cons	1.029*** (0.0114)	14.12*** (0.941)	1.008*** (0.0172)	0.675 (1.512)
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	2556	2556	2556	2556
R^2	0.331	0.415	0.027	0.037

Note: ** and *** denote significant at the level of 5% and 1%, respectively._cons represents a constant term, N represents the number of samples.

findings reveal that *DE* significantly promotes GTP, but not significantly affects GTE. This means that the digital economy mainly promotes GTFP through motivating technological progress in production technology capabilities, manufacturing process progress, etc. Compared with the growth of green efficiency, the growth of China's GTFP mainly depends on the progress of green technology. Green technology efficiency reflects the ability to release the potential of existing technology to a greater extent, create economic output and reduce environmental pollution emissions by coordinating production factors under the condition that technology remains unchanged. Strong coordination and efficient integration of resources are the primary conditions for the development of the data element market. However, the cultivation of data element market is still in the exploration stage and there are barriers to data resource sharing. The coordination between production factors is not enough, which leads to the decline of economic output capacity and utilization efficiency of production factors.

4.2 Endogeneity analysis

4.2.1 Instrument variable approach

Considering that the above benchmark regression model may have endogeneity, which may affect the estimation results. First, the higher level of regional green development, the better external resources may be, which will inevitably accelerate the development of digital economy, causing the problem of reverse causality. Second, there are many other unobservable factors that affect the GTFP, which may cause the problem of missing control variables. Therefore, this paper uses instrument variables (IV) to solve above endogenous problems.

On the one hand, historical variables have good exogeneity, many scholars tend to use historical information to solve endogenous problems (Au and Henderson, 2006). This paper adopts the number of telephones, post offices, and total postal services owned by per 10,000 people in 1984 as instrument variables (Huang et al., 2019). The early stage of China's Internet development is mainly started with analogue telephones lines. Hence the Internet development level is high in regions with more fixed telephone subscribers, meeting the relevance conditions. The post office was a main traditional tool for information transmission and exchange in the past, which was the executive department of laying fixed line. Its regional distribution affects the distribution of fixed telephone to a certain extent, thus affecting the early access of the Internet (Huang et al., 2019). Therefore, it can be expected that the Internet development level is relatively high in regions with more post offices and postal services, meeting the relevance conditions. At the same time, the number of fixed telephones, post offices and postal services in history can hardly affect the green development, hence meeting the exogenous conditions.

On the other hand, geographic location variable can also act as exogenous instrument variables (Bai and Zhang, 2021). This paper selects the distance to coastal port, and the distance between each city and Hangzhou as IV, respectively (Bai and Yu, 2021). Geographic location is a fixed fait accompli which is not affected by external factors, thus meeting the exogenous conditions. As the core resource and open platform of a region, coastal port is a basic pivotal facility and an important support for economic development. It can bring linkage effect and radiation effect to the regional digital economy. In addition, the development of digital finance represented by Alipay originates in Hangzhou. In summary, the distance to coastal port, the distance to Hangzhou is related to the development level of regional digital economy. The closer the city is to the coastal port and Hangzhou, the higher the level of digital development will be.

In order to make the instrument variables meet the time variability of panel data, this paper uses the interactive term of the logarithm of the above variables and the logarithm of the number of broadband Internet access ports as the instrument variables of the digital economy (Nunn and Qian, 2014). Table 5 reports the estimated results. The first stage regression results of 2SLS indicate that the regression coefficients of *Telephone-1984, Post office-1984* and *Total postal services-1984* are respectively 0.1213, 0.04796, and 0.09297, passing the statistical test at 1%. At the same time, the estimated coefficients of *Distance to coastal port* and *Distance to Hangzhou* are significantly negative at 5% and 1%, respectively. The above first stage results indicate that *DE* is significantly related to the instrumental variables. The F statistics of the first stage are 149.22, 146.96, 156.39, 171.75 and 172.65, respectively, which are far greater than the critical value of the rule of thumb 10, proving that there is no problem of weak IV. The second stage estimated results of 2SLS show that no matter what instrumental variables are selected, *DE* is still significant positive at the level of 5% or more, indicating that the digital economy has significantly promoted urban GTFP. These results indicate that the relationship between the digital economy and green development is still stable and effective after overcoming the endogenous issues.

4.2.2 Exogenous policy impact test

The quasi-natural experiment is applied to further eliminate the endogenous problems, demonstrating robustness of results. To address the slow network speed, low broadband coverage together with uneven regional development of information infrastructure construction, the State Council of China released the implementation plan of the "Broadband China" strategy in 2013. This plan deployed the broadband development goals and paths in the next 8 years and selected 120 cities (clusters) in three batches in 2014, 2015 and 2016 as the "Broadband China" pilot cities. The "Broadband China" strategy drives the implementation of new infrastructure construction such as 5G and gigabit broadband, accelerating the popularization and development of urban Internet. The digital economy can't develop without the support of network infrastructure. In other words, the more perfect the urban network infrastructure is, the higher the level of urban digital economy development. As an exogenous impact, the "Broadband China" demonstration policy can effectively represent the development of the digital economy (Zhao et al., 2020). Consequently, the demonstration policy of "Broadband China" is used as a quasi-natural experiment to test the causal influence of the digital economy on GTFP. Considering that this strategy is a policy experiment from pilot to popularization in batches, the multi-period difference in difference (DID) method proposed by Beck et al. (2010) is adopted in this paper. The empirical model is set in Formula (2):

$$\boldsymbol{GTFP_{it}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 Policy_{it}} + \boldsymbol{\alpha_c X_{it}} + \boldsymbol{\sigma_i} + \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{it}} \tag{2}$$

$Policy_{it}$ is a dummy variable of "Broadband China", which indicates whether city i is a demonstration city of "Broadband China" in year t. If city i joined the Broadband China policy demonstration, $Policy_{it}$ takes 1; otherwise, it was part of the control group, $Policy_{it}$ is 0.

Table 6 reports the regression results. As shown in column (1), the coefficient of *Policy* is 0.0784 and passes the 1% significance level, which indicates that the demonstration policy of Broadband China has improved the urban GTFP. After replacing GTFP with GTP and GTE respectively, the results show that the pilot policy significantly promotes GTP, but not significantly affects GEC. Hypothesis H1 is confirmed again. The parallel trend results are shown in Table 7. The estimated coefficients of Pre1, Pre2, Pre3 and Pre4 are not significant, and the results show that there is no systematic difference between the change trends of demonstration cities and non-demonstration cities before the implementation of

TABLE 5 Estimation results of models with instrumental variables.

	(1)	(2)	(3)	(4)	(5)
First Stage	DE				
Telephone-1984	0.1213*** (0.0207)				
Post office-1984		0.04796*** (0.01277)			
Total postal services-1984			0.09297*** (0 0.01437)		
Distance to Hangzhou				−0.0224** (0.0092)	
Distance to coastal port					−0.0012*** (0.0034)
First stage F value	149.22	146.96	156.39	171.75	172.65
Second Stage	GTFP				
DE	0.568*** (0.136)	1.276*** (0.202)	1.132*** (0.192)	1.830** (0.766)	0.503** (0.214)
Controlled variable	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
N	2024	2033	2096	2556	2556

Note: ** and *** denote significant at the level of 5% and 1%, respectively. N represents the number of samples.

TABLE 6 Regression results.

Variables	GTFP	GTP	GTE
	(1)	(2)	(3)
Policy	0.0784*** (0.0167)	0.0853*** (0.0124)	−0.0105 (0.0202)
_cons	13.95*** (1.262)	13.44*** (0.938)	0.954 (1.521)
Controlled variable	YES	YES	YES
City fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
N	2556	2556	2556
R^2	0.201	0.425	0.037

Note: ** and *** denote significant at the level of 5% and 1%, respectively._cons represents a constant term, N represents the number of samples.

TABLE 7 Parallel trend test regression results.

Period	GTFP	Period	GTFP
Pre4	0.0249 (0.0446)	Post1	0.0586 (0.0455)
Pre3	−0.0125 (0.0433)	Post2	0.0847* (0.0456)
Pre2	0.000140 (0.0450)	Post3	0.115** (0.0459)
Pre1	0.0390 (0.0452)	Post4	0.159*** (0.0501)
Current	0.0478 (0.0453)	Post5	0.242*** (0.0569)
_cons	13.17*** (1.269)	R^2	0.211
N	2556	N	2556

Note: *, ** and *** denote significant at the level of 10%, 5% and 1%, respectively._cons represents a constant term, N represents the number of samples.

policies, meeting the parallel trend test. In terms of dynamic effects, from the second year to the fifth year of the demonstration cities, Post2 passes the 10% significance level, Post3 passes the 5% significance level, and Post4 and Post5 pass the 1% significance test. The positive promotion effect shows an increasing trend year by year, and the parallel trend hypothesis is satisfied.

TABLE 8 Robustness test regression results.

Variables	Replacing a core explanatory variable	Replacing dependent variable		Excluding samples of key cities
	(1)	(2)	(3)	(4)
DE	0.194*** (0.0546)	0.0667*** (0.0135)	0.0300*** (0.00959)	0.0654*** (0.0131)
Controlled variable	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	2556	2556	2556	2520
R^2	0.198	0.107	0.216	0.190

Note: *** denotes significant at the level of 1%.

4.3 Robustness tests

4.3.1 Replacing independent variable and dependent variable

To mitigate the error caused by the index construction method, this paper constructs a new index to replace the core explanatory variable and dependent variable. On the one hand, a new measure index of the digital economy is constructed by entropy method in this paper. Column (1) of Table 8 reports the regression result. The regression coefficient of *DE* is still significantly positive, passing the 1% confidence interval. It indicates that the empirical results of the positive impact of the digital economy on urban GTFP remain robust. On the other hand, this paper changes the calculation method of GTFP. Considering that the unexpected output used to measure the GTFP index is mainly Industrial soot, SO_2 and industrial wastewater, which may lead to estimation errors. This paper recalculates the urban GTFP by adding carbon dioxide emissions data as the unexpected output on the basis of the original unexpected output and using carbon dioxide emissions data as the unexpected output alone. As shown in column (2) and column (3) of Table 8, the regression coefficient of *DE* is still significantly positive, proving the robustness of the benchmark estimation results again.

4.3.2 Excluding samples of key cities

With a large population and relatively concentrated social resources, municipalities directly under the Central Government play an important role in China's economic development. In order to eliminate the impact of special samples on the results, this paper change the sample size to exclude the samples of these big cities, namely Beijing, Tianjin, Shanghai and Chongqing. It can be seen from column (4) of Table 8, the regression coefficient of *DE* is 0.0654, passing the 1% confidence interval, which has no substantial change compared with the baseline regression results.

4.4 Heterogeneity analysis

4.4.1 Heterogeneity based on urban resource dependence

Cities are the most concentrated and prominent regions of global ecological environment problems. With the strong resource orientation, the resource-based cities are generally facing serious ecological and environmental problems. In recent years, scholars have also been exploring the green development path of resource-based cities. To investigate whether the digital economy promotes the green development of cities with different resource dependence, the 284 cities are divided into resource-based and non-resource-based cities according to the National Sustainable Development Plan for Resource-based Cities (2013–2020).

Table 9 reports the regression results. The estimated results in columns (1) and (4) show that *DE* exerts a positive impact on GTFP at a significance level of 1% in non-resource-based cities, while not significant in resource-based cities. As the digital economy has obvious characteristics of time stages, it is necessary to compare the stage changes generated by the development of the digital economy in different resource-dependent cities. Since the "13th Five-Year Plan Proposal" in 2015 first proposed to expand the network economic space and implement the national big data strategy, the scale of the digital economy has achieved leapfrog development and relevant policies have been implemented. Therefore, this paper divides the sample into two time periods: 2011–2014 and 2015–2019. The regression results are shown in columns (2)–(3) and (5)–(6). The estimated coefficient of *DE* is significantly positive at the 1% level before and after 2015 in non-resource-based cities, and the direct effect increases from 0.0423 to 0.0429. As for resource-based cities, the coefficient of *DE* is not significant before 2015, but significantly after 2015. The result indicates that the digital economy significantly promotes GTFP in resource-based cities after 2015. The reason for this may be that early resource-based cities are rich in resources and their economic development is mainly based on energy-intensive industries such as coal, metallurgy and coking. These cities have a single industrial structure and weak development of successive industries, which are more likely to produce "black" industrial path dependence and more prominent environmental problems, resulting in the fact that the influence of the digital economy on GTFP in resource-based cities is not significant. After 2015, the strong economic vitality and industrial resilience of the digital economy bring about an efficient matching of technological resources and traditional factor resources, which makes resource-based cities have a stronger marginal effect in improving energy efficiency with digital empowerment. Therefore, the digital economy can change the economic development mode of resource-based cities with low added value and break the "resource curse" to low-carbon, green and intelligent and promote the green transformation of cities. The above results suggest that the impact of the digital economy on urban GTFP is heterogeneous in resource dependence.

10.3389/fenvs.2023.1124680

TABLE 9 Heterogeneity test regression results based on resource dependence.

Variables	Non-resource based city			Resource-based city		
	2011–2019 (1)	2011–2014 (2)	2015–2019 (3)	2011–2019 (4)	2011–2014 (5)	2015–2019 (6)
DE	0.0467*** (0.0151)	0.0423*** (0.0151)	0.0429* (0.0246)	0.0425 (0.0277)	0.0246 (0.0349)	0.0690* (0.0417)
Controlled variables	YES	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
N	1530	680	850	1026	456	570
R^2	0.267	0.138	0.247	0.167	0.157	0.192

Note: * and *** denote significant at the level of 10% and 1%, respectively.

TABLE 10 Heterogeneity test regression results based on City Locations.

Variables	Eastern coastal city	Non-eastern coastal city	East	Central	West
	(1)	(2)	(3)	(4)	(5)
DE	0.0638*** (0.0164)	0.0512** (0.0208)	0.0562*** (0.0200)	0.0893*** (0.0271)	0.00573 (0.0215)
Controlled variables	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
N	1143	1413	909	891	756
R^2	0.314	0.150	0.370	0.225	0.108

Note: ** and *** denote significant at the level of 5% and 1%, respectively.

4.4.2 Heterogeneity analysis of geographical location

The unbalanced and insufficient economic development in different regions of China may lead to a “digital divide” between regions (Ren et al., 2021). Based on this, we first divided the 284 cities into eastern coastal cities and non-eastern coastal cities according to the classification standard of China Ocean Statistical Yearbook. Additionally, we further divided the 284 cities into the eastern, central and western regions according to the economic development level. Table 10 reports the location heterogeneity regression results.

Our results in columns (1)–(2) present that the coefficient of *DE* is 0.0638 at the 1% significance level in eastern coastal cities, and 0.0512 at the 5% significance level in non-eastern coastal cities. These findings indicate that the digital economy plays a positive role in promoting GTFP in both eastern and non-eastern coastal cities. The significance and contribution of the digital economy to GTFP in eastern coastal cities are better than those in non-eastern coastal cities. The reason is that the eastern coastal areas have policy advantages and the geographical location advantages close to the ports, which are beneficial to attract production factors such as talents, technology and information and generate a strong level of digital technology application and innovation, thus promoting green development. Our results present that the coefficients of *DE* in east and central regions are 0.0562 and 0.0893 at the 1% significant level respectively, but not significantly in the western region (columns 3–5). Specifically, the positive impact of the digital economy on GTFP shows a trend of central > eastern > western. There are several possible reasons. First, the development level of the digital economy in the eastern and central regions is relatively high, which helps to promote GTFP. However, the construction and investment of digital infrastructure in the western regions is not perfect, resulting that the development level of digital economy in the western region is too low, which is not conducive to the green growth effect of cities. The above conclusions are consistent with the analysis results of the threshold effect of the digital economy below. Second, the level of green development and digital economy in the eastern region is higher than that in the central region. Due to the law of diminishing marginal effect, the marginal green emission reduction effect of the digital economy is lower than that in the central region. The above findings show that there is geographical location heterogeneity on the impact of the digital economy to GTFP.

4.4.3 Heterogeneity of openness and financial development perspectives

The impact of the digital economy on GTFP may be affected by a number of local characteristics. We focus on two potential moderators, namely, openness and financial development.

Many countries have formulated various incentive measures and policies to improve the degree of openness. Openness can drive regional economic growth by absorbing technology spillovers generated by foreign investment. The degree of openness of a city

TABLE 11 Heterogeneity test regression results based on External Opening and Financial Development.

Variables	High level of openness	Low level of openness	High level of financial development	Low level of financial development
	(1)	(2)	(3)	(4)
DE	0.0722*** (0.0176)	−0.00625 (0.0212)	0.0477*** (0.0168)	0.0162 (0.0232)
Controlled variable	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	965	1591	965	1591
R^2	0.334	0.142	0.316	0.156

Note: *** denotes significant at the level of 1%.

is measured by the proportion of the total amount of foreign capital actually utilized to GDP in that year. According to the median of the openness in the sample, the sample is divided into two groups. As shown in columns (1)–(2) of Table 11, the coefficient of *DE* is positive and has passed the significance level of 1% in cities with high level of openness, while the coefficient is not significant in areas with low level of openness. These results suggest that openness plays a positive moderating role. For one thing, the increase in foreign direct investment inflows has improved the ability to absorb, adapt and innovate technologies and strengthens industrial specialization, so as to promote the development of ICT (Arvin et al., 2021). For another, regions with a high degree of economic openness usually realize economies of scale by using foreign markets and improve their technological level accordingly, while the application of international advanced technology plays an important role in reducing energy consumption and pollution emissions (Adom and Amuakwa-Mensah, 2016).

As an important part of the country's economic development, financial development can stimulate enterprises to engage in technological innovation. We use the proportion of RMB deposits and loans of banking financial institutions to the regional GDP to measure the financial development level in each city. We divide the sample into two groups according to the intermediate level of financial development, and columns (3)–(4) of Table 11 present the regression results. The coefficient of *DE* is positive at 1% significance level in cities with high level of financial development, while the coefficient is not significant in areas with low level of financial development. The possible reason is that data plays a key role in the core function of finance to enhance resource allocation efficiency. A sound financial service system can ease the financing constraints of various innovative entities and provide digital payment services and financing services for the development of the digital economy.

The above results indicate that the influence of the digital economy on GTFP is heterogeneous, which is manifested in the difference between the level of urban openness and the level of financial development, both of which have played a positive regulatory role.

5 Influencing mechanism analysis

The results of the previous study indicate that the development of the digital economy can significantly promote the growth of urban GTFP. Then what is its transmission mechanism? We explore the possible mechanisms based on the mediating effect model (Baron and Kenny, 1986), and establish the following regression equation:

$$\boldsymbol{Mechanic_{it} = \beta_0 + \beta_1 DE_{it} + \beta_c X_{it} + \sigma_i + \delta_t + \varepsilon_{it}} \quad (3)$$

$$\boldsymbol{GTFP_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 Mechanic_{it} + \gamma_c X_{it} + \sigma_i + \delta_t + \varepsilon_{it}} \quad (4)$$

where Mechanic is the mechanism variable in this paper, three mediators are used, namely green technological innovation, industrial structure upgrading and energy conservation. The other variables are the same as in Equation 1, with individual fixed effects σ_i and year fixed effects δ_t added to the equation. First of all, on the basis that the coefficients of regression model (1) pass the significance test, the linear regression Equation 3 of digital economy (*DE*) for mechanism variables (Mechanic) is constructed. Then, add the mechanism variables in Equation 1 to verify the impact of digital economy and mechanism variables on GTFP, as shown in Equation 4. Finally, judge the significance of regression coefficient. If the coefficient in Equation 3 β_1 is not significant, the mediating test does not exist. If it is significant, and it indicates that *DE* has a significant effect on the mechanism variable; If the coefficient in Equation 4 γ_2 is significant, there is a mediation effect.

5.1 Green technological innovation effect

The digital economy encourages green technological innovation, thus promoting urban GTFP. To verify this mechanism, this paper uses the number of green invention patents per 10,000 people to measure urban green technological innovation. As shown in column (1) of Table 12, the coefficient of *DE* on green technological innovation is 0.101 at the 1% significance level. The result implies that the digital economy promotes urban green technological innovation. The coefficient of green technological innovation on urban GTFP is positive at the 1% significance level (column 2). In a word, green technological innovation is an effective mediating pathway whereby the digital economy can promote GTFP.

5.2 Industrial structure upgrading effect

Theoretically, the digital economy can change the original service mode and realize the green development through the optimization and

TABLE 12 Regression results of influencing mechanism.

Variables	Green innovation	GTFP	Industry structure	GTFP	Energy	GTFP
	(1)	(2)	(3)	(4)	(5)	(6)
DE	0.101*** (0.0194)	0.0646*** (0.0130)	0.0257*** (0.00905)	0.0666*** (0.0130)	−0.00249** (0.00125)	0.0658*** (0.0129)
Green Innovation		0.0344** (0.0140)				
Industry Structure				0.0583* (0.0301)		
Energy						−0.907*** (0.218)
Controlled variable	YES	YES	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
N	2556	2556	2556	2556	2556	2556
R^2	0.140	0.205	0.140	0.205	0.109	0.209

Note: *, **, and *** denote significant at the level of 10%, 5%, and 1%, respectively.

TABLE 13 Estimated results of spatial models with different weight matrices.

Variables	Geographical adjacency spatial weight	Geographical distance spatial weight	Economic distance spatial weight	Economic geographical nested spatial weight
	(1)	(2)	(3)	(4)
DE	0.0659*** (0.0120)	0.0712*** (0.0121)	0.0527*** (0.0121)	0.0506*** (0.0120)
W×DE	0.0364 (0.0273)	0.411** (0.194)	0.0471 (0.0344)	0.0871*** (0.0334)
Controlled variable	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Direct Effect	0.0689*** (0.0125)	0.0754*** (0.0128)	0.0548*** (0.0125)	0.0544*** (0.0125)
Indirect Effect	0.0634** (0.0318)	1.193* (0.644)	0.0729* (0.0403)	0.125*** (0.0401)
Total Effec	0.132*** (0.0366)	1.268* (0.647)	0.128*** (0.0439)	0.180*** (0.0438)
N	2547	2547	2547	2547

Note: *, **, and *** denote significant at the 10%, 5%, and 1% levels, respectively.

upgrading of industrial structure. According to the study of Zhao et al. (2021), this paper uses the ratio of the value added of tertiary industry to secondary industry to measure industrial structure upgrading. In column (3) of Table 12, the coefficient of *DE* is significantly positive, indicating that the digital economy has significantly promoted the upgrading of industrial structure. Column (4) shows that the coefficient of industrial structure upgrading is also positive at the 1% significance level. In a word, industrial structure upgrading is an effective mediating pathway whereby the digital economy can promote GTFP.

5.3 Energy conservation effect

Theoretically, the digital economy can promote the efficiency of energy utilization thus promoting the green development of cities. To prove this influence mechanism, this paper uses the city's total social electricity consumption per unit of GDP to measure energy consumption. As shown in column (5) of Table 12, the coefficient of *DE* is significantly negative at 5% confidence level. The result implies that the development of the digital economy significantly reduces energy consumption. In column (6), the energy consumption has a significant negative effect on the urban GTFP at 1% confidence level. In a word, energy conservation effect is an effective mediating pathway whereby the digital economy can promote GTFP. The digital economy can reduce energy consumption by optimizing production processes, reducing and replacing economic activities, introducing the use of complementary products and improving waste management processes (Cecere et al., 2014), thus promoting the urban GTFP.

To sum up, the results in this section show that the digital economy can improve the growth of GTFP by green technological innovation, industrial structure upgrading and energy conservation. Hypothesis 2 is verified.

10.3389/fenvs.2023.1124680

TABLE 14 Threshold effect test.

Threshold variables	Test	F Value	*p*-Value	Critical value		
				10%	5%	1%
DE	Single threshold value	54.51***	0.0000	25.6253	29.8302	39.0760
	Double threshold value	14.68	0.2030	19.4616	23.7434	36.0879

Note: *, **, and *** denote significant at the level of 10%, 5%, and 1%, respectively.

TABLE 15 Threshold estimates and 95% confidence interval.

Threshold variables	Test	Threshold estimates	Confidence interval
DE	Single threshold value	−0.7448	[−0.7561–0.7439]

TABLE 16 Regression results of panel threshold model.

Variables	Coefficient	T Value
lnpgdp	−0.749*** (0.205)	−3.65
Pgdp2	0.0335*** (0.00911)	3.67
Envir	0.00462 (0.0169)	0.27
Fdi	−0.887* (0.511)	−1.74
Indu	−0.00510*** (0.000981)	−5.20
Hum	0.252 (1.167)	0.22
Gover	−0.0282 (0.148)	−0.19
DE (q ≤ −0.7448)	0.00161 (0.0213)	0.08
DE (q > −0.7448)	0.132*** (0.0122)	10.83
_cons	5.427*** (1.162)	4.67
N	2556	2556
R^2	0.155	0.155

Note: * and *** denote significant at the level of 10% and 1%, respectively. _cons represents a constant term, N represents the number of samples.

6 Analysis of spatial spillover effects

In the previous analysis, we constructed a multiple linear regression and exogenous policy impact test to verify the influence of the digital economy on GTFP. However, due to the scale effect and networking characteristics of the digital economy, the flow of it among cities is not independent of each other. Based on this, this part invokes the spatial interaction term in Equation 1 using the spatial Durbin model (SDM) to examine the spatial spillover effect of the digital economy on GTFP. The model is constructed as follows:

$$\boldsymbol{GTFP_{it}} = \boldsymbol{\alpha_0} + \boldsymbol{\rho WGTFP_{it}} + \boldsymbol{\alpha_1 DE_{it}} + \boldsymbol{\theta WDE_{it}} + \boldsymbol{\alpha_c X_{it}} + \boldsymbol{\lambda WX_{it}} + \boldsymbol{\sigma_i} + \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{it}} \tag{5}$$

W represents the $n \times n$ dimensional spatial weight matrix; ρ represents the spatial correlation coefficient. This paper mainly uses four kinds of matrices of geographical adjacency, geographical distance, economic distance and economic-geographic nested.

It can be seen from Table 13 that after transforming the spatial weight matrices, the regression coefficients of *DE* are 0.0659, 0.0712, 0.0527, and 0.0506, all of which are positive at 1% significance level. Since the SDM explains the spatial economic correlations among cities, the estimated results of its spatial econometric model including spatial lags cannot directly report the real impact of the spatial spillover effects of the explanatory variables on the explained variables. The decomposition results through spatial effects show that all effects are significantly positive regardless of the spatial weights matrices chosen, and the indirect effect accounts for more than 50% of the total effect. The digital technology accelerates the diffusion of information and various resource elements and guide the cross-regional labor division and cooperation. It triggers a learning and imitation effect by facilitating knowledge spillover and innovation resources exchange (Proeger and Runst, 2020), thus driving the improvement of green total factor productivity in the neighboring areas. The results prove that the digital economy significantly enhances green GTFP of neighboring cities and hypothesis 3 is verified.

7 Threshold effect

Considering the network effect of the Internet and Metcalfe's Law, there may have a non-linear relationship of the digital economy on

GTFP. Therefore, we use the dynamic panel threshold regression model proposed by Hansen (1999) to test the threshold effect, as shown in the formula:

$$\boldsymbol{GTFP_{it}} = \boldsymbol{\varphi_0} + \boldsymbol{\varphi_1 DE_{it}} \times \boldsymbol{I}(\boldsymbol{q_{it}} \le \boldsymbol{Y}) + \boldsymbol{\varphi_2 DE_{it}} \times \boldsymbol{I}(\boldsymbol{q_{it}} > \boldsymbol{Y}) + \boldsymbol{\varphi_c X_{it}} + \boldsymbol{\sigma_i} + \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{it}} \tag{6}$$

Where, q_{it} is the threshold variable of digital economy, $I(\cdot)$ is the indicator function, and Y is the threshold parameter. Eq. 6 considers the case of a single threshold, and the multi threshold model can be extended from Eq. 6. Whether the single threshold model or the multi threshold model is used needs further testing.

Considering the "network effect" of the digital economy, there is a non-linear relationship (hypothesis 4). First of all, based on the Bootstrap method proposed by Hansen (1999), we repeatedly sampled 1000 times to verify whether there is a threshold effect with *DE* as the threshold variable. As shown in Table 14 and Table 15, *DE* has passed the single threshold test at the 1% significance level, and the threshold value is -0.7448, but the double threshold test has not passed the significance test.

Next, we estimate the parameters of the threshold model through empirical analysis. Table 16 reports the regression results of panel threshold model, indicating that there is a single threshold effect on the impact of the digital economy on GTFP. When *DE* is less than the threshold value of -0.7448, the impact is not significant. When *DE* crosses -0.7448, the regression coefficient increases to 0.132 at the 1% significance level. On the basis of the network effect, the value of the network depends upon the size of its other users. When the development level of the digital economy is low, its network effect is too small to form a network value advantage and economies of scale relative to competitors. Enterprises have no incentive to achieve energy conservation and emission reduction to obtain high profits, which is not conducive to the play of urban green growth effect. Therefore, when *DE* is lower than the threshold value of -0.7448, the digital economy has no significant impact on green development. As the broadband usage, digital infrastructure construction and Internet access continuously increase until the network effect exceeds a critical value, the enterprise's products or services can quickly obtain a sufficient number of users or suppliers, which is conducive to the exertion of the network effect and initiation of the positive influence mechanism, thus promoting urban GTFP.

8 Conclusions and discussions

8.1 Conclusions

The limited resources and environmental degradation make it necessary to achieve green development. This paper empirically proves the impact, transmission mechanism, spatial spillover effect and non-linear effect of the digital economy on green development using the data of 284 prefecture-level cities in China. Different from the research result of Lange et al. (2020), this paper believes that the hope of digitalization to promote sustainable development can be realized. The overall research conclusion has strong application value in the current era of digital transformation, providing a reference for emerging countries to achieving green development through the digital economy. The main research conclusions present as follows:

(1) The digital economy can significantly improve urban GTFP. The growth of China's GTFP is mainly attributed to green technological progress (GTP). (2) The boosting effect of the digital economy on GTFP has significant heterogeneity on city resource dependence, geographical location, openness and financial development level. First, the digital economy significantly boosts GTFP of resource-based cities after 2015 and the boosting effect is greater than that of non-resource-based cities. Next, the boosting effect of the digital economy on GTFP shows that the eastern coastal cities are greater than the non-eastern coastal cities, and the central-east regions are greater than the west regions. Finally, cities with higher level of financial development and openness, the stronger its promotion. This paper analyzes heterogeneity from a new perspective, enriching the existing heterogeneity analysis. It provides an empirical evidence for the government to improve the opening up, the level of financial development and accelerate the digital transformation of resource-based cities. (3) Green technological innovation, industrial structure upgrade and energy conservation are the important mediating mechanisms for the digital economy on GTFP. The more comprehensive mechanism test in this paper deepens the existing literature. (4) The spatial Durbin econometric model analysis reveals that the digital economy has a significant spatial spillover impact on GTFP, and it can promote GTFP on the surrounding areas. (5) Using the threshold model, it is found that the effect of the digital economy on urban GTFP growth is non-linear and has a single threshold. The low development level of the digital economy is not conducive to the green growth effect.

8.2 Discussions

8.2.1 Policy implications

On the basis of the above empirical results, the following important policy suggestions are put forward:

1) Accelerate the development of the digital economy to promote the green development of cities. First of all, it is necessary to actively improve the deep integration of digital technology and the real economy. Enterprises can increase the application of digital technologies such as industrial Internet, big data and 5G, giving full play to the green enabling role of digital technology from the energy supply side and the industrial demand side to energy saving and waste reduction in the production process. Secondly, intelligence or information technology should be introduced into urban management. For example, in the field of smart transportation, reduce carbon emissions through new energy technologies and intelligent networking. Finally, in terms of government governance, it is necessary to actively participate in the construction of digital society and digital government, realizing intelligent interconnection and data sharing. In addition, it is also necessary to promote the research, development and application of green energy-related patents, and promote the intelligent and green development of traditional industries by optimizing and upgrading the traditional industrial structure.

2) Implement targeted and precise regional policies to address the imbalance and regional differences brought about by the development of the digital economy. On the one hand, the government should base itself on the low-cost advantages of the central and western regions, increase the construction and investment of infrastructure related to the digital economy, and promote the penetration of the digital economy in these regions. On the other hand, local governments should speed up the digital transformation of resource-based cities for considering resource endowment conditions and local industrial chain ecology. Finally, it is worthwhile to improve the level of urban openness and financial development, enhancing the positive impact of the digital economy on urban GTFP. At the same time, considering that cities with developed digital economy have radiation and spillover effects, it is necessary to strengthen exchanges and cooperation in technology, talents, data and other resources between cities. It conduces to formation of complementary advantages and coordinated development between regions, so as to drive the green development of surrounding cities.

8.2.2 Future research directions and limitations

There are some limitations in this study. First of all, this paper combined urban panel data with certain sample limitations. Subsequent studies can further demonstrate the relationship between digital economy and green development from a micro perspective such as enterprise level or county level data. Secondly, this paper does not establish a theoretical model, and subsequent research can build models to enrich relevant theoretical mechanisms. Finally, there is no uniform standard and normative guidance for the selection and measurement of indicators of the digital economy. In future research, scholars can formulate unified urban digital economy measurement indicators to accurately measure comparable digital economy development scale. Subsequent studies can also further confirm the impact of various indicators of the digital economy segmentation on green development, such as industrial digitization and digital industrialization.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Conceptualization, YX and SW; methodology, YX; software, YX; validation, YX; formal analysis, YX, SW, and HL; investigation, YX; data curation, YX and HL; writing—original draft preparation, YX and SW; writing—review and editing, YX and SW; visualization, YX and SW; supervision, ZL; All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by National Social Science Foundation of China (grant number20STA029).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Adom, P. K., and Amuakwa-Mensah, F. (2016). What drives the energy saving role of FDI and industrialization in East Africa? *Renew. Sustain. Energy Rev.* 65, 925–942. doi:10.1016/j.rser.2016.07.039

Arvin, M. B., Pradhan, R. P., and Nair, M. (2021). Uncovering interlinks among ICT connectivity and penetration, trade openness, foreign direct investment, and economic growth: The case of the G-20 countries. *Telematics Inf.* 60, 101567. doi:10.1016/j.tele.2021.101567

Au, C. C., and Henderson, J. V. (2006). Are Chinese cities too small? *Rev. Econ. Stud.* 73, 549–576. doi:10.1111/j.1467-937X.2006.00387.x

Bai, P. W., and Yu, L. (2021). Digital economy development and firms' markup: Theoretical mechanisms and empirical facts. *China Ind. Econ.* 11, 59–77. doi:10.19581/j.cnki.ciejournal.2021.11.003

Bai, P. W., and Zhang, Y. (2021). The digital economy, the declining demographic dividend and the rights of low- and middle-skilled workers. *Econ. Res.* 5, 91–108.

Balogun, A. L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., et al. (2020). Assessing the potentials of digitalization as a tool for climate change adaptation and sustainable development in urban centres. *Sustain. Cities Soc.* 53, 101888. doi:10.1016/j.scs.2019.101888

Bano, S., Zhao, Y. H., Ahmad, A., Wang, S., and Liu, Y. (2018). Identifying the impacts of human capital on carbon emissions in Pakistan. *J. Clean. Prod.* 183, 1082–1092. doi:10.1016/j.jclepro.2018.02.008

Baron, R. M., and Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personality Soc. Psychol.* 51, 1173–1182. doi:10.1037//0022-3514.51.6.1173

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *J. Finance* 65, 1637–1667. doi:10.1111/j.1540-6261.2010.01589.x

Cai, W., and Li, G. (2018). The drivers of eco-innovation and its impact on performance: Evidence from China. *J. Clean. Prod.* 176, 110–118. doi:10.1016/j.jclepro.2017.12.109

Cardona, M., Kretschmer, T., and Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Inf. Econ. Policy* 25, 109–125. doi:10.1016/j.infoecopol.2012.12.002

Cecere, G., Corrocher, N., Gossart, C., and Ozman, M. (2014). Technological pervasiveness and variety of innovators in green ICT: A patent-based analysis. *Res. Policy* 43, 1827–1839. doi:10.1016/j.respol.2014.06.004

Chung, H. (2018). ICT investment-specific technological change and productivity growth in Korea: Comparison of 1996–2005 and 2006–2015. *Telecommun. Policy* 42, 78–90. doi:10.1016/j.telpol.2017.08.005

Danish, K. (2019). Effects of information and communication technology and real income on CO2 emissions: The experience of countries along Belt and road. *Telematics Inf.* 45, 101300. doi:10.1016/j.tele.2019.101300

Danish, K., and Ulucak, R. (2021). Renewable energy, technological innovation and the environment: A novel dynamic auto-regressive distributive lag simulation. *Renew. Sustain. Energy Rev.* 150, 111433. doi:10.1016/j.rser.2021.111433

Dinda, S. (2004). Environmental Kuznets curve hypothesis: A survey. *Ecol. Econ.* 49, 431–455. doi:10.1016/j.ecolecon.2004.02.011

Emrouznejad, A., and Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Plan. Sci.* 61, 4–8. doi:10.1016/j.seps.2017.01.008

Fukuyama, H., and Weber, W. L. (2009). A directional slacks-based measure of technical inefficiency. *Socio-Economic Plan. Sci.* 43, 274–287. doi:10.1016/j.seps.2008.12.001

G20 (2016). *G20 digital economy development and cooperation initiative [EB/OL]*. (2016-09-20) [2019-08-01] Available at: http://www.g20chn.org/hywj/dncgwj/201609/t20160920_3474.html (Accessed September 20, 2016).

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econ.* 93, 345–368. doi:10.1016/S0304-4076(99)00025-1

Hao, X. L., Wang, X. H., Wu, H. T., and Hao, Y. (2022). Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity? *Sustain. Dev.* doi:10.1002/sd.2397

He, F., and Liu, H. X. (2019). Assessment of the performance enhancement effect of digital change in real enterprises from the perspective of digital economy. *Reform* 4, 137–148.

Higón, D. A., Gholami, R., and Shirazi, F. (2017). ICT and environmental sustainability: A global perspective. *Telematics Inf.* 34, 85–95. doi:10.1016/j.tele.2017.01.001

Hu, X. Y., and Guo, P. F. (2022). A spatial effect study on digital economy affecting the green total factor productivity in the Yangtze River Economic Belt. *Environ. Sci. Pollut. Res.* 29, 90868–90886. doi:10.1007/s11356-022-22168-9

Huang, Q. H., Yu, Y. Z., and Zhang, S. L. (2019). Internet development and manufacturing productivity improvement: Intrinsic mechanism and Chinese experience. *China Ind. Econ.* 8, 5–23. doi:10.19581/j.cnki.ciejournal.2019.08.001

Iqbal, J., Khan, M., Talha, M., Farman, H., Jan, B., Muhammad, A., et al. (2018). A generic internet of things architecture for controlling electrical energy consumption in smart homes. *Sustain. Cities Soc.* 43, 443–450. doi:10.1016/j.scs.2018.09.020

Jiang, H. L., Jiang, P. C., Wang, D., and Wu, J. H. (2021). Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. *Sustain. Cities Soc.* 69, 102809. doi:10.1016/j.scs.2021.102809

Kim, K., Bounfour, A., Nonnis, A., and Ozaygen, A. (2021). Measuring ICT externalities and their contribution to productivity: A bilateral trade based approach. *Telecommun. Policy* 55, 102085. doi:10.1016/j.telpol.2020.102085

Lange, S., Santarius, T., and Pohl, J. (2020). Digitalization and energy consumption: Does ICT reduce energy demand? *Ecol. Econ.* 176, 106760–106773. doi:10.1016/j.ecolecon.2020.106760

Lennerfors, T. T., Fors, P., and Rooijen, V. J. (2015). ICT and environmental sustainability in a changing society: The view of ecological World Systems Theory. *Inf. Technol. People* 28, 758–774. doi:10.1108/ITP-09-2014-0219

Li, H. S., Tian, Y. X., and Li, W. J. (2014). Internet thinking and traditional enterprise reengineering. *China Ind. Econ.* 10, 135–146. doi:10.19581/j.cnki.ciejournal.2014.10.011

Li, J. X., Zhou, K., and Cheng, Z. H. (2022). Does China's "Belt and Road" Initiative promote green total factor productivity growth in countries along the route? *J. Clean. Prod.* 93, 133004. doi:10.1016/j.jclepro.2022.133004

Li, M. J., and Du, W. J. (2021). Can Internet development improve the energy efficiency of firms: Empirical evidence from China. *Energy* 237, 121590. doi:10.1016/j.energy.2021.121590

Li, X. H. (2019). New features of the digital economy and the formation mechanism of new dynamics of the digital economy. *Reform* 11, 40–51.

Li, Z., G., and Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: Evidence city-level empirical data in China. *J. Clean. Prod.* 351, 131570. doi:10.1016/j.jclepro.2022.131570

Li, Z. G., and Wang, J. (2021). Digital economy development, data factor allocation and manufacturing productivity improvement. *Econ.* 10, 41–50. doi:10.16158/j.cnki.51-1312/f.2021.10.005

Liu, Z., and Xin, L. (2019). Has China's Belt and road initiative promoted its green total factor productivity? Evidence from primary provinces along the route. *Energy Policy* 129, 360–369. doi:10.1016/j.enpol.2019.02.045

Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., and Hao, Y. (2022). *Digitalization and sustainable development: How could digital economy development improve green innovation in China? Business strategy and the environment*, 1–25. doi:10.1002/bse.3223

Ma, D., and Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* 145, 801–813. doi:10.1016/j.jbusres.2022.03.041

Martin, C. J., Evans, J., and Karvonen, A. (2018). Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in europe and north America. *Technol. Forecast. Soc. Change* 133, 269–278. doi:10.1016/j.techfore.2018.01.005

Mehrara, M., Rezaei, S., and Razi, D. H. (2015). Determinants of renewable energy consumption among ECO countries; based on Bayesian model averaging and weighted-average least square. *Int. Lett. Soc. Humanist. Sci.* 54, 96–109. doi:10.18052/www.scipress.com/ilshs.54.96

Miao, C. L., Fang, D. B., Sun, L. Y., and Luo, Q. L. (2017). Natural resources utilization efficiency un-der the influence of green technological innovation. *Resour. Conservation Recycl.* 126, 153–161. doi:10.1016/j.resconrec.2017.07.019

Nunn, N., and Qian, N. (2014). US food aid and civil conflict. *Am. Econ. Rev.* 104, 1630–1666. doi:10.1257/aer.104.6.1630

Obobisa, E. S., Chen, H. B., and Mensah, I. A. (2022). The impact of green technological innovation and institutional quality on CO2 emissions in African countries. *Technol. Forecast. Soc. Change* 180, 121670. doi:10.1016/j.techfore.2022.121670

Ozcan, B., and Apergis, N. (2018). The impact of internet use on air pollution: Evidence from emerging countries. *Environ. Sci. Pollut. Res.* 25, 4174–4189. doi:10.1007/s11356-017-0825-1

Pan, W. R., Xie, T., Wang, Z. W., and Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *J. Bus. Res.* 139, 303–311. doi:10.1016/j.jbusres.2021.09.061

Pan, Y. L., and Dong, F. (2022). Dynamic evolution and driving factors of new energy development: Fresh evidence from China. *Technol. Forecast. Soc. Change* 176, 121475. doi:10.1016/j.techfore.2022.121475

Park, Y., Meng, F., and Baloch, M. A. (2018). The effect of ICT, financial development, growth, and trade openness on CO2 emissions: An empirical analysis. *Environ. Sci. Pollut. Res.* 25, 30708–30719. doi:10.1007/s11356-018-3108-6

Pei, C. H., Ni, J. F., and Li, Y. (2018). Analysis of the political economy of the digital economy. *Finance Trade Econ.* 39, 5–22. doi:10.19795/j.cnki.cn11-1166/f.2018.09.001

Proeger, T., and Runst, P. (2020). Digitization and knowledge spillover effectiveness—evidence from the "German mittelstand". *J. Knowl. Econ.* 11, 1509–1528. doi:10.1007/s13132-019-00622-3

Qiu, B., Yang, S. H., and Xin, P. J. (2008). A study on FDI technology spillover channel and manufacturing productivity growth in China: An analysis based on panel data. *World Econ.* 8, 20–31.

Qiu, S. L., Wang, Z. L., and Liu, S. (2021). The policy outcomes of low-carbon city construction on urban green development: Evidence from a quasi-natural experiment conducted in China. *Sustain. Cities Soc.* 66, 102699. doi:10.1016/j.scs.2020.102699

Ramirez, L. L. J., Puerta Aponte, G., and Rodriguez Garcia, A. (2019). Internet of things applied in healthcare based on open hardware with low-energy consumption. *Healthc. Inf. Res.* 25, 230–235. doi:10.4258/hir.2019.25.3.230

Ren, S. M., Li, L. Q., Han, Y. Q., Hao, Y., and Wu, H. T. (2022). The emerging driving force of inclusive green growth: Does digital economy agglomeration work. *Bus. Strategy Environ.* 31, 1656–1678. doi:10.1002/bse.2975

Ren, S. Y., Hao, Y., Xu, L., Wu, H. T., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

Roscia, M., Longo, M., and Lazaroiu, G. C. (2013). Smart City by multi-agent systems. *Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, 371–376. doi:10.1109/ICRERA.2013.6749783

Sadorsky, P. (2012). Information communication technology and electricity consumption in emerging economies. *Energy Policy* 48, 130–136. doi:10.1016/j.enpol.2012.04.064

Salahuddin, M., and Alam, K. (2016). Information and communication technology, electricity consumption and economic growth in OECD countries: A panel data analysis. *Int. J. Electr. Power Energy Syst.* 76, 185–193. doi:10.1016/j.ijepes.2015.11.005

Schulte, P., Welsch, H., and Rexhäuser, S. (2016). ICT and the demand for energy: Evidence from OECD countries. *Environ. Resour. Econ.* 63, 119–146. doi:10.1007/s10640-014-9844-2

Stefanie, K., and David, T. (2021). Digitalisation, sustainable industrialisation and digital rebound – asking the right questions for a strategic research agenda. *Energy Res. Soc. Sci.* 82, 102295. doi:10.1016/j.erss.2021.102295

Tao, C. Q., Yi, M. Y., and Wang, C. S. (2023). Coupling coordination analysis and Spatiotemporal heterogeneity between data elements and green development in China. *Econ. Analysis Policy* 77, 1–15. doi:10.1016/j.eap.2022.10.014

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Policy* 47, 1367–1387. doi:10.1016/j.respol.2017.01.015

Tranos, E., Kitsos, T., and Ortega-Argilés, R. (2021). Digital economy in the UK: Regional productivity effects of early adoption. *Reg. Stud.* 55, 1924–1938. doi:10.1080/00343404.2020.1826420

Wang, H. R., Cui, H. R., and Zhao, Q. Z. (2021). Effect of green technology innovation on green total factor productivity in China: Evidence from spatial durbin model analysis. *J. Clean. Prod.* 288, 125624. doi:10.1016/j.jclepro.2020.125624

Wang, L., Chen, Y. Y., Ramsey, T. S., and Hewing, G. (2021). Will researching digital technology really empower green development. *Technol. Soc.* 66, 101638. doi:10.1016/j.techsoc.2021.101638

Wang, M., and Feng, C. (2021). Revealing the pattern and evolution of global green development between different income groups: A global meta-frontier by production technology approach. *Environ. Impact Assess. Rev.* 89, 106600. doi:10.1016/j.eiar.2021.106600

Watanabe, C., Naveed, K., Tou, Y., and Neittaanmäkia, P. (2018). Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technol. Forecast. Soc. Change* 137, 226–240. doi:10.1016/j.techfore.2018.07.053

Watanabe, C., Naveed, K., and Zhao, W. (2015). New paradigm of ICT productivity – increasing role of un-captured GDP and growing anger of consumers. *Technol. Soc.* 41, 21–44. doi:10.1016/j.techsoc.2014.10.006

Wu, H. T., Xue, Y., Hao, Y., and Ren, S. Y. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ.* 103, 105577. doi:10.1016/j.eneco.2021.105577

Wu, J. X., and Guo, Z. Y. (2016). Convergence analysis of carbon emissions in China based on the continuous dynamic distribution method. *Stat. Res.* 1, 54–60. doi:10.19343/j.cnki.11-1302/c.2016.01.008

Xu, X. C., Ren, X., and Chang, Z. H. (2019). Big data and green development. *China Ind. Econ.* 4, 5–22. doi:10.19581/j.cnki.ciejournal.2019.04.001

Xue, Y., Tang, C., Wu, H. T., Liu, J. M., and Hao, Y. (2022). The emerging driving force of energy consumption in China: Does digital economy development matter. *Energy Policy* 165, 112997. doi:10.1016/j.enpol.2022.112997

Yabo, L., and Jie, C. (2022). Research on the export quality effect of digital economy. *World Econ. Stud.* 17, 32–134. doi:10.13516/j.cnki.wes.2022.03.006

Yang, X., Li, X. P., and Zhong, Chunping. (2019). Study on the evolutionary trend of industrial biased technological progress and influencing factors in China. *Res. Quantitative Econ. Technol. Econ.* 4, 101–119. doi:10.13653/j.cnki.jqte.2019.04.006

Yi, M., Liu, Y. F., Sheng, M. S., and Wen, L. (2022). Effects of digital economy on carbon emission reduction: New evidence from China. *Energy Policy* 171, 113271. doi:10.1016/j.enpol.2022.113271

Yi, M., Wang, Y., Sheng, M., Sharp, B., and Zhang, Y. (2020). Effects of heterogeneous technological progress on haze pollution: Evidence from China. *Ecol. Econ.* 169, 106533. doi:10.1016/j.ecolecon.2019.106533

Yuan, Y. J., and Xie, R. H. (2015). FDI, environmental regulations and green total factor productivity growth in Chinese industry: An empirical study based on the luenberger index. *Int. Trade Issues* 8, 84–93. doi:10.13510/j.cnki.jit.2015.08.009

Zhang, D., and Vigne, S. (2021). How does innovation efficiency contribute to green productivity? A financial constraint perspective. *J. Clean. Prod.* 280, 124000. doi:10.1016/j.jclepro.2020.124000

Zhang, J. N., Lyu, Y. W., Li, Y. T., and Geng, Y. (2022). Digital economy: An innovation driving factor for low-carbon development. *Environ. Impact Assess. Rev.* 96, 106821. doi:10.1016/j.eiar.2022.106821

Zhang, J., Wu, G. Y., and Zhang, J. P. (2004). Interprovincial physical capital stock estimation in China: 1952-2000. *Econ. Res.* 10, 35–44.

Zhang, W., Liu, X. M., Wang, D., and Zhou, J. P. (2022). Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* 165, 112927. doi:10.1016/j.enpol.2022.112927

Zhao, J., Shahbaz, M., Dong, X., and Dong, K. (2021). How does financial risk affect global CO2 emissions? The role of technological innovation. *Technol. Forecast. Soc. Change* 168, 120751. doi:10.1016/j.techfore.2021.120751

Zhao, T., Zhang, Z., and Liang, S. K. (2020). Digital economy, entrepreneurial activity and high-quality development— an empirical evidence from Chinese cities. *Manag. World* 10, 65–76. doi:10.19744/j.cnki.11-1235/f.2020.0154

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 February 2023
DOI 10.3389/fenvs.2023.1134334

Bilateral impact of digital economy on air pollution: Emissions increase and reduction effects

Ruomei Wang[1] and Chenhui Ding[2]*

[1]School of Economics and Management, Anhui University of Science and Technology, Huainan, Anhui, China, [2]Business School, Hohai University, Nanjing, Jiangsu, China

Check for updates

OPEN ACCESS

EDITED BY
Grigorios L. Kyriakopoulos,
National Technical University of Athens, Greece

REVIEWED BY
Elchin Suleymanov,
Baku Enginering University, Azerbaijan
Iliana Papamichael,
Open University of Cyprus, Cyprus

*CORRESPONDENCE
Chenhui Ding,
dingchenhui@hhu.edu.cn

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management, a section of the journal Frontiers in Environmental Science

RECEIVED 30 December 2022
ACCEPTED 07 February 2023
PUBLISHED 20 February 2023

CITATION
Wang R and Ding C (2023), Bilateral impact of digital economy on air pollution: Emissions increase and reduction effects.
Front. Environ. Sci. 11:1134334.
doi: 10.3389/fenvs.2023.1134334

China's rapid industrialization and urbanization have led to ecological and environmental problems, particularly air pollution. Digitalization has become a key component in high-quality development to overcome the previous high-energy and high-pollution development model. However, a certain degree of "green blindness" exists in the digital development process, and the impact on air pollution is not always positive. Therefore, the impact of the digital economy on air pollution is worth exploring. In this study, the authors examines the emissions increase and reduction effect mechanisms of the digital economy on air pollution using panel data in 30 provinces in China from 2011 to 2020. The two-tier stochastic frontier model showed that the interaction between the emissions increase effect and emissions reduction effect of the digital economy reduced the actual air pollution emissions level below the frontier level by 0.15%, on average. Overall air pollution level is characterized prominently by emission reduction, owing to the asymmetric bilateral effect of the digital economy. Second, the time trend characteristics of the net effect of the digital economy on air pollution emissions showed a wave-like change; the average values of the net effect in the three major regions (i.e., the east, central, and west) were all negative. Third, along with the development of digital economy, human capital levels, and general economic levels, the emissions reduction effect of the digital economy on air pollution has strengthened, such that the net effect became positive to negative. However, significant heterogeneous characteristics were noted in the effects of the digital economy on air pollution under different levels of digital economy development, human capital, and economic development. This study provides practical paths for air pollution management, strengthening inter-regional environmental synergy management and high-quality economic development.

KEYWORDS

digital economy, air pollution, two-tier stochastic frontier model, emissions increase effect, emissions reduction effect, heterogeneity

1 Introduction

According to the World Health Organization, air pollution has caused 4.2 million premature deaths in 2019, and 89% of those premature deaths occurred in low- and middle-income countries, for example, South-East Asia and Western Pacific Regions (World Health Organization, 2022). Airborne particulate matter concentrations in many developing countries are 5–10 times higher than in developed countries (Ebenstein et al., 2017). China is the largest developing country, and the research on its air pollution is representative, which can be a reference for other developing countries. China's rapid industrialization and urbanization have led to ecological and environmental problems typified by air pollution. Air pollution seriously endangers human health, reduces the life expectancy of residents, causes unemployment, reduces *per capita* GDP, and impairs the quality of economic development as well as the environment (Huang et al., 2014; Chang et al., 2016; Ebenstein et al., 2017). High PM2.5 pollution raise overall health risk to the population and economic loss (Li and Zhang, 2019). Therefore, air pollution has become an important issue for governments and scholars around the world (Feng et al., 2019). The alarming nature of this problem has led China to adopt a series of environmental policies to address it. The 20th CPC National Congress once again proposed the thorough promotion of environmental pollution prevention and control while continuously attempting to preserve blue skies, clear waters, and clean lands.

Ecological and environmental problems can be attributed to issues with the development model and lifestyle (Guo et al., 2022). The data element has become the key to achieving high-quality development by breaking the existing previous high-energy consumption and high-pollution development model (Zhou et al., 2022). The Industry 4.0 strategy has greatly promoted the process of digitalization. Its main purpose is to achieve the intelligent manufacturing through the Cyber-Physical System (Lasi et al., 2014). The core of Industry 4.0 includes digitization, networking, automation and intelligence. Since the release of Industry 4.0, digital technologies such as big data, blockchain and cloud computing have continued to develop, providing support for humanity to enter the era of digital economy. Chinese government departments also attach importance to the development of digitalization. The digital economy is an important factor in optimizing and upgrading to the economic structure and achieving high-quality economic development in recent times in China. Therefore, exploring the possible effects of the digital economy on air pollution is of great theoretical value and practical significance and provides a new perspective for research on air pollution impact factors, air pollution management methods, and governance policies.

Emissions are an important factor influencing air pollution, but socioeconomic factors also play important roles (Wang et al., 2022c). Thus, many researchers have examined environmental pollution emissions and their influencing factors from different perspectives using various approaches (Weis et al., 2017; Hao et al., 2019; Hille et al., 2019; Lin and Xu, 2019; Zhang et al., 2019). These influencing factors include economic growth (Hao et al., 2019), industrial structure, technological innovation, environmental regulation (Zhang et al., 2019), direct foreign investment (Hille et al., 2019), international trade (Lin and Xu, 2019), energy structure, and urbanization (Weis et al., 2017). With the development of the digital economy, more scholars have started to focus on its impacts arising, such as the impact of the digital economy on general economic development (Jurayevich and Bulturbayevich, 2020), international trade (Ahmedov, 2020) and welfare (Grigorescu et al., 2021). However, along with the spread and development of information technology, digitalization exerts an increasing impact on environmental governance and green development.

The application of digital technologies is an effective means of addressing dynamic environmental issues (Feroz et al., 2021), such as air pollution and carbon emissions. In the context of rapid industrialization and urbanization, digitalization has a significant impact on the relationship between ecosystems and human wellbeing. Despite the increasing scale of the digital economy, relatively few studies exist on the relationship between the digital economy and environmental pollution. However, in the context of increasingly serious atmospheric pollution and the booming internet, the application of internet technology in the field of environmental protection is of great value for improving environmental quality and achieving sustainable economic development (Li et al., 2018). For example, big data contributes to many aspects of sustainable development, especially environment pollution management and preventive measures (Honarvar and Sami, 2019; Zhang et al., 2022). Studies that noted the positive role played by big data and internet technology in environmental sustainable development are increasing (Murshed, 2020; King et al., 2021; Chen, 2022), without enough consideration about the possible negative effects of the digital technology (Salahuddin and Alam, 2015; Usman et al., 2021). Few empirical studies have examined the impact of digital economy on air pollution comprehensively, both positive and negative.

Therefore, to exploring the actual effects of the digital economy on air pollution emissions in depth is necessary. This study constructs a two-tier stochastic frontier model using interprovincial panel data in China from 2011 to 2020 to measure the impact of the digital economy on air pollution. It examines whether the emissions increase or emissions reduction effects plays a dominant role to identify the net effect of the digital economy on air pollution.

The innovations of this study are as follows. First, this study provides a new research perspective. In the context of China's vigorous digital economy development, its inclusion in the framework of air pollution research has aided air pollution management. Although many results have been obtained on the economic effects of the digital economy, there is scant literature analyzing the environmental effects of the digital economy.

Second, this study proposes a probable mechanism of the impact of the digital economy on air pollution, explaining the emissions increase and emissions reduction effects of the digital economy on air pollution. This enriches theoretical research fields related to both the digital economy and air pollution. The study examines the environmental effects of the digital economy in an integrated manner and provides a theoretical basis for the empirical study of the effects of the digital economy on air pollution.

Third, on a practical level, the study provides a new solution to China's air pollution challenges by leveraging the digital economy as a path for achieving high-quality economic development and reducing negative environmental impacts.

Finally, a two-tier stochastic frontier model is applied for empirical validation. The authors further investigate the regional and temporal characteristics of the net effect of the digital economy on air pollution. The actual bilateral effects of the digital economy on air pollution emissions are explored based on three aspects under different levels of the digital economy, human capital, and economic development, which provides empirical evidence for China's different regions to propose the new pathway on air pollution management, and enriches the research on the relationship between digital economy and air pollution.

The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 presents a mechanistic analysis. Section 4 presents an empirical two-tier frontier model and describes the data and variables used in this study. Section 5 presents the empirical results. Finally, Section 6 presents the conclusions from this study with policy implications and future perspectives.

2 Literature review

Previous studies can be divided into three categories: first, some studies conclude that digital economy suppresses air pollution. Research on the application of digital economy development in the field of environmental governance and green development is gradually increasing, especially regarding the relationship between digital economy development and carbon emissions (Balogun et al., 2020; Chen, 2022). The advancement of digitalization has had an impact on changes in energy and the environment. The development of the digital economy with information technology as its core has allowed for the supervision and management of an intelligent environment, which can help solve problems such as declining environmental carrying capacity and resource scarcity (Li et al., 2021). This shows that the development of the digital economy is an important solution for developing clean energy, improving air pollution, and promoting low-carbon development (Wang et al., 2022b). For example, previous studies have argued that digital technologies can help to reduce carbon emissions. The ability to identify the latest trends in the energy market through pricing and cross-subsidization due to the use of digital technologies allows the government to regulate the overall energy supply, which in turn aids in the efficient use of energy and reduces carbon emissions (Bhattacharya et al., 2015). The penetration of digital technologies contributes to the transfer of production factors from inefficient to efficient sectors, which increases the efficiency of resource allocation and ultimately improves energy efficiency and reduces air pollution emissions. Digitization breaks regional boundaries and time constraints, accelerates the flow of production factors, reduces energy consumption due to spatial and temporal factors in production and life, reduces energy consumption rates, and curbs carbon emissions. For example, some scholars have pointed out that the development of the digital economy is beneficial for reducing greenhouse gas emissions (Murshed, 2020; Wang et al., 2022a) and fossil fuel consumption (Lange et al., 2020). King et al. (2021) also pointed out that the development of the digital economy, especially the application of information and communications technology (ICT) devices, promotes the health of the local environment and can improve environmental problems, such as air pollution. Therefore, the relationship between the digital economy and air pollution is a topic of interest for both governments and scholars.

Second, a few studies conclude that the digital economy increases air pollution. Some scholars have argued that the development of the digital economy has a negative impact on air pollution emissions. Digital technologies are based on electricity. For example, the development and operation of cloud computing, blockchain, and data centers require increasingly energy-intensive infrastructures (Yang et al., 2022), which can generate more air pollution emissions. Further, the digital sector based on information services is highly power-intensive, accounting for 10% of global electricity generation (Salahuddin and Alam, 2015). Therefore, the use of large amounts of electricity increases coal consumption, which in turn increases air pollution emissions. Additionally, the use of digital technologies in transportation will further increase the scale of traffic trips, which in turn will lead to increased energy consumption, undoubtedly increasing air pollution emissions. For example, Shvakov and Petrova (2020) found that digitization does not lead to a reduction in CO_2 emissions through an empirical study of data from ten digitized countries. Digitization in ICT applications had a suppressive effect on CO_2 emissions only in relatively less-polluted Asian countries, whereas it did not lead to favorable environmental effects in countries with higher carbon emissions (Usman et al., 2021).

In the third category, the digital economy has been assumed to have non-linear effects on air pollution. Based on discussions of the positive and negative effects of the digital economy on air pollution emissions, some scholars have further proposed that there may be non-linear effects from the digital economy on air pollution emissions. However, few studies have been conducted on the non-linear relationship between the digital economy and air pollution; only a few scholars have explored the non-linear relationship between the digital economy and carbon emissions. For example, Han et al. (2016) found that the impact of digital transformation on energy use is U-shaped, suggesting that the relationship between the digital economy and pollution emissions may be non-linear. In different countries, the impact of the digital economy on carbon emissions is heterogeneous (Danish et al., 2019). Li and Wang (2022) demonstrated the non-linear impact of the digital economy on carbon emissions by constructing a theoretical model and further proposed an inverse U-shaped relationship between the digital economy and local and neighboring regional carbon emissions.

First, most studies have discussed the relationship between environmental regulation, technological innovation or industrial structure, and environmental pollution; few studies have focused on the impact of the digital economy on air pollution. The combined environmental effects of digital economy have not been discussed enough. Second, as human society steps into the digital age, the impact of digital technologies, such as big data, on green development has been explored. On this basis, some scholars began to concentrate on the research of the relationship between digital economy and environmental pollution. Very little indepth and systematic research has been conducted on the relationship between digital economy and air pollution. Nevertheless, the conducted studies did not identify or capture the bilateral effects of digital economy development on air pollution and did not estimate the emissions increase effect, emissions reduction effect, or the net effect, thus failing to comprehensively reveal the trend or direction of air pollution improvements or provide an effective reference for policy recommendations. Additionally, existing ideas on the mechanism by which the digital economy affects air pollution emissions needs to be further clarified. Finally, the regional heterogeneity of the digital economy's impact on air pollution emissions has to be addressed.

In conclusion, most studies have only explored the positive effect of digital economy on air pollution, without exploring the negative impact of digital economy on air pollution. This paper will focus on the construction of a comprehensive mechanism for digital economy on air pollution, study the net effect of digital economy on air pollution by the two-tier stochastic frontier model and propose the empirical evidence and suggestions for the government and industry managers when formulating air pollution control management policies.

3 Mechanism analysis

3.1 Emissions reduction effect

The development of the digital economy has influenced technology, fossil energy consumption, environmental regulation, and industrial structure from the supply side, as well as the green product consumption demand and dependence on traditional energy sources from the demand side, thus finally reducing air pollution emissions.

From the supply side, the digital economy improves the level of production technology and promotes the development of green technological innovation. Digital development relying on advanced technologies, such as ICT, 5G, blockchain, big data, and cloud computing, has improved the efficiency of using and allocating resources in innovation systems. Digitalization relying on internet technology effectively solves the problem of information asymmetry in innovation systems (Yang et al., 2022) and can reduce transaction and information search costs. The digital economy is reshaping the spatial pattern of the economy (Li and Wang, 2022). Specifically, the development of the digital economy overcomes the limitations of geographical conditions, information transmission, and time costs; breaks through spatial boundaries; promotes the flow of production factors such as capital and technology; accelerates the flow and concentration of innovation resources; accelerates knowledge spillover; promotes enterprise technology innovation by improving the level of innovation cooperation (Gómez et al., 2017); promotes green technology innovation; and reduces negative environmental impacts.

Second, the digital economy can help increase production efficiency, improve energy use efficiency, and reduce fossil fuel consumption, thus reducing air pollution emissions. Usman et al. (2021) also noted that the internet has achieved an increase in energy efficiency in India. Amin and Rahman (2019) suggested that the internet has facilitated waste management and pollution reduction.

Third, the development of the digital economy is conducive to the regulation and management of environmental pollution. The open, interactive, and real-time nature of the internet makes it possible for the public to participate in environmental governance. For example, Johansson et al. (2015) argued that the internet provides a channel for residents to participate in environmental protection activities and enhances public awareness regarding environmental protection and monitoring. Additionally, the application of digital technology in yields more intelligent and precise environmental regulation and governance, thus strongly promoting the regulation and governance of environmental pollution emissions, including the problem of air pollution emissions (Granell et al., 2016). Digital technologies accelerate the diffusion of environmental information, and instant access to environmental data such as PM2.5 is convenient for environmental regulation. Hampton et al. (2013) argued that using big data, cloud computing, and internet-based digital technologies can help integrate and analyze environmental data, such as air, which will increase the efficiency of environmental management and improve air pollution.

Fourth, the digital economy can reduce air pollution emissions by influencing the industrial structure. The digital industry is environmentally friendly, has less of a negative impact on the environment, and can drive the digital transformation of other industries. As a new model and new industry, the digital economy promotes industrial integration, but also gives birth to new green and high-tech industries while promoting foundational green production methods. The digital economy contributes to the adjustment and upgrading of the industrial structure, which provides a more rational industrial structure and promotes lower energy consumption and more efficient energy use, thus reducing air pollution emissions (Zhao et al., 2022). On the one hand, the greening level of digital industry is generally higher than that of the traditional manufacturing, which can better reduce environmental pollution, including air pollution. The digital industry is more environmentally conscious and also have the digital finance support to improve greening levels. For example, Zameer et al. (2020) pointed out that big data is a key resource for enterprises to obtain green competitive advantages and to solve environmental problems. On the other hand, the development of digital economy promotes technological innovation, promotes advanced industrial structure and upgrades industrial structure (Chen et al., 2022). The spillover effect and diffusion effect between the ICT industry and other industries have promoted the upgrading of industrial structure (Heo and Lee, 2019). This means that the development of the digital industry itself and its integration with traditional industries to improve the allocation of production factors, promote the greening of industries and reduce environmental pollution. From this perspective, this can effectively reduce the negative environmental impacts, typically including air pollution. For example, Wu et al. (2021) conducted an empirical study using the dynamic spatial Durbin model and suggested that the internet promotes the upgrading of the industrial structure and contributes to improving the regional green total factor energy efficiency and reductions in environmental pollution emissions. The close integration of digitalization and high-tech technologies can not only generate new industrial models, but also accelerate the low-carbon transformation of existing sectors, reflecting the beneficial impact of digitalization on the structure of internet-supported industries (Ren et al., 2021). The rapid development of the digital economy has accelerated the phasing out of old industries that consume a substantial energy, pollute the environment, and emit significant amounts of carbon; the production technology and management mode of remaining industries have been improved, promoting the upgrading of the industrial structure.

In contrast, from the demand side, the booming development of the digital economy and industrialization of the digital economy have made it possible to provide consumers with more green products, promote changes in the consumption structure, and guide consumer demand in the direction of green and low-carbon. Changes in the market demand in turn allow the digital economy to promote green production and lifestyle changes and further reduce air pollution emissions. Second, digital development can reduce air pollution emissions by reducing reliance on traditional energy sources, leading to the realignment of energy demand. Energy digitization on the one hand improves energy efficiency and on the other hand optimizes the structure of energy consumption, reduces the use of traditional energy sources, increases the proportion of renewable energy sources, gradually reduces the use of traditional fossil fuels, and reduces air pollution emissions (Pradhan et al., 2020). For example, Ishida (2015) argued that the internet has reduced dependence on energy in many industries. Martynenko and Vershinina (2018) emphasized that digitalization renders the manufacturing process more modern and environmentally friendly, which aids in reducing resource waste of resources and mitigates problems with environmental pollution emissions arising from the development of traditional manufacturing to some extent. Therefore, this paper proposes the following research hypotheses:

Hypothesis 1: Digital economy has a positive impact on air pollution, that is, digital economy has emissions reduction effect on air pollution.

3.2 Emissions increase effect

Many studies have shown that the digital economy can reduce environmental pollution. However, we cannot disregard the negative impact of the digital economy on environmental pollution. The development of the digital economy has improved the efficiency of environmental management, but the scale expansion owing to the development of the digital economy has caused energy rebound effects and exacerbated pollutant emissions (Li and Wang, 2022). Han et al. (2016) found that the impact of digital transformation on energy use first decreases and then increases. Danish et al. (2019) observed that the digital economy has a heterogeneous impact on carbon emissions. Digitalization does not necessarily lead to a reduction in CO_2 emissions (Shvakov and Petrova, 2020). Thus, the digital economy's impact on air pollution is not always positive.

The emissions increase effect of the digital economy on air pollution emissions is mainly reflected in the following factors. First, the digital economy development drives the expansion of the scale of economic activities and affects pollution emissions through the scale effect (Zhou et al., 2018). In addition to improving energy efficiency and environmental management efficiency, the application of the digital economy allows enterprises to purchase new production facilities, improve the level of production technology and expand the scale of production, thus causing the energy rebound effect (Li and Wang, 2022), which can increase the amount of energy and resource consumption and subsequently generate air pollution emissions.

Second, the application of digital technology itself also consumes electricity, such as in the development of the digital economy, which requires big data, cloud computing, and other technology support. The operation of these internet facilities requires a large amount of electricity (Salahuddin and Alam, 2015). Peng (2013) emphasized that digital infrastructure increases the electricity demand. Therefore, the development of the digital economy increases the pressure on the environment. Moreover, China's power industry is dominated by coal-fired power generation, which leads to increased air pollution.

Third, the application of digital technology in other industry sectors also partially accelerates the development of these industries, optimizes the supply of products and services, enhances consumer demand, partially increases energy consumption, and may increase air pollution emissions. For example, the use of digital technology in transportation facilities has increased operational efficiency while shortening travel times, such that people now travel more resulting in increased energy consumption and fossil fuel combustion, thereby increasing air pollutant emissions. Similarly, the application of digital technology in the logistics industry has led to shorter delivery times, more accurate delivery services, gradual development of the industry even in remote areas, and increased demand for industry expansion. This also increases energy consumption and, thus, air pollution emissions.

Digitalization has a certain "green blindness" and may have negative externalities on the environment (Yang et al., 2022), leading to increased air pollution emissions. For example, the widespread use of digital technologies in other industries, such as mining, has increased the scale of rare metal and mineral extraction, leading to the excessive consumption of resources and negative environmental issues, in turn leading to increased air pollution emissions. In view of this, the authors assert the following hypothesis:

Hypothesis 2: Digital economy has a negative impact on air pollution, that is, digital economy has emissions increase effect on air pollution.

Therefore, based on the analysis of the emissions reduction and emissions increase effects of the digital economy on air pollution, the authors found that the impact of the digital economy on air pollution contains both a reduction effect, i.e., the digital economy increases air pollution to a level greater than that of frontier air pollution, and an increase effect, i.e., the digital economy decreases air pollution to a lower level than that of frontier air pollution. Ultimately, the actual impact of the digital economy on air pollution is a combination of the two effects. Figure 1 illustrates the above mechanism.

4 Methodology

4.1 Two-tier stochastic frontier model

According to previous analyses, two opposite effects of the digital economy on air pollution emissions exist: emissions increase and emissions reduction effects. Therefore, this study used the idea of Kumbhakar and Parmeter (2009) to construct a two-tier stochastic frontier model (Liu et al., 2019):

$$\mathrm{InPm2.5}_{it} = i(x_{it}) + \omega_{it} - u_{it} + \varepsilon_{it} = i(x_{it}) + \xi_{it} = x_{it}\delta + \xi_{it} \tag{1}$$

where $\mathrm{InPm2.5}_{it}$ is air pollution; x_{it} is a set of control variables affecting air pollution, specifically the *per capita* GDP, *per capita* road area, population density, urbanization rate, industrial structure,

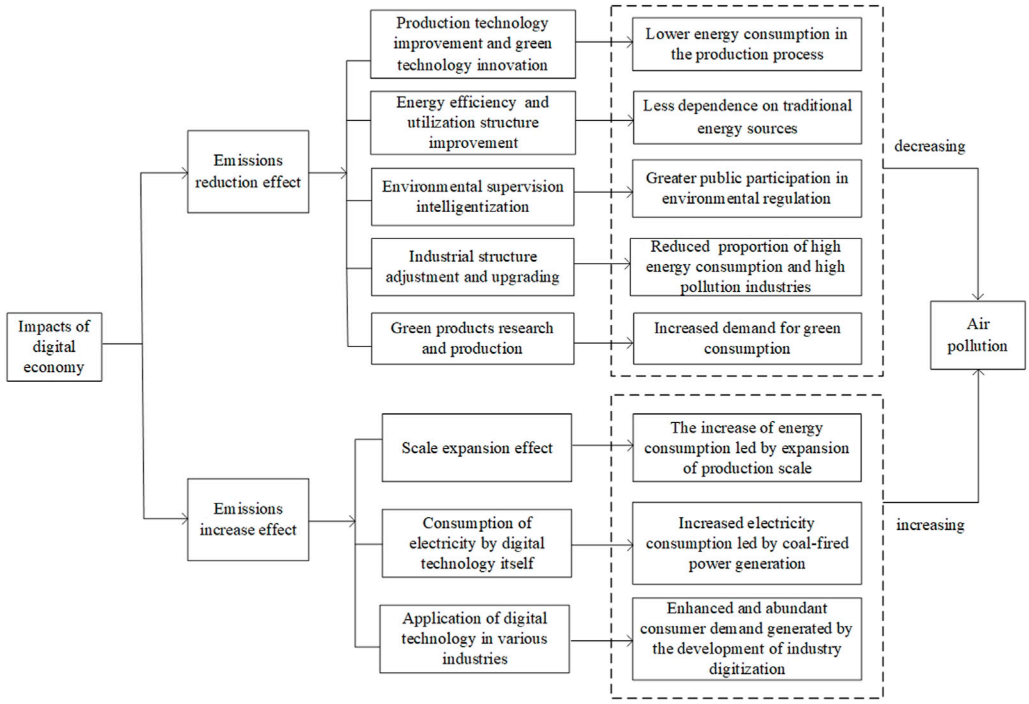


FIGURE 1
Mechanisms of bilateral effects of the digital economy on air pollution.

trade openness, government support, environmental regulation, average years of schooling, and energy consumption intensity; δ is the parameter vector to be estimated; $i(x_{it})$ is the frontier of air pollution; ξ_{it} is the composite error term; and $\xi_{it} = \omega_{it} - u_{it} + \varepsilon_{it}$, ε_{it} is the random error term, reflecting the deviation of air pollution from the frontier air pollution caused by unobservable factors. The conditional expectation of the composite residual term may not be equal to 0, which will lead to biased OLS estimation results. When the OLS estimation results are biased, the maximum likelihood estimation (MLE) method provides valid results. MLE, according to Eq. 1, ω_{it}, and u_{it} were decomposed to reflect the upward and downward bias effects in the optimal case, respectively. In Eq. 6, $\omega_{it} \geq 0$ denotes the emissions increase effect of the digital economy on air pollution; $u_{it} \leq 0$ denotes the emissions reduction effect of digital economy on air pollution; and $u_{it} \leq 0$, $\omega_{it} = 0$, or $\omega_{it} \geq 0$, $u_{it} = 0$ indicates that the model becomes a one-sided stochastic frontier model. In other words, the digital economy has only a unilateral effect on air pollution. When $\omega_{it} = u_{it} = 0$ the model becomes an OLS. If both are not zero, there is a bilateral effect of the digital economy on air pollution. As it may not be zero, this will lead to biased OLS model estimates.

According to Eq. 6, the actual air pollution is ultimately the result of a bilateral combination of both emissions increase and reduction effects of the digital economy. The emissions increase effect of the digital economy on air pollution increases air pollution to higher than the frontier air pollution amount, while the emissions reduction effect of the digital economy on air pollution decreases air pollution to lower than the frontier air pollution amount. The deviation in the actual air pollution can be measured by calculating the net effect of the joint influence of the two. Additionally, as the results obtained from the OLS estimations are biased, valid estimation results can be obtained using the MLE method. Therefore, the authors can use the following assumptions regarding the residual distribution. The random error term follows a normal distribution with a zero mean and zero variance. In other words, $\varepsilon_{it} \sim iddN(0, \sigma_\varepsilon^2)$; both ω_{it} and u_{it} follow an exponential distribution, i.e., $\omega_{it} \sim idd\,EXP(\sigma_\omega, \sigma_\omega^2)$, $u_{it} \sim iddNEXP(\sigma_u, \sigma_u^2)$, and the error terms satisfy the independence assumption condition between them and are not correlated with the inter-provincial characteristic variables. The probability density functions of ξ_{it} were derived based on the distribution assumed above (see Kumbhakar and Parmeter, 2009 for the full derivation):

$$f(\xi_{it}) = \frac{\exp(\alpha_{it})}{\sigma_u + \sigma_\omega}\Phi(\gamma_{it}) + \frac{\exp(\beta_{it})}{\sigma_u + \sigma_\omega}\int_{-\eta_{it}}^{\infty}\varphi(x)dx = \frac{\exp(\alpha_{it})}{\sigma_u + \sigma_\omega}\Phi(\gamma_{it}) + \frac{\exp(\beta_{it})}{\sigma_u + \sigma_\omega}\varphi(\eta_{it}) \tag{2}$$

where $\Phi(\cdot)$ and $\varphi(\cdot)$ are the standard normal cumulative distribution function (CDF) and standard normal distribution probability density function (PDF), respectively. The following settings were used for the other parameters:

$$\begin{aligned} \alpha_{it} &= \frac{\sigma_v^2}{2\sigma_\omega^2} + \frac{\xi_i}{\sigma_\omega} \quad \beta_{it} = \frac{\sigma_v^2}{2\sigma_u^2} - \frac{\xi_i}{\sigma_u} \\ \gamma_{it} &= -\frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_u} \quad \eta_{it} = \frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_\omega} \end{aligned} \tag{3}$$

Based on the parameter estimation in Eq. 3, the expression of MLE was constructed as follows:

$$1n\,L(X;\pi) = -n\ln(\sigma_\omega + \sigma_u) + \sum_{i=1}^{n} 1\,n\left[e^{\alpha_{it}}\Phi(\gamma_{it}) + e^{\beta_{it}}\Phi(\eta_{it})\right] \quad (4)$$

Among them, $\pi = [\beta, \sigma_v, \sigma_\omega, \sigma_u]$. Likelihood function expressed by Eq. 4 was further maximized, resulting in a maximum likelihood estimate for all parameter values. Additionally, the authors estimated ω_{it} and u_{it}. Therefore, the conditional density functions for both were derived as follows (Kumbhakar and Parmeter, 2009):

$$f(\omega_{it}|\xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\exp\left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\omega_{it}\right]\Phi\left(\frac{\omega_{it}}{\sigma_v} + \eta_{it}\right)}{\exp(\beta_{it} - \alpha_{it})\left[\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \text{ and} \quad (5)$$

$$f(u_{it}|\xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\exp\left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)u_{it}\right]\Phi\left(\frac{u_{it}}{\sigma_v} + \eta_{it}\right)}{\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})}. \quad (6)$$

Based on Eqs 5, 6, the conditional expectations of ω_{it} and u_{it} could be estimated as follows (Kumbhakar and Parmeter, 2009):

$$E(\omega_{it}|\xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{\sigma_v\left[\Phi(-\eta_{it}) + \eta_{it}\Phi(\eta_{ii})\right]}{exp(\beta_{it} - \alpha_{it})\left[\Phi(\eta_{it}) + exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \quad (7)$$

$$E(u_{it}|\xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{\exp(\alpha_{it} - \beta_{it})\sigma_v\left[\Phi(-\gamma_{it}) + \eta_{it}\Phi(\gamma_{ii})\right]}{\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})} \quad (8)$$

Using Eqs 7, 8, the authors estimated the absolute extent of air pollution deviation from frontier air pollution, facing both emissions increase and emissions reduction effects.

To facilitate comparison, the absolute degree value of the deviation from the degree of air pollution influenced by the digital economy was further converted into a percentage above or below the frontier level using the following conversion formula (Cheng and Hong, 2022):

$$E(1 - e^{-\omega_{it}}|\xi_{it}) = 1 - \frac{\frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)}\left[\Phi(\gamma_{it}) + \exp(\beta_{it} - \alpha_{it})\exp\left(\frac{\sigma_v^2}{2} - \sigma_v\eta_{it}\right)\Phi(\eta_{it} - \sigma_v)\right]}{\left[1 + \left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\right]exp(\beta_{it} - \alpha_{it})\left[\Phi(\eta_{it}) + exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \quad (9)$$

$$E(1 - e^{-u_{it}}|\xi_{it}) = 1 - \frac{\frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)}\left[\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\exp\left(\frac{\sigma_v^2}{2} - \sigma_v\gamma_{it}\right)\Phi(\gamma_{it} - \sigma_v)\right]}{\left[1 + \left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\right]\left[\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \quad (10)$$

Further, the net effect of the digital economy's impact on air pollution was derived based on Eqs 9, 10 as follows (Kumbhakar and Parmeter, 2009):

$$NE = E(1 - e^{-\omega_{it}}|\xi_{it}) - E(1 - e^{-u_{it}}|\xi_{it}) = E(e^{-u_{it}} - e^{-\omega_{it}}|\xi_{it}) \quad (11)$$

where NE represents the difference between the emissions increase effect and emissions reduction effect. If NE > 0, the emissions increase effect is stronger than the emissions reduction effect, i.e., the emissions increase effect plays a dominant role; if NE < 0, the emissions reduction effect is stronger than the emissions increase effect, i.e., the emissions reduction effect plays a dominant role.

4.2 Description of data and variables

With reference to the above theoretical and empirical model settings, as well as considering the data availability, the authors selected Chinese provincial panel data from 2011 to 2020 to analyze the impact of the digital economy on provincial air pollution. Tibet, Hong Kong, Macao, and Taiwan were excluded due to a lack of data. The data for the variables selected for this study were obtained from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, ESP Global Database and National Bureau of Statistics. Specifically, the variables involved were set as follows.

4.2.1 Explained variable

4.2.1.1 Air pollution

Given that pollution data in China are difficult to obtain, the available data have disadvantages, such as short continuous spans, and are not suitable for long panel analysis. Therefore, in this study, based on Li and Zhang (2019), the authors used air pollution raster data jointly published by Columbia University and the U.S. Atmospheric Composition Group. By matching the PM2.5 raster data with the latitude and longitude of each province through the ArcGIS software, the average value of all raster data in each province was calculated to represent the PM2.5 concentration per cubic meter of air in that province. This core air pollution indicator was processed logarithmically and denoted as lnPm2.5. This indicator has two advantages. First, air pollution data extracted from satellite maps are more objective and cover a wider area than ground-based observation data, avoiding potential data manipulation and missing data problems. Second, particulate matter is the most important pollutant emitted in China; PM2.5 not only incorporates combusted fossil fuels and their pollutant emissions in the air as further chemical reactants but also easily penetrates indoor areas (Chang et al., 2016), aiding in analyzing interior or exterior enterprise production.

4.2.2 Explanatory variables

4.2.2.1 Digital economy development level

The authors used the approach reported by Zhao et al. (2020), and combined it with those by Liu et al. (2020) and Huang et al. (2019). Indicators, including the number of internet broadband access users per 100 people, proportion of employees in the computer services and software industry to the employees in urban units, total amount of telecom services *per capita*, and number of mobile phone users per 100 people, were selected to indicate the level of digital economy development. Digital financial inclusion is an important manifestation of digital economy development measured using the provincial digital inclusive finance index in China compiled by Guo et al. (2020). This measures the breadth of digital financial coverage, depth of use, and the degree of digitization in three main aspects. Based on these measurement indices, the entropy weight method was used to measure the level of regional digital economy development, denoted as sdig.

4.2.3 Controlled variables

1) The level of economic development, denoted as lnPGdp after taking the logarithm, was measured by the *per capita* GDP as reported by Kuang et al. (2022). 2) The natural logarithm of the *per capita* road area, denoted as lnTF, was selected to measure transportation infrastructure with reference to Sun et al. (2019). 3) Following Yi et al. (2020), the natural logarithm of the ratio of the total population to the total area of the administrative district at the

TABLE 1 Descriptive statistical analysis of the main variables.

Variables	Symbols	Sample size(obs)	Average value	Standard deviation	Min value	Max value
Air pollution	lnPm2.5	300	3.586	0.395	2.258	4.450
Digital economy	sdig	300	0.327	0.142	0.125	0.937
Per capita GDP	lnPGdp	300	10.841	0.436	9.706	12.013
Per capita road area	lnTF	300	2.710	0.360	1.396	3.288
Population density	LnPM	300	7.892	0.410	6.639	8.710
Urbanization rate	lnCity	300	4.046	0.199	3.555	4.495
Industrial structure	lnIND	300	3.739	1.261	0.457	7.294
Trade openness	lnOpen	300	1.722	2.277	−3.679	7.541
Government support	lnGOV	300	3.147	0.376	2.400	4.160
Environmental regulation	EG	300	0.049	0.090	0.016	0.767
Average years of education	Hum	300	9.229	0.911	7.514	12.718
Energy consumption intensity	EQ	300	0.825	0.485	0.207	2.327

end of the year was used to measure the population density and was denoted as LnPM. 4) The urbanization rate was measured by the ratio of the number of residents to the total number of urban residents and denoted as lnCity after taking the logarithm based on Gan et al. (2020). 5) Cheng and Hong, 2022) examined industrial structure, where the natural logarithm of the proportion of the value added from secondary industry in the regional GDP (lnIND) was used to characterize the level of urbanization. 6) Government support was expressed as the logarithm of the share of the general budget expenditure in the GDP. 7) The degree of trade openness was expressed by the logarithm of the ratio of total imports and exports to the GDP, referring to Li et al. (2019). As imports and exports for the year are denominated in US dollars, they were converted to RMB 10 000 using the annual average US-China exchange rate published in the China Statistical Yearbook; the logarithm of the GDP was calculated and denoted as lnOPEN. 8) Environmental regulation, based on Tian and Feng (2022), was measured by the proportion of environmental pollution control investment in the GDP and denoted as EG. 9) The logarithm of the average number of years of schooling was used to measure human capital according to Su and Yu (2020) and denoted as Hum. 10) The energy consumption intensity, using the total energy consumption as a share of the GDP, was symbolized by EQ. Additionally, variables involving price factors were deflated in this study using 2011 as the base period. Table 1 presents the results of the descriptive statistics for the main variables.

5 Empirical analysis, results, and discussion

5.1 Two-tier stochastic frontier estimation

5.1.1 Baseline regression model

Based on the MLE, the bilateral effects of the digital economy on air pollution were decomposed according to the econometric Eq. 1 model. Table 2 lists the estimation results. Among them, the second column shows the OLS estimation results of model (1) without considering the deviation effect; model (2) does not control the time-fixed effect and area-fixed effect; model (3) controls for area-fixed effects only; model (4) controls for both area-fixed effects and time-fixed effects; model (5) considers only the unilateral estimation results of the emissions reduction effect of the digital economy on air pollution, i.e., the model residual term u_{it}; model (6) shows the unilateral estimation results considering only the digital economy's increase effect on air pollution, i.e., the model residual term ω_{it}; and the estimation results of model (7) consider both the emissions increase effect and emissions reduction effect of the digital economy on air pollution, i.e., the model residual term ω_{it} and u_{it}. According to the model likelihood ratio test (LR), after adding the deviation effect, model (7) was more reasonable than the OLS estimation and remaining models. After a comprehensive comparison, the authors finally used model (7) as the basis for the subsequent analysis of the bilateral effect decomposition measure of the digital economy.

Based on the estimation results of model (7), the estimated coefficient of the emissions increase effect of the digital economy was significantly positive, indicating that it increases the amount of air pollution. The estimated coefficient of the emissions reduction effect of the digital economy was significantly negative, indicating that it significantly suppressed increases in air pollution. Accordingly, the hypothesis that the effects of the digital economy on air pollution exist simultaneously in the theoretical hypothesis of this study was initially verified based on the estimation results of model (7).

5.1.2 Variance decomposition: Measuring bilateral effects of digital economy on air pollution

To comprehensively analyze which of the two effects of the digital economy on air pollution is dominant, the authors must decompose the emissions reduction and emissions increase effects of the digital economy on air pollution based on model (7) in Table 2. Table 3 lists the decomposition results. The degree of the emissions increase and emissions reduction effects of the digital economy on air pollution were

TABLE 2 Basic estimation results of the two-tier stochastic frontier model for the digital economy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	M0	M1	M2	M3	M4	M5
lnPGdp	0.139***	0.168***	0.035**	0.015	0.007	−0.002***	−0.005***
	(3.04)	(75.63)	(2.03)	(0.85)	(0.39)	(−8.32)	(−88.83)
lnTF	0.102*	0.101***	0.080	0.129**	0.134**	0.135***	0.101***
	(1.83)	(38.28)	(1.16)	(2.33)	(2.47)	(218.00)	(310.81)
LnPM	−0.030	−0.092***	−0.086**	0.019	−0.011	−0.026***	−0.012***
	(−0.67)	(−45.80)	(−2.42)	(0.64)	(−0.35)	(−68.11)	(−69.57)
lnCity	−1.064***	−1.258***	−0.962***	0.067	−0.216	−0.401***	−0.078***
	(−6.50)	(−128.77)	(−5.30)	(0.41)	(−1.16)	(−109.36)	(−90.98)
lnIND	0.205***	0.229***	0.048***	−0.000	0.005	0.007***	0.012***
	(7.86)	(316.23)	(3.09)	(−0.03)	(0.35)	(37.62)	(125.68)
lnOpen	−0.035*	−0.033***	−0.052***	−0.018**	−0.018**	−0.018***	−0.021***
	(−1.86)	(−39.58)	(−6.18)	(−2.30)	(−2.32)	(−272.23)	(−420.17)
lnGOV	−0.511***	−0.461***	−0.052	0.041	0.031	0.034***	−0.005***
	(−7.60)	(−123.94)	(−1.56)	(1.25)	(0.91)	(67.25)	(−29.20)
EG	0.088	0.029***	−0.267***	−0.180**	−0.181**	−0.180***	−0.313***
	(0.44)	(5.07)	(−4.05)	(−2.23)	(−2.28)	(−149.96)	(−958.97)
AEDU	0.365***	0.356***	−0.053**	−0.014	−0.007	0.012***	0.006***
	(10.58)	(159.97)	(−2.35)	(−0.81)	(−0.39)	(103.05)	(130.72)
EQ	0.039	0.126***	0.193***	0.073	0.089	0.138***	0.120***
	(0.70)	(47.62)	(2.85)	(1.18)	(1.52)	(234.70)	(543.29)
_cons	3.842***	4.591***	7.608***	3.470***	4.938***	5.466***	4.491***
	(4.05)	(121.73)	(9.19)	(4.19)	(5.27)	(351.20)	(906.09)
sigma_v							
_cons		−14.277	−2.680***	−2.901***	−3.184***	−17.975	−20.710
		(−0.04)	(−22.39)	(−17.49)	(−10.92)	(−0.06)	(−0.03)
sigma_u							
sdig					−2.464**		−1.319***
					(−2.48)		(−3.01)
_cons			−2.745***	−3.128***	−4.094***	−3.360***	−3.388***
			(−14.88)	(−16.81)	(−9.08)	(−41.28)	(−20.92)
sigma_w							
sdig						1.118**	0.329**
						(2.53)	(2.63)
_cons			−5.877	−4.876	−3.217***	−3.044***	−3.081***
			(−0.23)	(−0.64)	(−9.23)	(−19.02)	(−17.04)
pro fixed	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed	No	No	No	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300	300

Note: t statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 3 Variance decomposition: Emissions increase and emissions reduction effects of digital economy on air pollution.

	Variable meaning	Symbol	Coefficient
Digital economy	Random error term	sigma_v	0.0000
	Emissions increase effect	sigma_w	0.0512
	Emissions reduction effect	sigma_u	0.0530
Variance decomposition	Total random error term	Total sigma_sqs	0.0054
	Weight of the joint effect of emissions increase and emissions reduction effects	(sigu2 + sigw2)/Total	1.0000
	Weight of emissions increase effect	sigw2/(sigu2 + sigw2)	0.4829
	Weight of emissions reduction effect	sigu2/(sigu2 + sigw2)	0.5171
		sig_u–sig_w	0.0018

0.0512 and 0.0530, respectively, such that the degree of the net effect of the digital economy on air pollution was $E(\omega - u) = \sigma_{\omega}\text{-}\sigma_u = -0.0018$. The decomposition results show that the net effect of the digital economy on air pollution was manifested by the inhibition of the increase in air pollution. Generally, as the digital economy has both emissions increase and emissions reduction effects, the emissions reduction effect dominates, which eventually leads to actual air pollution lower than the frontier pollution level at the provincial level; in other words, the digital economy has a suppressive effect on air pollution.

Further, based on the decomposition model, the proportional size of the emissions increase and emissions reduction effects of the digital economy on air pollution were decomposed to more accurately compare the actual effects of the digital economy. Based on the results in Table 3, the emissions reduction effect of the digital economy accounted for 51.71%, whereas the emissions increase effect of the digital economy accounted for 48.29%. This result shows that the proportion of the air pollution emissions reduction effect of the digital economy was significantly larger than its air pollution emissions increase effect, indicating the domination of the reduction effect of the digital economy. This again shows the correctness of the above estimation result: the digital economy significantly suppresses air pollution aggravation through the reduction effect.

5.1.3 Degree of impact of the digital economy on the two effects of air pollution

After analyzing the effect of the digital economy on air pollution, the deviation in the regional air pollution compared to the optimal air pollution level was further calculated. The specific calculation was based on Eqs 7–11 in the model. These equations show the percentage of actual air pollution deviation from the air pollution frontier level and the final net effect weight after the digital economy influences air pollution. The authors compared the net effect size of the emissions increase effect and emissions reduction effect percentage. Thus, the real impact of the digital economy on air pollution was determined.

Based on the results in Table 4, the emissions increase effect of the digital economy resulted in air pollution higher than the frontier level by 4.87% while the emissions reduction effect of the digital economy resulted in air pollution lower than the frontier level by 5.02%. Finally, the combined effect of both caused air pollution to be lower than the frontier level by 0.15%. This suggests that the asymmetry of the bilateral effects of the digital economy is characterized by an overall emissions reduction effect on air pollution levels.

TABLE 4 Estimated net effect (%) of the digital economy on air pollution.

Variable	Mean	Variance	p25	p50	p75
Emissions increase effect	4.87	4.05	2.38	2.86	5.51
Emissions reduction effect	5.02	4.63	2.38	2.72	6.51
Net effect	−0.15	6.99	−3.85	0.00	3.02

Based on the above analysis, the distribution of the two effects of the digital economy on air pollution was further analyzed. Table 4 presents the differences in the two effects of the digital economy on air pollution at different percentile levels. Specifically, the emissions increase effect of the digital economy on air pollution increased from 2.38% to 5.51% at the p25, p50, and p75 quartiles, respectively, while the emissions reduction effect increased from 2.38% to 6.51%. The difference between the two effects is widening; at the national level, the emissions reduction effect consistently dominated during the sample period, suggesting that the digital economy improves air pollution, which is consistent with the above findings.

Figure 2 shows the frequency distribution of the emissions increase effect, emissions reduction effect, and net effect of the digital economy on air pollution. The emissions reduction effect of the digital economy on air pollution showed a right-trailing feature. The emissions reduction effect at approximately 40% indicates that air pollution in some provinces is more sensitive to the changes and hence, vulnerable to the level of digital economy development. The emissions increase effect of the digital economy to promote air pollution ended at approximately 25%, which is significantly lower than the emissions reduction effect, indicating that air pollution in some provinces is less affected by the emissions increase effect of the digital economy. The distribution of the net effect shows that most provinces are affected by the emissions reduction effect of the digital economy while only a few are affected by the emissions increase effect. These results show that the digital economy has a reducing effect on air pollution, which is consistent with the results of theoretical analysis.

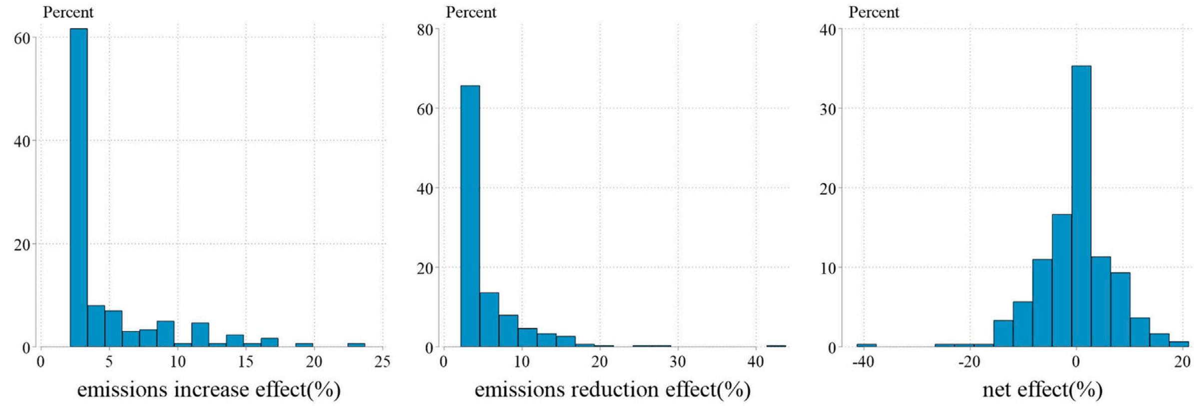


FIGURE 2
Distribution of the emissions increase effect, emissions reduction effect, and net effect of the digital economy.

5.2 Regional characteristics of air pollution affected by the digital economy

The distribution characteristics of the digital economy's net effect on air pollution in different provinces and regions were further examined (Table 5). In terms of the regional distribution, the net effect of the digital economy on air pollution was negative in all three regions with values of −1.22%, −0.28%, and −1.01%, indicating that the digital economy in all three regions had a suppressive effect on air pollution. Specifically, the net effect of the digital economy on air pollution was negative for the three major regions, ranking as East > West > Central. The eastern region has a higher level of digital economy development, better infrastructure, and stricter environmental regulations, which are conducive to air pollution control. Additionally, with the development of the digital economy, the regional industrial structure has been upgraded, which further strengthens the emissions reduction effect of digital economy. Second, the central and western regions have undertaken some of the high pollution, high emissions, and high energy-consuming industries from the eastern regions, leading to the intensification of environmental pollution in the region. The digital economy has been used at a large scale in production and urban operation and management, which accelerates the release of emissions reduction dividends. The distorted state of mismatch between the industrial structure and factor resources is notable; the development of the internet can yield a significant upgrading effect in the industrial structure, thus improving the level of air pollution. Particularly, the western region undertakes the transfer of industry and technology from the eastern cities to become the main position for energy savings and emissions reduction. The development of the digital economy can effectively promote the learning, digestion, and innovation of transferred technology in the western region to enhance the level of technological innovation, thus fully utilizing the advantage of technological innovation in the role of air pollution reduction.

5.3 Temporal characteristics of the digital economy affecting air pollution

To further identify the characteristics of the temporal trend changes in the digital economy's impact on air pollution, the differences in the impacts of digital economy on air pollution in different years were analyzed based on time variables, as shown in Figure 3. The emissions reduction effect of the digital economy dominated within the sample in most years, with effect sizes ranging from −1.39% to 1.21%. Overall, as time progressed, the emissions increase effect of the digital economy on air pollution alternately increased with the emissions reduction effect. The net effect of the digital economy changed in a wave-like manner under both effects combined. The net effect of the digital economy was positive in 2015, 2016, and 2018. This phenomenon shows that the two effects of the digital economy on air pollution co-existed and exhibited asymmetric changes, further validating the rationality of the theoretical analysis. This phenomenon can be explained by the fact that in the early stage of digital economy development, the effect of digital economy air pollution management emerged, air pollution partially improved, and the emissions reduction effect of the digital economy dominated during this period. Between 2014 and 2018, the digital economy further developed, but there was an "energy rebound" effect, a large amount of energy and materials, and infrastructure implementation, resulting in increased air pollution. During this period, the emissions increase effect of the digital economy was significantly stronger than its emissions reduction effect. After 2018, the net effect of the digital economy was significantly negative as the intelligence and precision of environmental regulation, governance, and services were being promoted to compensate for their existing deficiencies. In other words, the digital economy reduced air pollution as a net effect.

5.4 Analysis of differences between the impacts at different levels of digital economy development

Based on the previous analysis, digital economy is characterized by an overall inhibitory effect on air pollution levels. The distribution of bilateral effects under different levels of the digital economy development was analyzed by grouping digital economy development into high, medium, and low levels using the 25% and 75% quartiles as boundaries. Among them, digital economy with

TABLE 5 Characteristics of the annual distribution of the net effect of the digital economy on air pollution (%).

Province	Net effect mean	SD	p25	p50	p75
Shanghai	−3.68	15.44	−6.33	−0.48	6.41
Yunnan	3.26	6.43	−2.80	0.81	9.66
Inner Mongolia	−1.35	7.76	−6.10	0.00	5.08
Beijing	−7.61	10.47	−17.02	−2.76	0.66
Jilin	1.08	7.38	−4.55	0.00	4.51
Sichuan	−0.64	4.77	−3.73	−0.25	1.30
Tianjin	−1.22	4.43	−4.61	−1.62	1.90
Ningxia	0.14	6.08	−4.99	0.12	5.22
Anhui	−0.19	2.69	−1.15	0.20	1.70
Shandong	2.44	6.28	−0.13	0.19	8.77
Shanxi	−2.97	7.38	−9.25	0.00	0.87
Guangdong	−0.50	7.43	−5.89	0.00	1.12
Guangxi	0.90	6.45	−3.70	0.00	4.56
Xinjiang	4.85	10.01	−3.07	0.00	12.16
Jiangsu	−1.35	5.96	−3.08	0.00	1.61
Jiangxi	1.07	5.58	−2.25	−0.44	3.83
Hebei	0.55	3.92	−2.47	−0.08	2.76
Henan	−0.34	4.63	−1.24	0.00	2.52
Zhejiang	0.21	5.42	−3.68	−0.01	2.88
Hainan	−1.97	6.15	−7.10	−0.86	2.01
Hubei	−1.77	5.04	−5.59	−1.98	3.40
Hunan	0.05	5.97	−3.40	0.00	2.73
Gansu	1.93	6.03	−0.16	0.27	4.28
Fujian	−0.44	3.89	−3.22	−0.13	0.71
Guizhou	0.66	6.88	−1.48	−0.21	3.30
Liaoning	0.13	6.38	−4.69	0.22	3.41
Chongqing	0.65	7.12	−6.57	0.00	6.20
Shaanxi	−1.88	5.57	−7.32	0.00	1.81
Qinghai	2.60	8.22	−0.15	0.00	8.67
Heilongjiang	0.85	7.37	−3.26	0.00	7.09
Eastern Region	−1.22	7.67	−4.27	0.00	2.29
Central Region	−0.28	5.85	−4.10	0.00	2.97
Western Region	−1.01	6.93	−3.07	0.00	5.22

(Sdig) ≤ 0.223 represents the low-level group, 0.223 < (Sdig) ≤ 0.408 represents the medium-level group, and (Sdig) > 0.408 represents the high-level group; the results are listed in Table 6. As the development level of the digital economy increased, the mean value of the emissions increase effect of the digital economy on air pollution increased from 4.68% in the low-level group to 5.09% in the high-level group; the mean value of its emissions reduction effect from 4.12% in the low-level group to 6.29% in the high-level group. The combined effect of both allowed the mean value of the net effect to turn from positive to negative, indicating that although the emissions reduction effect of the digital economy on air pollution was always dominant on considering the complete sample, there was significant heterogeneity in the effect of the digital economy on air pollution at different levels of the digital economy. This may be because the integration of the digital economy and environmental governance not only changes the traditional environmental governance model but can also impact air pollution by improving the efficiency of environmental governance decision-making and regulation, as well as more efficient environmental governance models, such as network participation in governance. Considering the initial development of the digital economy, various factors are not well configured, and the effect of environmental governance is still unclear. As the level of the digital economy continues to improve, intelligent monitoring systems, energy-saving technologies, and environmental protection technologies will greatly improve the level of pollution generation and emissions monitoring, as well as the efficiency of resource utilization, which in turn can improve the level of environmental pollution prevention and control in enterprises and reduce air pollution. In summary, the impact of the digital economy on air pollution is a long-term cumulative process that requires dynamic consideration of its impact on air pollution.

5.5 Analysis of differences in impact of digital economy under different human capital levels

The development of the digital economy has placed a higher demand on human capital. When the human capital of a region is sufficiently large, its industrial structure and population structure will improve accordingly while the agglomeration effect of human capital can partially buffer negative effects such as air pollution due to the digital economy. To test this conjecture, the average number of years of education was chosen to characterize human capital (Han et al., 2019). Human capital was grouped according to 25% and 75% quartiles. When human capital (EDU) ≤ 8.725, it was classified as a low-skilled group; when 8.725 < human capital (EDU) ≤ 9.485, it was classified as a medium-skilled group; and when human capital (EDU) > 9.485, it was classified a high-skilled group. Table 7 lists the results. The emissions increase effect of the digital economy on air pollution increased from 5.43% in the low-level group to 4.57% in the high-level group. The emissions reduction effect increased from 3.87% in the low-level group to 6.26% in the high-level group. The net effect of the combined effect of both turned positive to negative. This result suggests that an increase in human capital skills can partially strengthen the emissions reduction effect of the digital economy on air pollution. The possible reason for this is that the level of human capital is closely related to the technological progress of the region while the impact of the digital economy on air pollution is mainly reflected in energy savings and consumption reduction through technological progress and improvements to industrial digitalization. When the level of human capital was low, the technology level was also correspondingly low. At this time, clean production technologies provided by technological innovation to

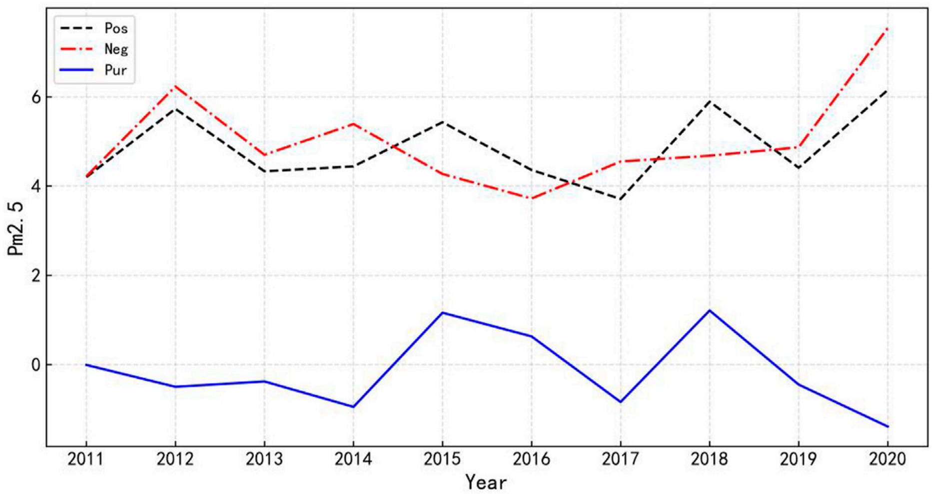


FIGURE 3
Characteristics of the annual distribution of the net effect of the digital economy on air pollution (%). Note: Pos indicates the emissions increase effect; Neg indicates the emissions reduction effect; and Pur indicates the net effect.

TABLE 6 Differences in the net effect (%) of air pollution at different levels of the digital economy.

Sdig	Effect decomposition	Average value	Standard deviation	p25	p50	p75
Low level group	Emissions increase effect	4.68	3.72	2.25	2.30	5.90
	Emissions reduction effect	4.12	3.43	2.23	2.28	5.15
	Net effect	0.55	5.91	−2.89	0.00	3.64
Medium level group	Emissions increase effect	4.85	4.23	2.40	2.57	5.23
	Emissions reduction effect	4.83	4.72	2.43	2.61	5.91
	Net effect	0.02	7.19	−3.46	0.00	2.76
High level group	Emissions increase effect	5.09	4.05	2.90	3.16	5.08
	Emissions reduction effect	6.29	5.25	2.84	3.18	8.33
	Net effect	−1.20	7.56	−5.48	−0.03	2.29

energy and production systems were being applied but could not actually improve air pollution prevention or management. Therefore, the emissions increase effect of the digital economy dominates at this stage. When human capital reached a high level, the technological innovation effect of the digital economy increased; its energy-saving and emissions reduction effects are also enhanced, effectively reducing the level of air pollution.

5.6 Analysis of differences in impact of digital economy at different economic development levels

The level of economic development in a region undoubtedly affects the local digital economy and air pollution. Accordingly, this study selected the *per capita* GDP to characterize the level of economic development and followed the grouping logic above to divide the level of economic development into three groups: high, medium, and low groups. Table 8 lists the results. The net effect of the digital economy on air pollution was 1.50% when economic development was in the low-level group ($PGdp \leq 3.717$), −0.22% when economic development was in the medium-level group ($3.717 < PGdp \leq 6.686$), and −3.40% when economic development was in the high-level group ($PGdp > 6.686$). The results showed that the digital economy's emissions reduction effect on air pollution increased as the level of economic development increased. When the level of economic development was sufficiently high, the digital economy development level was also relatively high; the scale of enterprises in these regions became larger. The size of enterprises is closely related to whether they can substantially invest in implementing intelligence and automation. With the

TABLE 7 Differences in the impact of the digital economy (%) on air pollution under different levels of human capital.

EDU	Effect decomposition	Average value	Standard deviation	p25	p50	p75
Low-skilled group	Emissions increase effect	5.43	4.80	2.28	2.57	7.71
	Emissions reduction effect	3.87	2.91	2.27	2.54	3.76
	Net effect	1.57	6.32	−1.36	0.00	5.28
Medium-skilled group	Emissions increase effect	4.73	3.83	2.37	2.73	5.58
	Emissions reduction effect	4.97	3.72	2.37	2.70	6.65
	Net effect	−0.24	6.30	−4.14	0.00	3.35
High-skilled group	Emissions increase effect	4.57	3.64	2.62	3.16	4.71
	Emissions reduction effect	6.26	6.88	2.63	2.98	7.42
	Net effect	−1.70	8.51	−4.69	0.00	2.13

Note: Years of education *per capita* = elementary school literacy * 6 + junior high school literacy * 9 + high school literacy * 12 + college and above literacy * 16.

TABLE 8 Differences in the impact of the digital economy (%) on air pollution at different levels of economic development.

PGdp	Effect decomposition	Average value	Standard deviation	p25	p50	p75
Low level group	Emissions increase effect	5.07	4.00	2.28	2.45	7.09
	Emissions reduction effect	3.57	2.58	2.24	2.34	3.76
	Net effect	1.50	5.45	−1.36	0.00	4.81
Medium level group	Emissions increase effect	4.85	4.39	2.38	2.68	5.18
	Emissions reduction effect	5.06	3.82	2.44	2.77	6.87
	Net effect	−0.22	6.75	−4.38	0.00	2.62
High level group	Emissions increase effect	4.70	3.38	2.69	3.24	4.78
	Emissions reduction effect	6.37	6.83	2.63	2.98	8.33
	Net effect	−1.67	8.44	−5.18	0.00	2.28

TABLE 9 Effect and variance decomposition of the impact of the digital economy on air pollution.

	Variable meaning	Symbols	Measurement coefficient
Digital economy	Random error term	sigma_v	0.0000
	Emissions increase effect	sigma_w	0.0380
	Emissions reduction effect	sigma_u	0.0701
Variance decomposition	Total random error term	Total sigma_sqs	0.0064
	Weight of the joint effect of emissions increase and emissions reduction effects	(sigu2 + sigw2)/Total	1.0000
	Weight of emissions increase effect	sigw2/(sigu2 + sigw2)	0.2274
	Weight of emissions reduction effect	sigu2/(sigu2 + sigw2)	0.7726
		sig_u − sig_w	0.0321

expansion of the enterprise scale, enterprises have sufficient capital to invest in production to improve productivity and intelligence, which will promote environmental protection and clean production, thus partially strengthening the effect of the digital economy on air pollution reduction.

5.7 Robustness test

To test the robustness of the results obtained, the authors used principal component analysis to recalculate the level of digital economy development based on Zhao et al. (2020) for robustness

TABLE 10 Degree of deviation in air pollution (%) due to the digital economy impact effect.

Variable	Average value	Standard deviation	p25	p50	p75
Emissions increase effect	3.49	3.70	1.79	1.95	2.92
Emissions reduction effect	6.35	6.63	1.83	2.65	9.07
Net effect	−2.86	8.59	−7.23	−0.80	1.53

testing. The emissions increase effect, emissions reduction effect, and net effect of the digital economy on air pollution were estimated again. The results are shown in Table 9. The results showed that the emissions increase effect of the digital economy on regional air pollution intensity was 0.0380 and the emissions reduction effect was 0.0701, consistent with previous results. This indicates that there is a bilateral effect from the digital economy on regional air pollution. In terms of the net effect, the emissions increase effect of the digital economy accounted for 22.74, and the emissions reduction effect accounted for 77.26%. This indicates that the robustness of the results can be further verified as the emissions reduction effect of the digital economy dominated the impact of the digital economy on air pollution, thus allowing the air pollution to deviate from its frontier level.

The emissions reduction effect, emissions increase effect, and net effect of the interaction between the digital economy on air pollution were further estimated. The results are listed in Table 10. The results show that as the development level of the digital economy increased, its emissions increase effect increased regional air pollution by 3.49%. In contrast, its emissions reduction effect reduced regional air pollution by 6.35%. The net effect yielded a regional air pollution level value relatively lower than the frontier level by 2.86%, which was roughly the same as that obtained during previous estimation.

6 Conclusion and policy recommendations

6.1 Conclusion

In this study, a two-tier stochastic frontier model was introduced to analyze the impact of the digital economy on air pollution using provincial Chinese panel data from 2011 to 2020. Based on existing studies, the authors analyzed the bilateral effects of the digital economy on air pollution through theoretical mechanism analysis and further empirically verified the effects using a two-tier stochastic frontier model. Specifically, this model was used to measure the net effect sizes of emissions increases, emissions reductions, and their mutual effects. On this basis, the impact of the digital economy on air pollution under different levels of the digital economy, human capital, and economic development was further discussed. The results of this study provided the following conclusions.

1. *Emissions increase effect and emissions reduction effect of digital economy on air pollution.* With the continuous development of China's digital economy, the emissions increase effect of the digital economy has allowed the air pollution to be higher than the frontier level by 4.87% while the emissions reduction effect of the digital economy has resulted in air pollution lower than the frontier level by 5.02%. The interaction of the two has eventually led to an actual air pollution emissions level that is 0.15% lower than the frontier level. Thus, the asymmetry of the bilateral effects of the digital economy at this stage caused an overall emissions reduction effect of the digital economy on the air pollution level. The digital economy development level was recalculated using principal component analysis and replaced with explanatory variables. The model results were consistent with those previous studies; therefore, the study findings remain robust. Therefore, when formulating policies to solve the air pollution problem, local government departments should consider the comprehensive impact of digital economy on air pollution. Otherwise, trying to reduce air pollution only by expanding the development scale of digital economy cannot fundamentally solve the air pollution problem.
2. *Spatial and temporal heterogeneity of bilateral effects of digital economy on air pollution.* The time-trend characteristics of the digital economy's net effect on air pollution emissions showed a wave-like change. The regional characteristics revealed that the average value of the net effect was negative. With the change in the time trend, the net effect of the digital economy on air pollution emissions increased alternately with the emissions reduction effect. The two effects co-existed and showed asymmetric changes, which resulted in a wave-like pattern for the net effect of the digital economy. The regional characteristics of the net effect of the digital economy on air pollution emissions showed that the mean values of the net effect in the three regions, i.e., east, central, and west, were negative: −1.22%, −0.28%, and −1.01%, respectively. The net effect of air pollution is dynamic, and although emissions reduction effect currently dominates, attention must be paid to reducing the negative environmental impact brought about by the development process of the digital economy; and the development gap of net effect of different regions cannot be ignored. The eastern or western region's digital economy has a greater emissions reduction effect, respectively on air pollution than the central region. By promoting the role of the digital economy in the green development of industries, green technological innovation and environmental regulation, the emission reduction of the digital economy is brought into play effect.
3. *Bilateral effects of the digital economy on air pollution under different constraints*. Along with the increase in the digital economy development level, human capital level, and economic development, the emissions reduction effect of the digital economy on air pollution was strengthened, thus achieving a positive to negative net effect. However, there were significant heterogeneous characteristics in the effects of the digital economy on air pollution under different

levels of digital economy development, human capital, and economic development. In particular, when the level of digital economy development from low to high, although both the emissions increase and emissions reduction effects of the digital economy on air pollution were strengthened, the emissions reduction effects was gradually stronger than the emissions increase effect, and the comprehensive impact on air pollution is changing from "increasing pollution" to "reducing pollution."

6.2 Policy recommendations

Based on the findings, the authors propose the following policy recommendations. The construction of a digital economy is important for enhancing the emissions reduction effect of the digital economy on air pollution.

First, it is necessary to comprehensively promote the digital economy such that it plays an effective role in enhancing the efficiency of energy use, improving the level of green technological innovation, giving birth to green industries, actively guiding enterprises to carry out digital transformation, and strengthening the construction of regional digitalization. Presently, China has implemented relevant regional policies for construction of digital economy, but he construction of the digital economy early zone needs to be strengthened. Particularly, the construction of the digital economy in areas with conditions of digitalization should be actively promoted to achieve the maximum effect of the digital economy word emissions reduction.

Second, under the constraints of different levels of digital economy development, human capital level, and economic development in different regions, a digital economy construction cooperation platform should be implemented, with the establishment of a mechanism for the cooperation and cultivation of innovative talents. This can aid in gathering innovative talent elements, receiving economic radiation from economically developed regions, and jointly building an integrated region for digital economy development. At this stage, the infrastructure and public services supporting the implementation of digital economy construction cooperation platforms and digital economy belts are relatively lagging, especially in the central and western regions. For the central and western regions, cooperation with the eastern region must be further strengthened to promote the construction of digital economy supporting facilities. The advanced technology spillover and management experience of digital economy construction must be more fully absorbed to improve the level of the digital economy in low-level provinces.

Moreover, from a pollution reduction perspective, in addition to focusing on the emissions reduction effect of the digital economy on air pollution, the government must also further improve regulations on air pollution, propose strict standards for emission generation and treatment of air contaminants, strengthen the supervision of enterprise air pollution emissions behavior, strengthen government supervision by increasing resources and environmental taxes, and accelerate the exit or transformation of polluting industries. Governments can encourage enterprises to carry out green innovation activities, accelerate the development of industrial green transformation to reduce air pollution emissions at the source, and promote green and low-carbon development to improve the efficiency of digital economy emissions reduction.

6.3 Deficiency and prospect of research

First, the authors note that the focus of this study is on provincial-level studies; thus, it could not fully capture the responses to firm characteristic heterogeneity. In the future, with the support of firm-level data, further extensions to this study could examine the bilateral effects of corporate digital development on environmental pollution at the firm level from a microscopic perspective.

Second, this study mainly explored bilateral effects of the digital economy on air pollution. The follow-up research can discuss more types of environmental pollution, such as carbon dioxide emissions, wastewater pollution, solid waste pollution, etc., and examine the bilateral effects of digital development on corresponding pollution based on the data availability to form a more comprehensive and complex research system.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

RW: Conceptualization, methodology, writing–original draft, writing–review and editing, project administration, supervision, funding acquisition. CD: Data curation, methodology, validation, investigation, writing–original draft, formal analysis, writing–review and editing.

Funding

This work was supported by the following programs: 1)"Talent introduction scientific research start-up fund of Anhui University of Science and Technology." 2)"Postgraduate Research and Practice Innovation Program of Jiangsu Province"(KYCX22_0691).

Acknowledgments

The authors would like to acknowledge the reviewers and editors for their valuable guidance and helpful comments.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Ahmedov, I. (2020). The impact of digital economy on international trade. *Eur. J. Bus. Manag. Res.* 5 (4). doi:10.24018/ejbmr.2020.5.4.389

Amin, S. B., and Rahman, S. (2019). *Energy resources in Bangladesh: Trends and contemporary issues*. Cham: Springer International Publishing. doi:10.1007/978-3-030-02919-7

Balogun, A.-L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., et al. (2020). Assessing the potentials of digitalization as a tool for climate change adaptation and sustainable development in urban centres. *Sustain. Cities Soc.* 53, 101888. doi:10.1016/j.scs.2019.101888

Bhattacharya, A., Oppenheim, J., and Stern, N. (2015). *Driving sustainable development through better infrastructure: Key elements of a transformation program*.

Chang, T., Graff Zivin, J., Gross, T., and Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *Am. Econ. J. Econ. Policy* 8 (3), 141–169. doi:10.1257/pol.20150085

Chen, L. (2022). How CO_2 emissions respond to changes in government size and level of digitalization? Evidence from the BRICS countries. *Environ. Sci. Pollut. Res. Int.* 29, 457–467. doi:10.1007/s11356-021-15693-6

Chen, S., Ding, D., Shi, G., and Chen, G. (2022). Digital economy, industrial structure, and carbon emissions: An empirical study based on a provincial panel data set from China. *China Popul. Resour. Environ.* 20 (4), 316–323. doi:10.1016/j.cjpre.2022.11.002

Cheng, K., and Hong, Z. (2022). Effect of urban population aggregation index on air pollution: Based on the bilateral stochastic frontier model. *China Popul. Resour. Environ.* 32 (2), 51–62.

DanishZhang, J., Wang, B., and Latif, Z. (2019). Towards cross-regional sustainable development: The nexus between information and communication technology, energy consumption, and CO2 emissions. *Sustain. Dev.* 27 (5), 990–1000. doi:10.1002/sd.2000

Ebenstein, A., Fan, M., Greenstone, M., He, G., and Zhou, M. (2017). New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proc. Natl. Acad. Sci. U. S. A.* 114 (39), 10384–10389. doi:10.1073/pnas.1616784114

Feng, H., Zou, B., and Ding, Y. (2019). Satellite detection of aerosol-produced temperature change. *Remote Sens. Lett.* 10 (9), 854–863. doi:10.1080/2150704X.2019.1629707

Feroz, A. K., Zo, H., and Chiravuri, A. (2021). Digital transformation and environmental sustainability: A review and research agenda. *Sustainability* 13 (3), 1530. doi:10.3390/su13031530

Gan, T., Liang, W., Yang, H., and Liao, X. (2020). The effect of Economic Development on haze pollution (PM2.5) based on a spatial perspective: Urbanization as a mediating variable. *J. Clean. Prod.* 266, 121880. doi:10.1016/j.jclepro.2020.121880

Gómez, J., Salazar, I., and Vargas, P. (2017). Does information technology improve open innovation performance? An examination of manufacturers in Spain. *Inf. Syst. Res.* 28 (3), 661–675. doi:10.1287/isre.2017.0705

Granell, C., Havlik, D., Schade, S., Sabeur, Z., Delaney, C., Pielorz, J., et al. (2016). Future Internet technologies for environmental applications. *Environ. Modell. Softw.* 78, 1–15. doi:10.1016/j.envsoft.2015.12.015

Grigorescu, A., Pelinescu, E., Ion, A. E., and Dutcas, M. F. (2021). Human capital in digital economy: An empirical analysis of Central and Eastern European countries from the European Union. *Sustainability* 13 (4), 2020. doi:10.3390/su13042020

Guo, B., Wang, Y., and Zhang, H. (2022). Does digital economy improve urban air quality: Quasi natural experiment based on national big data comprehensive pilot zone. *J. Guangdong Univ. Fin. Econ.* 37, 58–74.

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., and Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Econ. Q.* 19, 1401–1418. doi:10.13821/j.cnki.ceq.2020.03.12

Hampton, S. E., Strasser, C. A., Tewksbury, J. J., Gram, W. K., Budden, A. E., Batcheller, A. L., et al. (2013). Big data and the future of ecology. *Front. Ecol. Environ.* 11 (3), 156–162. doi:10.1890/120103

Han, B., Wang, D., Ding, W., and Han, L. (2016). Effect of information and communication technology on energy consumption in China. *Nat. Hazards* 84, 297–315. doi:10.1007/s11069-016-2188-1

Han, X., Song, W., and Li, B. (2019). Can the Internet become a new momentum to improve the efficiency of regional innovation in China – CNKI. *China Ind. Econ.*, 119–136.

Hao, Y., Huang, Z., and Wu, H. (2019). Do carbon emissions and economic growth decouple in China? An empirical analysis based on provincial panel data. *Energies* 12 (12), 2411. doi:10.3390/en12122411

Heo, P. S., and Lee, D. H. (2019). Evolution of the linkage structure of ICT industry and its role in the economic system: The case of korea. *Inf. Technol. Dev.* 25 (3), 424–454. doi:10.1080/02681102.2018.1470486

Hille, E., Shahbaz, M., and Moosa, I. (2019). The impact of fdi on regional air pollution in the republic of Korea: A way ahead to achieve the green growth strategy? *Energy Econ.* 81, 308–326. doi:10.1016/j.eneco.2019.04.004

Honarvar, A. R., and Sami, A. (2019). Towards sustainable smart city by particulate matter prediction using urban big data, excluding expensive air pollution infrastructures. *Big Data Res.* 17, 56–65. doi:10.1016/j.bdr.2018.05.006

Huang, Q., Yu, Y., and Zhang, S. (2019). Internet development and productivity growth in manufacturing industry: Internal mechanism and China experiences. *China Ind. Econ.* (08), 5–23. doi:10.19581/j.cnki.ciejournal.2019.08.001

Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., et al. (2014). High secondary aerosol contribution to particulate pollution during haze events in China. *Nature* 514, 218–222. doi:10.1038/nature13774

Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telemat. Inf.* 32 (1), 79–88. doi:10.1016/j.tele.2014.04.003

Johansson, L., Epitropou, V., Karatzas, K., Karppinen, A., Wanner, L., Vrochidis, S., et al. (2015). Fusion of meteorological and air quality data extracted from the web for personalized environmental information services. *Environ. Modell. Softw.* 64, 143–155. doi:10.1016/j.envsoft.2014.11.021

Jurayevich, M. B., and Bulturbayevich, M. B. (2020). The impact of the digital economy on economic growth. *IJIE* 3 (6), 16–18. doi:10.31149/ijie.v3i6.394

King, A. C., Odunitan-Wayas, F. A., Chaudhury, M., Rubio, M. A., Baiocchi, M., Kolbe-Alexander, T., et al. (2021). Community-based approaches to reducing health inequities and fostering environmental justice through global youth-engaged citizen science. *Int. J. Environ. Res. Public Health* 18 (3), 892. doi:10.3390/ijerph18030892

Kuang, C., Li, W., and Huang, X. (2022). Spatial-temporal evolution and driving factors of coupling coordination between carbon emission intensity and high-quality economic development in urban agglomerations in the middle reaches of the Yangtze Riv. *Econ. Geogr.* 42 (08), 30–40. doi:10.15957/j.cnki.jjdl.2022.08.004

Kumbhakar, S. C., and Parmeter, C. F. (2009). The effects of match uncertainty and bargaining on labor market outcomes: Evidence from firm and worker specific estimates. *J. Prod. Anal.* 31, 1–14. doi:10.1007/s11123-008-0117-3

Lange, S., Pohl, J., and Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecol. Econ.* 176, 106760. doi:10.1016/j.ecolecon.2020.106760

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., and Hoffmann, M. (2014). Industry 4.0. *Bus. Inf. Syst. Eng.* 6 (4), 239–242. doi:10.1007/s12599-014-0334-4

Li, B., Han, X., and Li, N. (2019). Does IPR strength affect the OFDI reverse innovation spillover in China. *China Soft Sci.*, 46–60.03

Li, K., Fang, L., and He, L. (2018). How urbanization affects China's energy efficiency: A spatial econometric analysis. *J. Clean. Prod.* 200, 1130–1141. doi:10.1016/j.jclepro.2018.07.234

Li, W., and Zhang, K. (2019). The effects of air pollution on enterprises' productivity: Evidence from Chinese industrial enterprises. *Manag. World* 35 (10), 95–112. + 119. doi:10.19744/j.cnki.11-1235/f.2019.0134

Li, Y., Yang, X., Ran, Q., Wu, H., Irfan, M., and Ahmad, M. (2021). Energy structure, digital economy, and carbon emissions: Evidence from China. *Environ. Sci. Pollut. Res. Int.* 28, 64606–64629. doi:10.1007/s11356-021-15304-4

Li, Z., and Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: Evidence city-level empirical data in China. *J. Clean. Prod.* 351, 131570. doi:10.1016/j.jclepro.2022.131570

Lin, B., and Xu, M. (2019). Does China become the "pollution heaven" in south-south trade? Evidence from sino-Russian trade. *Sci. Total Environ.* 666, 964–974. doi:10.1016/j.scitotenv.2019.02.298

Liu, J., Yang, Y., and Zhang, S. (2020). Research on the measurement and driving factors of China's digital economy. *Shanghai J. Econ.* (06), 81–96. doi:10.19626/j.cnki.cn31-1163/f.2020.06.008

Liu, Y., Yao, X., and Wei, T. (2019). Energy efficiency gap and target setting: A study of information asymmetry between governments and industries in China. *China Econ. Rev.* 57, 101341. doi:10.1016/j.chieco.2019.101341

Martynenko, T. S., and Vershinina, I. A. (2018). Digital economy: The possibility of sustainable development and overcoming social and environmental inequality in Russia. *Rev. espac.* 39 (44).

Murshed, M. (2020). An empirical analysis of the non-linear impacts of ICT-trade openness on renewable energy transition, energy efficiency, clean cooking fuel access and environmental sustainability in South Asia. *Environ. Sci. Pollut. Res. Int.* 27, 36254–36281. doi:10.1007/s11356-020-09497-3

Peng, G. C. A. (2013). Green ICT: A strategy for sustainable development of China's electronic information industry. *China. Int. J.* 11 (3), 68–86. doi:10.1353/chn.2013.0031

Pradhan, R. P., Arvin, M. B., Nair, M., and Bennett, S. E. (2020). Sustainable economic growth in the European Union: The role of ICT, venture capital, and innovation. *Rev. Financ. Econ.* 38 (1), 34–62. doi:10.1002/rfe.1064

Ren, S., Hao, Y., Xu, L., Wu, H., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

Salahuddin, M., and Alam, K. (2015). Internet usage, electricity consumption and economic growth in Australia: A time series evidence. *Telemat. Inf.* 32 (4), 862–878. doi:10.1016/j.tele.2015.04.011

Shvakov, E. E., and Petrova, E. A. (2020). "Newest trends and future scenarios for a sustainable digital economy development," in *Scientific and technical revolution: Yesterday, today and tomorrow lecture notes in networks and systems.* Editors E. G. Popkova and B. S. Sergi (Cham: Springer International Publishing), 1378–1385. doi:10.1007/978-3-030-47945-9_150

Su, Y., and Yu, Y. Q. (2020). Spatial agglomeration of new energy industries on the performance of regional pollution control through spatial econometric analysis. *Sci. Total Environ.* 704, 135261. doi:10.1016/j.scitotenv.2019.135261

Sun, D., Zeng, S., Lin, H., Meng, X., and Yu, B. (2019). Can transportation infrastructure pave a green way? A city-level examination in China. *J. Clean. Prod.* 226, 669–678. doi:10.1016/j.jclepro.2019.04.124

Tian, Y., and Feng, C. (2022). The internal-structural effects of different types of environmental regulations on China's green total-factor productivity. *Energy Econ.* 113, 106246. doi:10.1016/j.eneco.2022.106246

Usman, A., Ozturk, I., Ullah, S., and Hassan, A. (2021). Does ICT have symmetric or asymmetric effects on CO2 emissions? Evidence from selected asian economies. *Technol. Soc.* 67, 101692. doi:10.1016/j.techsoc.2021.101692

Wang, J., Dong, K., Dong, X., and Taghizadeh-Hesary, F. (2022a). Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Econ.* 113, 106198. doi:10.1016/j.eneco.2022.106198

Wang, J., Wang, K., Dong, K., and Shahbaz, M. (2022b). How does the digital economy accelerate global energy justice? Mechanism discussion and empirical test. *Energy Econ.* 114, 106315. doi:10.1016/j.eneco.2022.106315

Wang, S., Feng, H., Zou, B., Yang, Z., and Ding, Y. (2022c). Correlation between biomass burning and air pollution in China: Spatial heterogeneity and corresponding factors. *Glob. Planet. Change* 213, 103823. doi:10.1016/j.gloplacha.2022.103823

Weis, W. A., Soares, C. H. L., de Quadros, D. P. C., Scheneider, M., and Pagliosa, P. R. (2017). Urbanization effects on different biological organization levels of an estuarine polychaete tolerant to pollution. *Ecol. Indic.* 73, 698–707. doi:10.1016/j.ecolind.2016.10.029

World Health Organization (2022). *Ambient (outdoor) air pollution*. 2022 [cited 2023 20 January, 2023]; Available at: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

Wu, H., Hao, Y., Ren, S., Yang, X., and Xie, G. (2021). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* 153, 112247. doi:10.1016/j.enpol.2021.112247

Yang, Z., Gao, W., Han, Q., Qi, L., Cui, Y., and Chen, Y. (2022). Digitalization and carbon emissions: How does digital city construction affect China's carbon emission reduction? *Sustain. Cities Soc.* 87, 104201. doi:10.1016/j.scs.2022.104201

Yi, F., Ye, H., Wu, X., Zhang, Y. Y., and Jiang, F. (2020). Self-aggravation effect of air pollution: Evidence from residential electricity consumption in China. *Energy Econ.* 86, 104684. doi:10.1016/j.eneco.2020.104684

Zameer, H., Wang, Y., Yasmeen, H., and Mubarak, S. (2020). Green innovation as a mediator in the impact of business analytics and environmental orientation on green competitive advantage. *Manag. Decis.* 60 (2), 488–507. doi:10.1108/MD-01-2020-0065

Zhang, D., Pan, S. L., Yu, J., and Liu, W. (2022). Orchestrating big data analytics capability for sustainability: A study of air pollution management in China. *Inf. Manage.* 59, 103231. doi:10.1016/j.im.2019.103231

Zhang, M., Liu, X., Ding, Y., and Wang, W. (2019). How does environmental regulation affect haze pollution governance?—an empirical test based on Chinese provincial panel data. *Sci. Total Environ.* 695, 133905. doi:10.1016/j.scitotenv.2019.133905

Zhao, J., Jiang, Q., Dong, X., Dong, K., and Jiang, H. (2022). How does industrial structure adjustment reduce CO_2 emissions? Spatial and mediation effects analysis for China. *Energy Econ.* 105, 105704. doi:10.1016/j.eneco.2021.105704

Zhao, T., Zhang, Z., and Liang, S. (2020). Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China – CNKI. *Manag. World* 36 (10), 65–76. doi:10.19744/j.cnki.11-1235/f.2020.0154

Zhou, B., Zhao, H., Yu, J., He, T., and Liu, J. (2022). Does the growth of the digital economy boost the efficiency of synergistic carbon-haze governance? Evidence from China. *Front. Environ. Sci.* 10, 984591. doi:10.3389/fenvs.2022.984591

Zhou, X., Zhou, D., and Wang, Q. (2018). How does information and communication technology affect China's energy intensity? A three-tier structural decomposition analysis. *Energy* 151, 748–759. doi:10.1016/j.energy.2018.03.115

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 21 February 2023
DOI 10.3389/fenvs.2023.1137271

Check for updates

OPEN ACCESS

EDITED BY
Grigorios L. Kyriakopoulos,
National Technical University of Athens, Greece

REVIEWED BY
Narongsak Sukma,
Mahanakorn University of Technology, Thailand
Siamak Hoseinzadeh,
Sapienza University of Rome, Italy
Ioannis Sebos,
National Technical University of Athens, Greece

*CORRESPONDENCE
Le Wang,
wangleyi17@163.com

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management, a section of the journal Frontiers in Environmental Science

RECEIVED 04 January 2023
ACCEPTED 08 February 2023
PUBLISHED 21 February 2023

CITATION
Li J, Wang L and Nutakor F (2023), Empirical research on the influence of corporate digitalization on green innovation.
Front. Environ. Sci. 11:1137271.
doi: 10.3389/fenvs.2023.1137271

Empirical research on the influence of corporate digitalization on green innovation

Jinke Li, Le Wang* and Felix Nutakor

School of Business, Qingdao University, Qingdao, China

The link between corporate digitization and green innovation is now receiving attention from all spheres of life in light of the rapidly developing digital economy and the goal of sustainable development. This study explores how corporate digitalization affects green innovation, its mediating mechanism, and moderating effects by integrating resource-based theory, attention-based view, and institutional theory. We utilize the panel data of Chinese Shanghai and Shenzhen A-share manufacturing corporation data from 2011 to 2020 as samples and use the fixed effect model in linear regression of panel data for regression analysis. Research findings: 1) corporate digitalization fosters not only green innovation directly but also promotes green innovation by enhancing human capital. 2) Executive team environmental attention encourages the beneficial correlation between human capital and green innovation. 3) Media attention promotes the favorable relationship between corporate digitalization and green innovation. 4) Heterogeneity analysis revealed that the corporate digitalization effect on green innovation is more significant when firms are more prominent in high-tech industries. The findings encourage corporations to strengthen their digital strategy, infrastructure, and applications. In addition, they can also inspire green innovation to enable companies to develop sustainably.

KEYWORDS

corporate digitalization, green innovation, human capital, executive team environmental attention, media attention

1 Introduction

In the past few years, manufacturing corporates in China have been caught in the dilemma of low quality, low efficiency, and severe ecological damage while using resources for rapid development (Ji and Zhang, 2019). We must therefore draw attention to the waste and pollution problems in the manufacturing industry. The UN proposed the Sustainable Development Goal in 2021. To address the issues of global climate change, pollution, and waste, it took into account economic, social, and environmental concerns (Sinha et al., 2021). More and more academic research is being done from the standpoint of environmental science under the setting of the sustainable development goal (Sukma and Leelasantitham, 2022a). For instance, from the macro-level perspective, Hoseinzadeh et al. (2022a, 2022b) applied the PRISMI PLUS Toolkit to the city of Spain and the island of Procida with a comprehensive analysis of energy, economic and environmental. They demonstrated the approach to integrating renewable energy (solar and wind energy). This is crucial for the region's sustainable development and energy independence, as well as for reaching the decarbonization goal. Fayazi Rad et al. (2022) applied the advanced hydrogen production device to the road infrastructure sector in Iran, which reduced carbon dioxide emissions and increased sustainability. Similarly; Hoseinzadeh and Astiaso Garcia (2022) explored renewable energy systems using solar and wind energy with great potential on Italian islands for economic and environmental benefits and sustainable development. From the viewpoint of environmental science and the microscale level of enterprises, studying how corporate behavior favorably impacts the economy, society, and environment has become crucial to advancing the sustainable development goal (Sukma and Leelasantitham, 2022b). Green innovation is a critical component of accomplishing the goal of sustainable development (Song and Yu, 2018). Corporate green innovation may promote sustainable growth, minimize adverse environmental effects, and increase environmental and economic advantages (Hojnik and Ruzzier, 2016). Therefore, from a micro perspective, corporations must seek out green innovation to promote sustainable development goals.

Meanwhile, digital technology is advancing rapidly and integrating with traditional businesses. These organizational environmental elements have a consequence on how companies change. Corporations must adhere to digital development and update their technologies, allowing them to drive green innovation and digitally enable stable, sustainable improvement (Wen et al., 2021; Sukma and Leelasantitham, 2022b). It is practical to look at how corporate digitalization affects green innovation to promote corporate development.

Several researchers have already researched the connection between corporate digitization and green innovation. The environment may benefit from corporate digitalization (Danish, 2019). Big data technologies can simulate green innovation's process and predict its course, which can positively affect green innovation practices (El-Kassar and Singh, 2019; Li and Shen, 2021) and enable companies to gain green competitiveness (Tian et al., 2022). Digitalization increases information transparency, which fosters shared commitment and trust, significantly boosts innovation, and enables sustainable development (Dong et al., 2021; Sukma and Leelasantitham, 2022a). Corporate digitalization can increase the number and quality of green innovations (Rao et al., 2022). But as the study goes on, some researchers have discovered the phenomena known as the "digital paradox" because of the growth of digital technology (Gebauer et al., 2020), which instead increases energy consumption and pollution (Avom et al., 2020). Several researchers have presented a non-linear perspective on the impacts of corporate digitalization on green innovation. The "data-driven" effect of corporations promotes the upgrading of green innovation strategies, while corporate digitalization can inhibit green innovation due to the "curse of competence" and digital overload (Hajli, 2015; Dong and Netten, 2017; Gebauer et al., 2020; Cao et al., 2021; Li and Shen, 2021). There is disagreement over how corporate digitalization affects green innovation. Therefore, it is crucial to ascertain if corporate digitalization can foster green innovation.

Most current research concentrates on the direct relationships between corporate digitalization and green innovation. However, they still have not fully reveal how corporate digitalization affects green innovation internally. Corporate digitalization is only a means of green innovation (Bartel et al., 2007). Corporate environmental programs intimately tie to stakeholders who influence or engage in environmental actions (Ioanna et al., 2022). The stakeholders of green innovation in enterprises are shareholders, managers, and employees (Mitchell et al., 1997). Stakeholders' behavior affects the effectiveness of IT projects and the quality of IT systems; whether corporate digitalization (such as IT technology) can successfully foster green innovation depends on people's background knowledge and experience (Sukma and Leelasantitham, 2022b). Thus, human capital is the nucleus resource of green innovation. Advanced digital resources for green innovation may be learned, absorbed, and used by human capital at a greater level. Following the resource-based theory, this study explores the mediating mechanism between corporate digitalization and green innovation from the human capital standpoint.

Most previous research has considered the moderating effect of corporate digitalization and green innovation from a single internal or external perspective (Wei and Sun, 2021; Cardinali and De Giovanni, 2022), while we account for moderating effects from dual perspectives of corporations' internal and external environmental attention in this empirical study. Within the enterprise, the executive team's level of environmental awareness determines how much green innovation a company engages in, and it affects how resources are allocated for corporate green innovation (Wang L. et al., 2022). So we select executive team environmental attention as an internal environmental factor to explore its moderating effect on human capital and green innovation. The attention-based view combined with institutional theory provides a better understanding of how firms develop a competitive advantage (Ocasio, 2011). According to institutional theory, businesses must pursue green innovation initiatives to meet external institutional demand and boost organizational legitimacy. Prior research has concentrated on how coercive forces (such as government environmental rules) affect green innovation (Wu et al., 2022) while ignoring the impact of non-coercive pressures. Outside the enterprises, the media, as a non-coercive pressure, plays a guiding role in the topics concerned by corporates and the public. Media attention to environmental behavior can guide companies to use resources and technology for green innovation (Wang and Zhang, 2021). So we choose media attention as an external environmental factor to assess the moderating effects of media attention on corporate digitalization and green innovation.

Then, the following queries merit consideration:

Q1: What correlation exists between green innovation and corporate digitalization? Will it be heterogeneous among different corporations?

Q2: Can human capital serve as a mediating mechanism in corporate digitalization and green innovation?

Q3: From dual perspectives of internal and external environmental attention, what moderating effect does executive team environmental attention have on human capital and green innovation? And how can media attention play a moderating impact between corporate digitalization and green innovation?

To address the issues above, first, we analyze Q1 and Q2 per the resource-based theory and Q3 in accord with the attention-based view and institutional theory. Second, we utilize the fixed effect model in the linear regression of panel data to conduct an empirical test using the panel data of A-share manufacturing businesses in China from 2011 to 2020 as samples. After that, the robustness test is carried out, and the endogenous problem is alleviated. In further research, heterogeneity analysis is carried out according to enterprise size and technological attributes.

The following are the main contributions: first, we empirically verify the micro mechanism of corporate digitalization and green innovation using the realistic background of green development and the digital economy. Second, from the view of human capital, we have unlocked the mediating role of corporate digitalization promoting green innovation, which offers suggestions for fully utilizing the environmental benefit potential of corporate digitalization. Third, we examine the moderating effect in light of dual internal and external environmental attention. We include executive team environmental attention as an internal factor in the "corporate digitalization-human capital-green innovation" research framework. Media attention is an external factor in the "corporate digitalization-green innovation" research framework. As a result, it provides a more situational empirical analysis of the relationship between green innovation and corporate digitalization.

2 Theoretical analysis and research hypotheses

2.1 The impact of corporate digitalization on green innovation

Corporate digitization is a strategic act. It uses digital resources to formulate and execute corporate actions to achieve digitalization at all levels of manufacturing, sales service, and management (Bharadwaj et al., 2013; Nambisan et al., 2019).

The resource-based theory states that corporations can achieve superior performance and a competitive edge by utilizing priceless, uncommon, unique, and irreplaceable resources (Wernerfelt, 1984; Barney, 1991). Thus, Valuable and unique digital resources within a corporation may provide it with a competitive edge. The company's internal resources may also be combined with digital resources for green innovation. The following are the primary aspects that corporate digitalization has affected green innovation.

In R&D and manufacturing, companies use digital technologies such as blockchain to collect and analyze financial market information to provide financing support for R&D and manufacturing of green innovations. Corporate digitalization enables reallocating and optimizing resources and efficiently uses resources in manufacturing business processes, generating green energy-saving technologies (Chuang and Huang, 2018; Cardinali and De Giovanni, 2022). Advanced sensors, artificial intelligence, and other digital technologies enable to monitor of the manufacturing process autonomously, in real-time, and precisely. These also optimize the procedure for high loss and low output, thus achieving green process innovation (Müller and Voigt, 2018; Li et al., 2022). Big data analytics and other digital technologies can access and analyze enormous volumes of data, identify obstacles to green innovation, and evaluate possible advantages through insight.

Corporate digitalization in sales can obtain high-quality information and improve information processing to meet consumers' green needs. This study by Johnson et al. (2017) claimed that green customer preferences could be gathered and analyzed using digital resources. Therefore, the development of corporate digitalization can quickly gain insight into green information in the market, close the distance with customers and conduct real-time communication to promote green innovation (Hajli, 2015; Dong and Netten, 2017). Additionally, corporate digitization supports green innovation by enabling businesses to swiftly respond to changing environmental conditions and get dynamic knowledge about external ecological governance and other issues. Consequently, we put up the following hypotheses.

Hypothesis 1: Corporate digitalization will foster green innovation.

2.2 The impact of corporate digitalization on human capital

Human capital combines workers' experience, talents, and physical strength and has economic value (Youndt et al., 2004; Subramaniam and Youndt, 2005). In this study, human capital refers to stakeholders' skills, knowledge, and experience, which can guide enterprises to realize strategic decisions. According to most academics, corporate digitalization benefits the human capital of businesses.

Corporate digitalization can optimize its human resource structure to enhance the human capital level. In the process of external recruitment, corporate digitalization requires the intellectual development of enterprises. Advanced equipment with cutting-edge technology will replace the low-skilled workforce, thus increasing the demand for highly qualified workers. Therefore, corporates can use digital technologies to break the limitation of information time and space, place recruitment information precisely, establish a job seeker information database, and conduct precise recruitment to optimize human capital structure and accumulate human capital (Gilch and Sieweke, 2021). In the internal performance appraisal process, digital resources dynamically detect employees' work and provide reasonable performance incentives according to their abilities. The excellent performance evaluation system is conducive to attracting higher levels of talent and adjusting the human capital structure (Baptista et al., 2020; Schuetz and Venkatesh, 2020), thus improving the human capital level of the company.

Corporate digitalization can also enhance the quality of their human resources to enhance the human capital level. Employees need to learn and use digital technologies to cope with the unconventional tasks such as R&D and production that emerge from the digital development of companies (Kozanoglu and Abedin, 2021; Cetindamar et al., 2022). Employees then utilize common digital platforms and digital technologies to interact and cooperate with individuals in the same business or even across industries, making it simpler to get new information and experience both within and outside the workplace (Leonardi, 2021; Cetindamar et al., 2022), thereby improving human capital. The following hypotheses are offered based on the analysis above.

Hypothesis 2: Corporate digitalization will improve corporates human capital level.

2.3 The impact of human capital on green innovation

New or enhanced goods, procedures, management, and services make up a green innovation. It can minimize the adverse environmental effects while simultaneously adding value to customers and businesses (Hojnik and Ruzzier, 2016). Green innovation bases its attention on innovation and places a greater emphasis on environmental conservation and green value. People are the core carrier of all production factors (Marchiori et al., 2022), but the significant determinants of green innovation are the knowledge, technology, skill, and experience integrated into human capital. Developing an innovation strategy as part of a talent plan is essential for encouraging green innovation. Some academics contend that a corporates' ability to green innovation is influenced by its amount of human capital (Adomako and Nguyen, 2020; Gerhart and Feng, 2021; Munawar et al., 2022). The following factors dominate how corporate human capital affects green innovation:

In corporate manufacturing, when updating environmental protection equipment and improving production and management practices, the experience and knowledge possessed by human capital can replace the need for natural resources and reduce environmental degradation and resource waste (Yao et al., 2019; Ahmed et al., 2020). In sales services, companies with higher human capital have more robust analytical capabilities and extensive information sources (King and Tucci, 2002). This enables them to understand customers' environmental consumption needs on time and have the ability to predict future ecological consumption needs (Munawar et al., 2022) to encourage green innovation among corporations. Additionally, research suggests that people are more likely to support the advancement and use of green technology if their human capital is better, their personal qualities are higher, and so on (Yong et al., 2019; Mansoor et al., 2021; Asiaei et al., 2022), and resist the consumption pattern that is not conducive to environmental sustainability (Yao et al., 2019). We put out the following hypotheses in light of the study above.

Hypothesis 3: The increase in corporate human capital level will encourage green innovation.

2.4 The mediating role of human capital

The resource-based view asserts that human capital is a valuable asset. Human capital refers to stakeholders' skills, knowledge, and experience. Referring to the research of Ioanna et al. (2022), we use priority to map and analyze the stakeholders of corporate green innovation in Figure 1. First, the CEO, managers, and shareholders have the highest priority since they will implement the company's strategy. Second, the R&D department, manufacturing department, customer service department, and functional department staff are responsible for making decisions, so they have medium priority. Finally, the enterprise's external stakeholders—consumers, suppliers, the government, and the general public—impact its strategic conduct. Still, they have no decision-making or execution authority and have the lowest priority. The following mainly analyzes the mediating role of human capital owned by internal stakeholders in enterprise between corporate digitalization and green innovation.

In recruitment and selection, corporates use digital technologies to establish a job search information database to understand the environmental protection concepts of job seekers (Deng et al., 2022) and select employees with solid environmental awareness to enhance corporate green human capital. In internal learning and training, corporate digitalization can use the Intranet to establish an environmental knowledge management system, and provide employees with environmental protection training, to enhance human capital's ability to acquire, analyze and integrate environmental experience, which is beneficial for green innovation (Antunes and Pinheiro, 2020; Cardinali and De Giovanni, 2022). In addition, digital elements precisely match external environmental changes with internal data processing to achieve "linkage empowerment". The relationship network formed by the "internal and external linkage" of digital resources can enhance the interaction with strategic partners and stakeholders, strengthen cooperative relationships, and promote organizational learning of green knowledge (Deng et al., 2022), then encouraging green innovation. Researchers put out the following hypotheses in light of the study above.

Hypothesis 4: Corporate digitization promotes green innovation by improving the human capital level.

2.5 The moderating effect of executive team environmental attention

As per the attention-based view (ABV), corporate managers' attention determines organizational behavior (Ocasio, 1997). When the executive team pays attention to external environmental information, it determines whether the event is an opportunity or a challenge for their corporates based on their experience and takes further actions to achieve the corporate's strategy (Ocasio, 1997; Boone et al., 2019). Corporate green innovation behavior results from the guidance of the executive team's environmental attention. The empirical research of Wang L. et al. (2022) also argued that corporate green innovation strategies result from the guidance of the executive team's environmental attention. Most previous studies took the executive team's environmental attention as a driving factor for corporate green innovation but ignored its moderating effect.

Corporate human capital's successful implementation of green innovation activities is closely related to the executive team's environmental attention. The process of attention to action is the moderating effect of the executive team's environmental attention on human capital and green innovation. With being intensely environmentally conscious, the executive pays more attention to the environmental system, media coverage, and public awareness, and they can better understand the environment's information (Peng and Liu, 2016). As a result, they make more significant efforts to implement green innovation inside corporations. They are fully aware of the significance of environmental concerns and how to relate them to business development. The executive team will devote more human resources to green innovation because of this

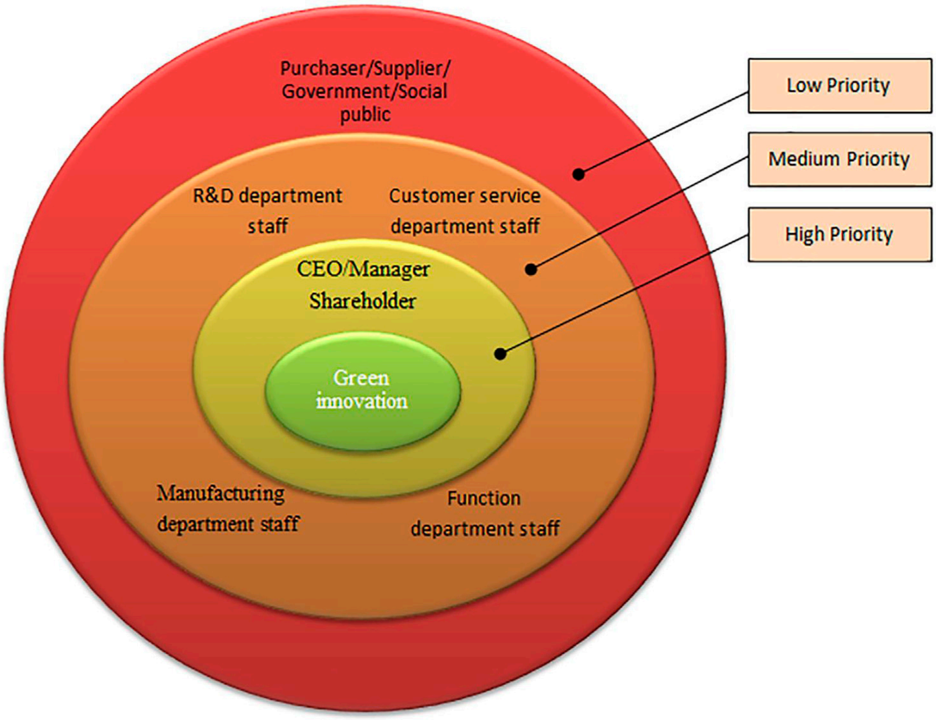


FIGURE 1
Stakeholders mapping.

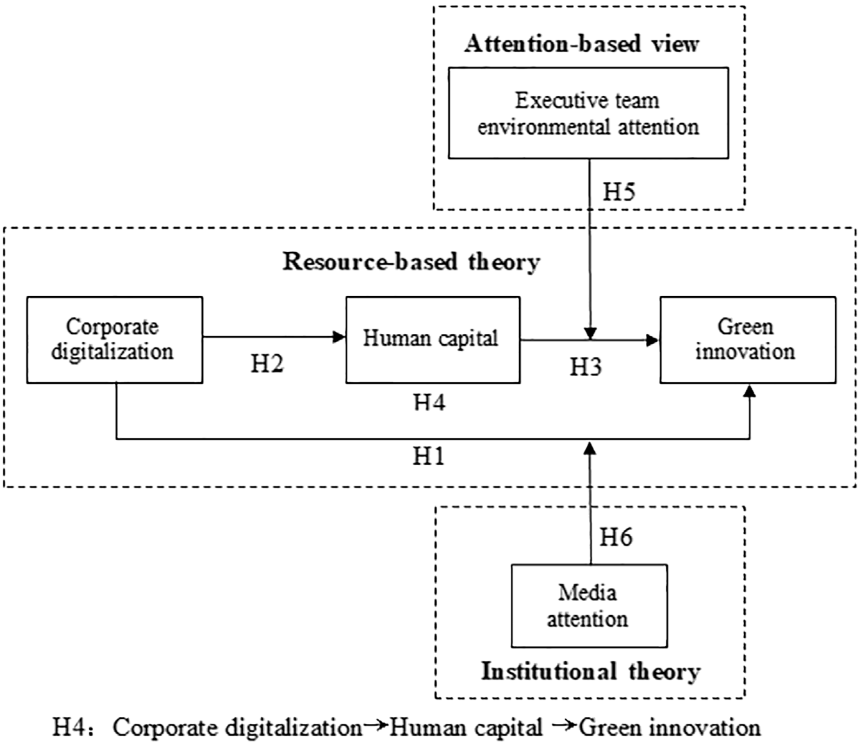


FIGURE 2
Research conceptual model.

choice, which will also impact corporate resource allocation. Considering this, here are some hypotheses that we put forth.

Hypothesis 5: The executive team's environmental attention promotes the positive relationship between human capital and green innovation.

2.6 The moderating effect of media attention

According to institutional theory, organizations need to increase organizational legitimacy in response to external institutional pressures. Studies have demonstrated that when environmental awareness grows, informal institutional pressure (such as media attention) encourages corporations to implement green innovations and achieve environmental legitimacy (Wang and Zhang, 2021; He et al., 2022). Thus, corporations with more media attention can strengthen their digital strategies and use digital resources and technologies to implement green innovation.

On the one hand, the media provides public information about corporate digitization and green innovation. As the general public becomes more environmentally conscious, investors will use the information on corporate green investments reported in the media as a reference, and consumers will be more willing to purchase environmental products stimulated by advertisements (Nyilasy et al., 2014; Zahid et al., 2018). To enhance their environmental legitimacy, companies use media information to understand the relevant green needs of their stakeholders and use corporate digitalization to encourage green innovation based on the relevant ecological dynamics. On the other hand, as an informal supervision mechanism outside the corporate (Chang et al., 2020), the media promotes a positive connection between corporate digitalization and green innovation. Media attention can expose corporate environmental violations (Chang et al., 2020; Wang and Zhang, 2021). The social pressure created by media exposure of corporate environmental violations can affect the image and reputation of a corporate (Wang F. et al., 2022). Therefore, corporates will balance economic and environmental benefits to maintain their reputation, build a green image (Cheng and Liu, 2018), and encourage green innovation through corporate digitalization. The following hypotheses have been put forth based on the study mentioned above.

Hypothesis 6: Media attention promotes the positive relationship between corporate digitalization and green innovation.

Based on the above hypotheses, our Research conceptual model is shown in Figure 2.

3 Research design

3.1 Sample and data

The research sample used in this work was the data of Chinese Shanghai and Shenzhen A-shares manufacturing enterprises from 2011 to 2020. We screened the initial data as follows: 1) dismissed ST, *ST, and other specially treated enterprises during the observation period, and 2) dismissed the samples with missing values for the main variables. Finally, we obtained the balance panel data of 405 companies with 4,050 observations.

We choose the sample for the following considerations: First, A-share companies refer to ordinary shares listed in Chinese Shanghai and Shenzhen and are subscribed to and traded in RMB. Chinese stocks also have B-shares, H-shares, N-shares, *etc.*, which are foreign stocks and need more sample data. We selected Chinese Shanghai and Shenzhen A-shares listed companies based on the data's accuracy and the research sample's integrity. Second, large-scale manufacturing is the major contributor to excessive resource consumption and environmental damage. Using manufacturing corporations as research samples, we can propose specific implications for minimizing environmental damage. Third, per the Listing Rules of the Shanghai Stock Exchange (Revised in 2019), "ST (Special Treatment)" will be added to the Stock's name if a listed firm encounters financial losses for two consecutive years or if its net assets are less than the face value of the Stock. When a company loses money for three consecutive years or has suffered financial losses for less than 3 years, "*ST" will be appended to the Stock's name, indicating that delisting may occur at any time. Thus, we dismiss ST and *ST companies since they apply to bankruptcy accounting rather than standard accounting rules and might raise suspicions of financial fraud.

Data sources: Corporate digitalization data came from the China Financial Research Center platform; corporate green innovation data came from CNRDS databases; human capital data came from the Wind database; media attention data came from the financial news of Chinese listed companies in CNRDS databases; executive team environmental attention data came from Wingo financial text data platform; all other related data came from CSMAR databases.

3.2 Main variables description

3.2.1 Dependent variable: Green innovation

According to studies by Johnstone et al. (2010) and Li et al. (2017), the quantity of green patent applications of enterprises reflects green innovation. We gauge green innovation (GI) by utilizing the number of green patent applications plus one and taking the natural logarithm. Adding one is to avoid the circumstance that the quantity is zero and cannot take a natural logarithm. Table 2 displays the variable's construction and sources.

3.2.2 Independent variable: Corporate digitalization

Since annual reports can reflect the development direction and strategic decisions of corporates (Donovan et al., 2021), most scholars use text analysis to estimate the number of digital keywords in annual reports to measure corporate digitalization (Hossnofsky and Junge, 2019; Ricci et al., 2020; Li and Shen, 2021; Wen et al., 2022). Following the studies of the previous academics, we measure corporate digitization (Dig) by the ratio of a digitalization-related word number in annual reports to the overall word number. Table 2 displays the variable's construction and sources.

TABLE 1 Executive team environment attention keywords.

Executive team environment attention keywords
safe production, protection, exceedance, ozone layer, dust removal, atmosphere, low carbon, carbon dioxide, prevention, exhaust, waste gas waste, wastewater, waste, sludge, dust, wind, boiler, filter, environmental, environment, recycling, methane, emission reduction, consumption reduction, degradation, noise reduction, energy saving, conservation, purification, sustainable development, renewable, air, waste, waste, process reengineering, green, energy consumption, energy, emission, exhaust, discharge, destruction, habitat, clean, fuel, waste, ecology, biomass, water treatment, acid, solar, natural gas, soil, desulfurization, denitrification, tail gas, greenhouse gas, pollution, sewage, no acid, solar, natural gas, soil, desulfurization, denitrification, tail gas, greenhouse gas, pollution, sewage, non-hazardous, paperless, species, consumption, recycling, soot, flue gas, liquefied gas, toxic, organic, waste heat, reuse, noise, heavy metals, natural resources

TABLE 2 Variable definitions and construction.

Variable types	Variable	Variable name	Variable measurement	Sources
Dependent Variable	GI	Green innovation	Natural logarithm of 1 plus the quantity of green patents application	CNRDS
Independent Variable	Dig	Corporate digitalization	Frequency of digitalized related words/whole quantity of Annual words (%)	China Financial Research Center platform
Mediating variable	HC	Human capital	Bachelor's degree or above/Number of employees	Wind
Moderating Variables	TMEA	Executive team environmental attention	Environment-related word frequency/Total number of MD&A words (%)	Wingo financial text data platform
	MA	Media attention	the natural log of 1 plus online financial news quantity	Wind
Control Variables	Age	Corporate age	Natural logarithm of 1 plus the corporate establishment years	CSMAR
	Growth	Operating income growth rate	(Operating income current year amount - Operating income prior year amount)/Operating income prior year amount	CSMAR
	Share	Ownership concentration	Sum of the shares held by the top 10 shareholders	CSMAR
	ROA	Return on assets	Net income/total assets ending balance (%)	CSMAR
	SOE	Nature of ownership	0 for other corporates, 1 for state-owned ones	CSMAR
	MPR	Marginal profit ratio	(Sale revenue-Variable cost)/Sale revenue	CSMAR

3.3.3 Mediating variable: Human capital

Employee skills and knowledge levels will increase as business human capital increases. Employee education levels correlate with their skill and knowledge levels. Improved education levels correlate with higher employee quality. As a result, they will learn, assimilate, and apply digital materials more sensitive (Bartel et al., 2007; Zhang et al., 2022). Referring to the research of Wiersema and Bantel (1992), the researchers evaluate human capital (HC) in this study by the percentage of employees with bachelor's degrees or higher in the enterprise.

3.3.4 Moderating variables: Executive team environmental attention and media attention

Attention will be reflected in the vocabulary used by individuals. Frequently used vocabulary information can reflect the focus of individual attention (Sapir, 1944). Therefore, the pertinent environmental keywords in annual reports will show senior executives' attention. First, we adopt environmental attention keywords list of Wu and Hua (2021), as shown in Table 1. Second, relying on the research of Wang L. et al. (2022) and Wu and Hua (2021), we count the environmental attention keywords in the managerial discussion and analysis (MD&A) section through the Wingo financial text data platform. Then we utilize the proportion of executive team environment attention keywords in MD&A to the entire words number as a measure for executive team environmental attention (TMEA).

Similar to research by Wang F. et al. (2022) and Cheng and Liu (2018), the number of pertinent news reports usually measures media attention. With the Internet's rapid expansion, online reporting has become the primary media attention channel. To gauge media attention (MA), this study employs online financial news quantity plus one and takes the natural logarithm.

3.3.5 Control variables

Following prior studies by (Chuang and Huang, 2018; Cardinali and De Giovanni, 2022; Li et al., 2022), the control variables in this research are Age, Growth, Share, return on assets (ROA), nature of ownership (SOE), and marginal profit ratio (MPR). Table 2 displays the Variable's construction and sources.

3.4 Regression models

Panel linear regression models involve mixed regression models, fixed effect models, and random effect models. The fundamental premise of the mixed regression model is the absence of an individual effect. However, there might be a unique situation in corporate development because each enterprise has a specific geographical, social, and economic context. In a panel regression model, there are two forms of individual effects: the random effect and the fixed effect. The Hausman test should be conducted to verify whether the data apply to the fixed effect model or the random effect model. Because the general Hausman test statistics are not robust in heteroscedasticity, we conduct the robust Hausman test employing Stata17.0 (Wooldridge, 2010). The outcome exhibits that $p = 0.0074$, that is, $p < 0.01$, disproving the null assumption of a random effect. So the fixed effect model is accepted. Then, we add the annual dummy variable to examine whether there is a yearly effect. The test outcome of the combined significance of annual dummy variables demonstrates that F (9, 404) = 8.46, Prob > F = 0.000, clearly rejecting the null hypothesis of "no time impact", and the model exists as an annual effect. Therefore, we choose the two-way fixed effect for individuals and time model and heteroscedasticity-robust standard errors during parameter estimation to prevent heteroscedasticity issues.

This study presents corporate human capital (HC) as a mediating variable to examine whether corporate digitalization can affect green innovation through corporate human capital. There was control over the yearly fixed effect and the individual fixed effect based on the theoretical analysis previously presented to assess the mechanism of corporate digitalization's influence on green innovation. Consistent with the analysis principle of the mediation effect (Baron and Kenny, 1986), the two-way fixed effect model in linear regression of panel data, the measurement model is developed:

$$GI_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Control_{it} + \gamma_i + \gamma_t + \varepsilon_{it} \tag{1}$$

$$HC_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Control_{it} + \gamma_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$$GI_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 HC_{it} + \beta_3 Control_{it} + \gamma_i + \gamma_t + \varepsilon_{it} \tag{3}$$

To further examine the moderating effect, this study introduces the interaction terms of human capital and executive team environmental attention, and the interaction terms of corporate digitalization and media attention, and builds the following model:

$$GI_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 HC_{it} + \beta_3 TMEA_{it} + \beta_4 HC_{it} \times TMEA_{it} + \beta_5 Control_{it} + \gamma_i + \gamma_t + \varepsilon_{it} \tag{4}$$

$$GI_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 MA_{it} + \beta_3 Dig_{it} \times MA_{it} + \beta_4 Control_{it} + \gamma_i + \gamma_t + \varepsilon_{it} \tag{5}$$

Among them, i indicates the listed company; t indicates time; the dependent variable GI_{it} indicates green innovation of firm i in year t; independent variable Dig_{it} indicates corporate digitalization of firm i in year t; mediating variable HC_{it} indicates human capital of firm i in year t; moderating variables $TMEA_{it}$ indicates executive team environmental attention of firm i in year t, MA_{it} indicates media attention of firm i in year t; $Control_{it}$ indicates control variables; γ_i specifies the individual fixed effect; γ_t designates the annual fixed effect. ε_{it} specifies random perturbation terms.

TABLE 3 Descriptive statistics.

Variable	N	Mean	SD	Min	Max
GI	4,050	0.654	1.079	0	6.267
Dig	4,050	0.126	0.212	0	3.169
HC	4,050	0.279	0.177	0.023	1
TMA	4,050	0.768	0.824	0	7.411
MA	4,050	5.285	1.097	0.693	9.763
Age	4,050	2.824	0.363	1.099	3.714
Growth	4,050	0.473	7.327	−2.083	423.0
Share	4,050	55.73	14.78	8.780	94.48
ROA	4,050	0.038	0.0860	−2.008	0.863
SOE	4,050	0.402	0.490	0	1
MPR	4,050	1.014	0.209	−3.929	8.059

3.5 Descriptive statistics

Table 3 displays the findings of the descriptive statistics. The minimum and highest values of green innovation (GI) are 0 and 6.267, showing a disparity in various corporates' green innovation. Corporate digitalization (Dig) ranges from 0% to 3.169%, with a mean value of only 0.126% and a standard error is 0.177%, demonstrating that there are significant variances and that corporate digitization is often at a low degree. Human capital (HC) has a mean value of 0.279 and the minimum value of 0.023, which shows that there is also a difference in human capital levels among companies. The fraction of environmental issues in MD&A is relatively low, and there is a big difference between firms, according to the mean value of executive team environmental attention (TMEA), which is 0.768, and the minimum value, which is 0. The overall mean of media attention (MA) is 5.285, and the standard deviation is 1.097, showing a lot of variance in media attention giving to different firms. Additionally, the age of the sample firms ranges from 1.099 to 3.714 and the proportion of top 10 shareholders ranges from 8.78% to 94.48%, falling within an appropriate range. Operating income is increasing at a rate greater than 0.1, demonstrating that the company has a good growth trend. The sample companies' average growth rate is 0.43, suggesting that they are generally in a solid growth phase. ROA greater than 0 signifies a good return on assets, and the mean value of the sample companies is 0.038, showing that the average profitability of the companies is high. MPR greater than 0 indicates that increasing product sales increase corporate revenue. The average MPR of the sample companies is 1.014, meaning a satisfactory average marginal profit margin. The outcomes of the descriptive statistics reflect that the data selection is appropriate.

3.6 Correlation analysis

We conducted a simple OLS regression for correlation analysis, and Table 4 displays the findings. Corporate digitalization and green

TABLE 4 Correlation analysis.

Variable	GI	Dig	HC	TMA	MA	Age	Growth	Share	ROA	SOE	MPR
GI	1										
Dig	0.123***	1									
HC	0.194***	0.376***	1								
TMA	0.187***	−0.090***	−0.038**	1							
MA	0.318***	0.026	0.078***	−0.022	1						
Age	0.020	0.007	0.050***	0.019	−0.006	1					
Growth	−0.010	−0.003	−0.002	0.003	−0.007	−0.005	1				
Share	0.046***	−0.043***	−0.068***	0.005	0.138***	−0.233***	0.036**	1			
ROA	0.018	−0.014	0.042***	−0.036**	0.104***	−0.022	0.002	0.184***	1		
SOE	0.070***	−0.012	0.070***	0.006	0.094***	0.217***	−0.005	−0.002	−0.012	1	
MPR	0.011	0.017	0.037**	−0.016	0.012	0.021	0.001	−0.036**	0.357***	0.001	1

*p < 0.1, **p < 0.05, ***p < 0.01.

innovation's Pearson correlation coefficient fulfilled the 1% statistical test. Additionally, human capital, executive team environmental attention, media attention, and green innovation are positively correlated. The results indicate that corporates with higher digitalization, higher human capital levels, more executive team environmental attention, and more media attention will be more conducive to green innovation. The VIF is 1.21 at the maximum after the variance inflation factor test, demonstrating no multicollinearity. Therefore, our variable selection is reasonable.

4 Discussion

In this section, the outcomes of models (1)–(5) using the two-way fixed effect model with heteroscedasticity-robust standard errors are derived and contrasted with the results of several experts' earlier studies. Second, the robustness test (such as replacing variables measurement and estimated models) is conducted, and the endogenous problem is alleviated. Additionally, the fixed effect model is utilized to explore the heterogeneity of corporate scale and technology features. Finally, the study's theoretical and practical enlightenment is provided.

4.1 Regression analysis

Table 5 displays the outcomes of corporate digitalization on green innovation and mediating function of human capital. Column 1) of Table 5 evaluates the impact of corporate digitalization on green innovation. With a correlation value of 0.391, the findings demonstrate that corporate digitalization and green innovation are statistically relevant at the 5% level, indicating corporate digitalization fosters green innovation, which confirmed the findings of Danish. (2019), Li and Shen (2021), Tian et al. (2022), and Rao et al. (2022), so H1 has been verified. However, this goes against the conclusion reached by Avom et al. (2020). The correlation between corporate digitalization and human capital is relevant at the 5% level, as displayed in column 2) of Table 5, with a correlation value of 0.072, affirmed that corporate digitization promotes the enhancement of human capital level, indicating that H2 has been verified. As is evident from column 3) in Table 5, human capital and green innovation are relevant at a 5% level, and the coefficient value is 0.594, showing increasing the level of human capital encourages green innovation, and H3 has been verified. These results also confirm Munawar et al. (2022), Yao et al. (2019), and Asiaei et al. (2022).

This study further verifies the mediating role of human capital between green innovation and enterprise digitalization. According to column 4) in Table 5, corporate digitalization and green innovation are highly associated at the 10% level, while human capital and green innovation are related at the 5% level. It is preliminarily shown that human capital mediates the connection between corporate digitalization and green innovation to some extent, so H4 is preliminarily verified.

To further verify the mediating effect, Bootstrap method regression was used with 1,000 sampling times (Preacher and Hayes, 2008), and as shown in Table 6, there is no 0 within the 95% confidence interval. Further analysis reveals that human capital has a partial mediation function in corporate digitalization and green innovation. The results also confirm the finding of Ren et al. (2022).

A regression test is carried out following model 4) to investigate the moderating role of executive team environmental attention on the interaction between human capital and green innovation. The outcomes are in Table 5's column 5). The model findings reveal that the interaction term between human capital and executive team environmental attention is associated at the 5% level, which verifies H5. A regression test is performed according to model 5) to assess the moderating impact of media attention within corporate digitalization and green innovation. The statistics are displayed in column 6) of Table 5. The interaction effect between corporate digitalization and media attention is positive at the 1% level. It suggests that media attention is favorably moderating the link between corporate digitalization and green innovation, supporting H6.

10.3389/fenvs.2023.1137271

TABLE 5 Regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GI	HC	GI	GI	GI	GI
Dig	0.391**	0.072**		0.352*	0.322	0.358*
	(0.198)	(0.028)		(0.201)	(0.196)	(0.183)
HC			0.594**	0.543**	0.601**	
			(0.261)	(0.264)	(0.238)	
TMA					0.038	
					(0.030)	
HC×TMA					0.542**	
					(0.224)	
MA						0.043*
						(0.024)
Dig×MA						0.304***
						(0.113)
Age	0.053	−0.073***	0.107	0.092	0.088	0.047
	(0.209)	(0.028)	(0.210)	(0.208)	(0.208)	(0.197)
Growth	−0.001***	−0.001**	−0.001*	−0.001*	−0.001**	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share	0.002	0.000	0.002	0.002	0.002	0.002
	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.049	−0.004	0.053	0.051	0.044	0.039
	(0.144)	(0.028)	(0.138)	(0.141)	(0.142)	(0.141)
SOE	0.009	0.029	−0.014	−0.007	0.011	−0.005
	(0.112)	(0.020)	(0.111)	(0.111)	(0.106)	(0.108)
MPR	−0.018	0.003	−0.019	−0.020	−0.020	−0.017
	(0.036)	(0.010)	(0.035)	(0.036)	(0.036)	(0.036)
Constant	0.211	0.394***	−0.020	−0.003	−0.026	0.051
	(0.567)	(0.078)	(0.582)	(0.576)	(0.579)	(0.569)
Year FE	YES	YES	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES	YES	YES
N	4,050	4,050	4,050	4,050	4,050	4,050
R-squared	0.036	0.142	0.036	0.039	0.046	0.043

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses. The following table is the same.

TABLE 6 Mediating effect test results.

Effect test	Observed Coef	Bootstrap Std.Err	z	P>|z|	Normal-based [95%Conf.Interval]	
Direct effect	0.3183	0.0483	6.59	0.000	0.2236	0.4130
Indirect effect	0.2950	0.0918	3.21	0.001	0.1151	0.4748

TABLE 7 Robustness test: Replace dependent variable indicator.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GI	HC	GI	GI	GI	GI
Dig	0.393**	0.072**		0.355*	0.339*	0.354**
	(0.184)	(0.028)		(0.188)	(0.184)	(0.167)
HC			0.584***	0.533**	0.572***	
			(0.223)	(0.227)	(0.214)	
TMA					0.010	
					(0.027)	
HC×TMA					0.340*	
					(0.182)	
MA						0.058***
						(0.021)
Dig×MA						0.334***
						(0.110)
Age	0.080	−0.073***	0.134	0.119	0.115	0.075
	(0.186)	(0.028)	(0.189)	(0.187)	(0.187)	(0.170)
Growth	−0.001*	−0.001**	−0.000	−0.000	−0.000	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share	0.003	0.000	0.002	0.002	0.002	0.002
	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.026	−0.004	0.030	0.027	0.028	0.014
	(0.128)	(0.028)	(0.123)	(0.125)	(0.127)	(0.124)
SOE	0.046	0.029	0.023	0.031	0.040	0.031
	(0.092)	(0.020)	(0.090)	(0.090)	(0.086)	(0.087)
MPR	−0.008	0.003	−0.009	−0.010	−0.012	−0.007
	(0.031)	(0.010)	(0.029)	(0.030)	(0.030)	(0.029)
Constant	−0.077	0.394***	−0.304	−0.287	−0.287	−0.304
	(0.517)	(0.078)	(0.538)	(0.534)	(0.537)	(0.500)
Year FE	YES	YES	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES	YES	YES
N	4,050	4,050	4,050	4,050	4,050	4,050
R-squared	0.033	0.142	0.033	0.036	0.040	0.046

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses. The following table is the same.

4.2 Robustness test

4.2.1 Replace the dependent variable indicator

Since green invention patents are more innovative and creative (Tong et al., 2014), green invention patents may more accurately represent corporate green innovation. In the robustness test, we use green invention patents quantity plus one and take the natural logarithm to evaluate green innovation. Table 7 displays the outcomes, and it is clear that the regression outcomes are in line with those of prior regressions, making the outcomes of this study robust.

4.2.2 Replace the independent variable indicator

Grounded on the study of Wen et al. (2022), this research adopts the aggregate quantity of corporate digitalization-related terms in annual reports plus one and takes the natural logarithm to evaluate

TABLE 8 Robustness test: Replace independent variable indicator.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GI	HC	GI	GI	GI	GI
Dig	0.051**	0.006*		0.048**	0.044**	0.043**
	(0.020)	(0.003)		(0.020)	(0.020)	(0.020)
HC			0.594**	0.562**	0.620***	
			(0.261)	(0.258)	(0.232)	
TMA					0.033	
					(0.030)	
HC×TMA					0.555**	
					(0.221)	
MA						0.046*
						(0.024)
Dig×MA						0.026**
						(0.013)
Age	0.060	−0.072***	0.107	0.100	0.094	0.071
	(0.209)	(0.027)	(0.210)	(0.208)	(0.208)	(0.206)
Growth	−0.001***	−0.001***	−0.001*	−0.001	−0.001*	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share	0.002	0.000	0.002	0.002	0.002	0.002
	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.038	−0.005	0.053	0.040	0.036	0.038
	(0.142)	(0.028)	(0.138)	(0.139)	(0.141)	(0.139)
SOE	0.014	0.029	−0.014	−0.002	0.015	0.009
	(0.112)	(0.021)	(0.111)	(0.111)	(0.106)	(0.110)
MPR	−0.015	0.003	−0.019	−0.017	−0.019	−0.017
	(0.036)	(0.011)	(0.035)	(0.035)	(0.035)	(0.036)
Constant	0.135	0.385***	−0.020	−0.081	−0.093	−0.082
	(0.566)	(0.078)	(0.582)	(0.576)	(0.579)	(0.593)
Year FE	YES	YES	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES	YES	YES
N	4,050	4,050	4,050	4,050	4,050	4,050
R-squared	0.036	0.136	0.036	0.039	0.046	0.040

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses. The following table is the same.

corporate digitization. Table 8 displays the outcomes of the two-way fixed effects model. The findings are in line with those of the prior study, as seen from the table, making the conclusions in this work robust.

4.2.3 Model replacement

Green innovation in this article is the number of green patent applications, but the quantity of green patents has an amount of 0 values in the actual data of selected firms. Therefore, this paper further employs the Tobit regression model for robustness testing. Table 9 presents the findings, and it is clear that the Tobit model outcomes coincide with the previous two-way fixed effects regression results mentioned above.

4.2.4 Endogenous test

The two-way fixed effects model and robust standard errors are utilized in the testing, but the possible presence of two-way causality

TABLE 9 Robustness test: Tobit model estimation.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GI	HC	GI	GI	GI	GI
Dig	1.009***	0.091***		0.846***	0.834***	0.929***
	(0.244)	(0.011)		(0.245)	(0.243)	(0.243)
HC			1.815***	1.649***	1.652***	
			(0.342)	(0.344)	(0.342)	
TMA					0.158***	
					(0.054)	
HC×TMA					0.750***	
					(0.257)	
MA						0.151***
						(0.044)
Dig×MA						0.307**
						(0.147)
Age	−0.121	−0.060***	−0.079	−0.062	−0.069	−0.141
	(0.253)	(0.012)	(0.251)	(0.251)	(0.246)	(0.249)
Growth	−0.008	−0.001***	−0.007	−0.008	−0.008	−0.008
	(0.013)	(0.000)	(0.013)	(0.014)	(0.014)	(0.013)
Share	0.004	0.000**	0.003	0.004	0.004	0.003
	(0.004)	(0.000)	(0.004)	(0.004)	(0.004)	(0.004)
ROA	−0.024	−0.001	−0.061	−0.071	−0.120	−0.042
	(0.393)	(0.015)	(0.392)	(0.391)	(0.389)	(0.388)
SOE	0.204	0.030***	0.135	0.154	0.192	0.176
	(0.152)	(0.007)	(0.151)	(0.151)	(0.148)	(0.149)
MPR	0.048	0.003	0.059	0.060	0.072	0.063
	(0.239)	(0.006)	(0.235)	(0.235)	(0.232)	(0.238)
Constant	−1.058	0.360***	−1.491**	−1.581**	−1.644**	−1.692**
	(0.754)	(0.036)	(0.755)	(0.753)	(0.742)	(0.766)
sigma_u	1.888***	0.160***	1.861***	1.851***	1.793***	1.830***
	(0.090)	(0.006)	(0.089)	(0.088)	(0.086)	(0.089)
sigma_e	1.119***	0.058***	1.117***	1.115***	1.112***	1.114***
	(0.024)	(0.001)	(0.024)	(0.023)	(0.023)	(0.023)
Year FE	YES	YES	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES	YES	YES
N	4,050	4,050	4,050	4,050	4,050	4,050

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses. The following table is the same.

can cause bias in the study results. To address the possible endogeneity problem, we use two approaches. First, the independent variables lagging one stage behind are used for regression with green innovation of corporates, as indicated in column 1) of Table 10. Corporate digitalization lagging one period still has a correlation with green innovation at the 1% level. Second, relying on the research of Li and Shen (2021), the average value of corporate digitalization in the same city and

 10.3389/fenvs.2023.1137271

TABLE 10 Endogeneity test results.

Variable	(1)	(2)	(3)
		First stage regression	Second stage regression
	GI	Dig	GI
L.Dig	0.578***		
	(0.209)		
Dig			0.656***
			(0.093)
Avg-Dig		1.001***	
		(0.009)	
Age	0.107	−0.020***	−0.009
	(0.273)	(0.005)	(0.056)
Growth	−0.001**	0.000	−0.002
	(0.000)	(0.000)	(0.002)
Share	0.003	0.000	0.004***
	(0.002)	(0.000)	(0.001)
ROA	0.047	0.043**	0.152
	(0.126)	(0.021)	(0.214)
SOE	0.015	0.019***	0.160***
	(0.116)	(0.003)	(0.035)
MPR	−0.016	0.002	0.017
	(0.030)	(0.009)	(0.087)
Constant	0.070	0.034*	0.137
	(0.749)	(0.019)	(0.195)
Year FE	YES	YES	YES
Symbol FE	YES	YES	YES
N	3,645	4,050	4,050
R-squared	0.037	0.757	0.031
Under identification test (KP LM statistic)			204.011***
Weak identification test (KP Wald F statistic)			2,763.371 [16.38]

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses. The critical value of the F test for weak instrumental variables identified at the significance level of 10% in Square.

industry is selected as the instrumental variable and assigned Avg-Dig. The mean value of corporate digitalization (Dig) within the same city and industry links to corporate digitization, but it has no direct bearing on corporate green innovation. Therefore, the instrumental variable ensures the relevance and externality of the instrumental variable. The Kleibergen-Paap rk LM statistic is relevant at the 1% level, which denies the null hypothesis that the instrumental variable is not adequately identified. The Kleibergen-Paap rk Wald F statistic is larger than the F statistic at the 10% significance level proposed by Stock et al. (2002), with weak instrumental variables being the null hypothesis denied. The instrumental variables employed for this work are, in aggregate, appropriate and reliable. Columns 2) and 3) of Table 10 display the two-stage least squares regression for the instrumental variables, and the outcomes remain robust.

4.3 Heterogeneity analysis

The inconsistent corporate traits may contribute to the variation in the effects of corporate digitalization on green innovation, given contradictory findings in previous studies by other scholars. Therefore, this paper further conducts grouping regression for sample firms according to corporate size and technological attributes.

TABLE 11 Further analysis results.

	(1) Large-scale corporates	(2) Small-scale corporates	(3) High-tech corporates	(4) Non-high-tech corporates
Variable	GI	GI	GI	GI
Dig	1.065***	−0.021	0.905**	0.349
	(0.378)	(0.198)	(0.381)	(0.213)
Age	0.528	−0.055	−0.551	0.228
	(0.613)	(0.228)	(0.342)	(0.244)
Growth	−0.001*	−0.001	−0.000	−0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Share	0.004	−0.001	−0.004	0.004
	(0.004)	(0.002)	(0.004)	(0.002)
ROA	0.328	−0.096	0.209	0.013
	(0.431)	(0.115)	(0.286)	(0.160)
SOE	−0.118	0.116	0.401	−0.003
	(0.168)	(0.162)	(0.351)	(0.129)
MPR	−0.009	−0.006	−0.019	−0.022
	(0.166)	(0.028)	(0.027)	(0.062)
Constant	−0.958	0.482	1.697**	−0.227
	(1.723)	(0.631)	(0.797)	(0.679)
Year FE	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES
N	2025	2025	786	3,264
R-squared	0.062	0.016	0.038	0.043

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard error statistics are in parentheses.

In this paper, we grouped firms according to the median assets of all sample firms. Firms with assets more than the median assets of the sample firms are grouped into large-scale firms, while the rest are small and medium-scale firms. The regression coefficient in the group of large-scale enterprises is considerably relevant at the 1% level, while the group of small-scale firms is not, by the grouping statistics in columns 1) and 2) of Table 11. The cause may be that large-scale corporations with resources and capabilities are conducive to carrying out digital transformation activities and have higher risk-taking and resource allocation capabilities, which will accelerate green innovation. Therefore, the consequence of corporate digitalization on green innovation is more obvious in large-scale enterprise groups compared to small and medium-scale enterprises.

In this paper, we classify enterprises into high-tech and non-high-tech corporations based on whether they qualify as high-tech corporates. The outcomes are in Table 11's columns 3) and 4). The statistical test of corporate digitalization on green innovation is relevant at the 5% level in the high-tech corporate group, while the non-high-tech corporate group is not significant. The reason may be that high-tech corporations have a stronger innovation foundation and capability, and their digitalization level is also higher, and they can smoothly embed corporate digitalization into organizational decision-making and production process for green innovation. Given this, green innovation of high-tech firms is more significantly affected by corporate digitalization than non-high-tech ones.

4.4 Theoretical implications

The following are the main contributions of this work. First, empirical studies of corporate digitalization on green innovation at the micro-scale are not numerous and do not yield consistent findings given the reality of the digital economy and corporate environmental development. This paper empirically verifies the beneficial influence of corporate digitalization on green innovation at the micro level of corporates, which enriches the micro research on green innovation in the setting of the digital era. Second, prior research has concentrated on the direct impacts of corporate digitalization and green innovation (El-Kassar and Singh, 2019; Li and Shen, 2021), but human capital is the core resource of production factors, and digital resources need to be shared, absorbed, and transformed into human capital by employees to promote green innovation better. This research reveals the mediating role in the evolutionary path from corporate digitalization to green innovation from the human capital perspective. Third, most previous research has considered the moderating effect of corporate digitalization and green innovation from a single internal or external perspective (Wei and Sun, 2021; Cardinali and De Giovanni, 2022). In this study, we choose boundary conditions from internal and external perspectives, such as executive teams' environmental attention and media attention. Then we respectively identify their moderating mechanisms in "corporate digitalization--human capital--green innovation" and "corporate digitalization--green innovation", which provide a more contextualized perspective for a comprehensive examination of corporate digitalization and green innovation.

4.5 Practical implications

The research's results suggest the following practical implications. First, the government should actively guide corporate in digital transformation and green development. According to the differences in corporate scale and technological attributes, the government should promptly introduce different relevant support policies, such as subsidies, tax relief, simplification of administrative approval, and improvement of environmental regulations. These measures can reduce the hindrance and risk of corporates in digital transformation and green development. Second, corporates should strengthen digital strategy, enhance digital infrastructure construction and application, improve environmental awareness, and promote green R&D and manufacturing and green sales services by relying on digital technology to realize effective sharing of green information and resources inside and outside corporates. According to the view of human capital, corporates should make use of digitalization to improve the level of human capital, such as fully introducing professionals in the field of digital technology, using various digital platforms for employee training, and encouraging employees to use information management systems for knowledge share. In addition, corporates should pay attention to matching people and jobs, actively carry out green practices and training, and utilize human capital to support green innovation. Third, the executive team should strengthen their attention to the environment, keep abreast of internal and external green information, and allocate internal and external resources reasonably to promote green innovation. Employees should support the executive team in making decisions that are conducive to the sustainable growth of the corporates. Fourth, the media should increase their coverage of corporate environmental practices and keep their reports factual, timely, and accurate to convey information to the public. Corporations should accept media attention and establish an excellent communication mechanism with the media. It will not only enable the media to perform an effective monitoring function but help corporates to develop a positive green image and maintain their reputation in front of the general public.

4.6 Limitations and future directions

However, this work does have some limitations. Firstly, this paper only uses digitization-related word frequency to measure the overall situation of corporate digitization. It is not yet a good reflection of the investment and level of digitization in business processes such as manufacturing and sales services. In the future, the measurement of corporate digitization can be further refined in terms of specific details. Second, these research samples are limited to manufacturing corporates, and in the future, we can explore whether the model has consistent findings and inherent mechanisms for different types of corporates. Finally, the dimensions of green innovation can be further refined in the future, for instance, social-based innovation and self-interest innovation, to enrich relevant research and get more targeted practical implications.

5 Conclusion

The study of corporate digitalization and green innovation is the focus of current academic concern and also has important practical significance for digital economy development and corporate sustainability. This study explores the effect of corporate digitalization on green innovation and the function of human capital as an intermediary. It further discusses the moderating effects of two environmental attention, specifically the internal factors—executive team environmental attention, and the external factors—media attention. An empirical test was employed using the fixed effect model based on the panel data of A-share manufacturing companies in Chinese Shanghai and Shenzhen from 2011 to 2020. These are the conclusions: 1) Corporate digitalization can greatly enhance corporate green innovation. After the robustness and endogeneity tests, the findings are still valid. 2) Based on the influence mechanism, corporate digitalization can foster green innovation by enhancing corporates' human capital. 3) The executive team's environmental attention inspires a favorable interaction between human capital and green innovation, and media attention plays the same function in corporate digitalization and green innovation. 4) Further research reveals that the consequence of corporate digitalization on green innovation is more significant for large-scale and high-tech enterprises. This research expands on existing micro-research on green innovation in the context of the digital age. It identifies the mediating role in the evolutionary path from corporate digitalization to green innovation in a more contextualized perspective. Additionally, the study provides practical guidance for businesses, the executive team, and the media, along with positive recommendations to the government to support sustainable growth and corporate digital development.

Data availability statement

Publicly available datasets were used in this work. The specific panel data of this study has been uploaded to the Supplementary Material section.

Author contributions

JL, LW, and FN wrote, edited, and modified the work. LW analyzed the data, created and edited the charts. JL, LW, and FN revised the manuscript. All authors contributed to the work and approved it for publication.

Funding

This work is funded by the National Social Science Foundation of China (No.22BJY227), Natural Science Foundation of Shandong Province (No. ZR2020MG034) and Social Science Foundation of Shandong Province (No. 21CSDJ09).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1137271/full#supplementary-material

References

Adomako, S., and Nguyen, N. P. (2020). Human resource slack, sustainable innovation, and environmental performance of small and medium-sized enterprises in sub-Saharan Africa. *Bus. Strateg. Environ.* 29, 2984–2994. doi:10.1002/bse.2552

Ahmed, Z., Asghar, M. M., Malik, M. N., and Nawaz, K. (2020). Moving towards a sustainable environment: The dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. *Resour. Policy* 67, 101677. doi:10.1016/j.resourpol.2020.101677

Antunes, H. de J. G., and Pinheiro, P. G. (2020). Linking knowledge management, organizational learning and memory. *J. Innov. Knowl.* 5, 140–149. doi:10.1016/j.jik.2019.04.002

Asiaei, K., O'Connor, N. G., Barani, O., and Joshi, M. (2022). Green intellectual capital and ambidextrous green innovation: The impact on environmental performance. *Bus. Strateg. Environ.* 32, 369–386. doi:10.1002/bse.3136

Avom, D., Nkengfack, H., Fotio, H. K., and Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technol. Forecast. Soc. Change* 155, 120028. doi:10.1016/j.techfore.2020.120028

Baptista, J., Stein, M. K., Klein, S., Watson-Manheim, M. B., and Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *J. Strateg. Inf. Syst.* 29, 101618. doi:10.1016/j.jsis.2020.101618

Barney, J. (1991). Firm resources and sustained competitive advantage. *J. Manage.* 17, 99–120. doi:10.1177/014920639101700108

Baron, R. M., and Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Pers. Soc. Psychol.* 51, 1173–1182. doi:10.1037/0022-3514.51.6.1173

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How does information technology affect productivity? Plant-Level comparisons of product innovation, process improvement, and worker skills. *Q. J. Econ.* 122, 1721–1758. doi:10.1162/qjec.2007.122.4.1721

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., Venkatraman, N., University, O. S. C., Boston, U., et al. (2013). Digital business strategy: Toward a next generation of insights. *MIS Q.* 37, 471–482. doi:10.25300/MISQ/2013/37:2.3

Boone, C., Lokshin, B., Guenter, H., and Belderbos, R. (2019). Top management team nationality diversity, corporate entrepreneurship, and innovation in multinational firms. *Strateg. Manag. J.* 40, 277–302. doi:10.1002/smj.2976

Cao, S., Nie, L., Sun, H., Sun, W., and Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *J. Clean. Prod.* 327, 129458. doi:10.1016/j.jclepro.2021.129458

Cardinali, P. G., and De Giovanni, P. (2022). Responsible digitalization through digital technologies and green practices. *Corp. Soc. Responsib. Environ. Manag.* 29, 984–995. doi:10.1002/csr.2249

Cetindamar, D., Abedin, B., and Shirahada, K. (2022). The role of employees in digital transformation: A preliminary study on how employees' digital literacy impacts use of digital technologies. *IEEE Trans. Eng. Manag.*, 1–12. doi:10.1109/TEM.2021.3087724

Chang, Y., He, Y., Jin, X., Li, T., and Shih, C. M. (2020). Media coverage of environmental pollution and the investment of polluting companies. *Asia-Pacific J. Financ. Stud.* 49, 750–771. doi:10.1111/ajfs.12315

Cheng, J., and Liu, Y. (2018). The effects of public attention on the environmental performance of high-polluting firms: Based on big data from web search in China. *J. Clean. Prod.* 186, 335–341. doi:10.1016/j.jclepro.2018.03.146

Chuang, S.-P., and Huang, S.-J. (2018). The effect of environmental corporate social responsibility on environmental performance and business competitiveness: The mediation of green information technology capital. *J. Bus. Ethics* 150, 991–1009. doi:10.1007/s10551-016-3167-x

Danish, K. (2019). Effects of information and communication technology and real income on CO2 emissions: The experience of countries along Belt and Road. *Telemat. Inf.* 45, 101300. doi:10.1016/j.tele.2019.101300

Deng, H., Duan, S. X., and Wibowo, S. (2022). Digital technology driven knowledge sharing for job performance. *J. Knowl. Manag.* 27, 404–425. doi:10.1108/JKM-08-2021-0637

Dong, J. Q., Karhade, P. P., Rai, A., and Xu, S. X. (2021). How firms make information technology investment decisions: Toward a behavioral agency theory. *J. Manag. Inf. Syst.* 38, 29–58. doi:10.1080/07421222.2021.1870382

Dong, J. Q., and Netten, J. (2017). Information technology and external search in the open innovation age: New findings from Germany. *Technol. Forecast. Soc. Change* 120, 223–231. doi:10.1016/j.techfore.2016.12.021

Donovan, J., Jennings, J., Koharki, K., and Lee, J. (2021). Measuring credit risk using qualitative disclosure. *Rev. Acc. Stud.* 26, 815–863. doi:10.1007/s11142-020-09575-4

El-Kassar, A. N., and Singh, S. K. (2019). Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc. Change* 144, 483–498. doi:10.1016/j.techfore.2017.12.016

Fayazi Rad, L., Amini, M., Ahmadi, A., and Hoseinzadeh, S. (2022). Environmental and economic assessments of hydrogen utilization in the transportation sector of Iran. *Chem. Eng. Technol.* 1–13. doi:10.1002/ceat.202100500

Gebauer, H., Fleisch, E., Lamprecht, C., and Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Bus. Horiz.* 63, 313–323. doi:10.1016/j.bushor.2020.01.005

Gerhart, B., and Feng, J. (2021). The resource-based view of the firm, human resources, and human capital: Progress and prospects. *J. Manage.* 47, 1796–1819. doi:10.1177/0149206320978799

Gilch, P. M., and Sieweke, J. (2021). Recruiting digital talent: The strategic role of recruitment in organisations' digital transformation. *Ger. J. Hum. Resour. Manag.* 35, 53–82. doi:10.1177/2397002220952734

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. *Int. J. Inf. Manage.* 35, 183–191. doi:10.1016/j.ijinfomgt.2014.12.005

He, Z., Cao, C., and Feng, C. (2022). Media attention, environmental information disclosure and corporate green technology innovations in China's heavily polluting industries. *Emerg. Mark. Financ. Trade* 58, 3939–3952. doi:10.1080/1540496X.2022.2075259

Hojnik, J., and Ruzzier, M. (2016). The driving forces of process eco-innovation and its impact on performance: Insights from Slovenia. *J. Clean. Prod.* 133, 812–825. doi:10.1016/j.jclepro.2016.06.002

Hoseinzadeh, S., and Astiaso Garcia, D. (2022). Techno-economic assessment of hybrid energy flexibility systems for islands' decarbonization: A case study in Italy. *Sustain. Energy Technol. Assessments* 51, 101929. doi:10.1016/j.seta.2021.101929

Hoseinzadeh, S., Groppi, D., Sferra, A. S., Di Matteo, U., and Astiaso Garcia, D. (2022a). The PRISMI plus toolkit application to a grid-connected mediterranean island. *Energies* 15, 8652. doi:10.3390/en15228652

Hoseinzadeh, S., Nastasi, B., Groppi, D., and Astiaso Garcia, D. (2022b). Exploring the penetration of renewable energy at increasing the boundaries of the urban energy system – the PRISMI plus toolkit application to Monachil, Spain. *Sustain. Energy Technol. Assessments* 54, 102908. doi:10.1016/j.seta.2022.102908

Hossnofsky, V., and Junge, S. (2019). Does the market reward digitalization efforts? Evidence from securities analysts' investment recommendations. *J. Bus. Econ.* 89, 965–994. doi:10.1007/s11573-019-00949-y

Huang, S. Z., Chau, K. Y., Chien, F., and Shen, H. (2020). The impact of startups' dual learning on their green innovation capability: The effects of business executives' environmental awareness and environmental regulations. *Sustainability* 12, 6526. doi:10.3390/su12166526

Ioanna, N., Pipina, K., Despina, C., Ioannis, S., and Dionysis, A. (2022). Stakeholder mapping and analysis for climate change adaptation in Greece. *Euro-Mediterranean J. Environ. Integr.* 7, 339–346. doi:10.1007/s41207-022-00317-3

Ji, Q., and Zhang, D. (2019). How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* 128, 114–124. doi:10.1016/j.enpol.2018.12.047

Johnson, J. S., Friend, S. B., and Lee, H. S. (2017). Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *J. Prod. Innov. Manag.* 34, 640–658. doi:10.1111/jpim.12397

Johnstone, N., Haščič, I., and Popp, D. (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environ. Resour. Econ.* 45, 133–155. doi:10.1007/s10640-009-9309-1

King, A. A., and Tucci, C. L. (2002). Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities. *Manage. Sci.* 48, 171–186. doi:10.1287/mnsc.48.2.171.253

Kozanoglu, D. C., and Abedin, B. (2021). Understanding the role of employees in digital transformation: Conceptualization of digital literacy of employees as a multi-dimensional organizational affordance. *J. Enterp. Inf. Manag.* 34, 1649–1672. doi:10.1108/JEIM-01-2020-0010

Leonardi, P. M. (2021). COVID-19 and the new technologies of organizing: Digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. *J. Manag. Stud.* 58, 249–253. doi:10.1111/joms.12648

Li, D., and Shen, W. (2021). Can corporate digitalization promote green innovation? The moderating roles of internal control and institutional ownership. *Sustainability* 13, 13983. doi:10.3390/su132413983

Li, D., Zheng, M., Cao, C., Chen, X., Ren, S., and Huang, M. (2017). The impact of legitimacy pressure and corporate profitability on green innovation: Evidence from China top 100. *J. Clean. Prod.* 141, 41–49. doi:10.1016/j.jclepro.2016.08.123

Li, H., Tang, H., Zhou, W., and Wan, X. (2022). Impact of enterprise digitalization on green innovation performance under the perspective of production and operation. *Front. Public Heal.* 10, 971971. doi:10.3389/fpubh.2022.971971

Mansoor, A., Jahan, S., and Riaz, M. (2021). Does green intellectual capital spur corporate environmental performance through green workforce? *J. Intellect. Cap.* 22, 823–839. doi:10.1108/JIC-06-2020-0181

Marchiori, D. M., Rodrigues, R. G., Popadiuk, S., and Mainardes, E. W. (2022). The relationship between human capital, information technology capability, innovativeness and organizational performance: An integrated approach. *Technol. Forecast. Soc. Change* 177, 121526. doi:10.1016/j.techfore.2022.121526

Mitchell, R. K., Agle, B. R., and Wood, D. J. (1997). Toward a theory of stakeholder identification and salience: Defining the principle of who and what really counts. *Acad. Manag. Rev.* 22, 853–886. doi:10.5465/AMR.1997.9711022105

Müller, J. M., and Voigt, K. I. (2018). Sustainable industrial value creation in SMEs: A comparison between industry 4.0 and made in China 2025. *Int. J. Precis. Eng. Manuf. - Green Technol.* 5, 659–670. doi:10.1007/s40684-018-0056-z

Munawar, S., Yousaf, D. H. Q., Ahmed, M., and Rehman, D. S. (2022). Effects of green human resource management on green innovation through green human capital, environmental knowledge, and managerial environmental concern. *J. Hosp. Tour. Manag.* 52, 141–150. doi:10.1016/j.jhtm.2022.06.009

Nambisan, S., Wright, M., and Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Res. Policy* 48, 103773. doi:10.1016/j.respol.2019.03.018

Nyilasy, G., Gangadharbatla, H., and Paladino, A. (2014). Perceived greenwashing: The interactive effects of green advertising and corporate environmental performance on consumer reactions. *J. Bus. ethics* 125, 693–707. doi:10.1007/s10551-013-1944-3

Ocasio, W. (2011). Attention to attention. *Organ. Sci.* 22, 1286–1296. doi:10.1287/orsc.1100.0602

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strateg. Manag. J.* 18, 187–206. doi:10.1002/(SICI)1097-0266(199707)18:1+<187:AID-SMJ936>3.0.CO;2-K

Peng, X., and Liu, Y. (2016). Behind eco-innovation: Managerial environmental awareness and external resource acquisition. *J. Clean. Prod.* 139, 347–360. doi:10.1016/j.jclepro.2016.08.051

Preacher, K. J., and Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behav. Res. Methods* 40, 879–891. doi:10.3758/BRM.40.3.879

Rao, S., Pan, Y., He, J., and Shangguan, X. (2022). Digital finance and corporate green innovation: Quantity or quality? *Environ. Sci. Pollut. Res.* 29, 56772–56791. doi:10.1007/s11356-022-19785-9

Ren, S., Hao, Y., and Wu, H. (2022). Digitalization and environment governance: Does internet development reduce environmental pollution? *J. Environ. Plan. Manag.*, 1–30. doi:10.1080/09640568.2022.2033959

Ricci, F., Scafarto, V., Ferri, S., and Tron, A. (2020). Value relevance of digitalization: The moderating role of corporate sustainability. An empirical study of Italian listed companies. *J. Clean. Prod.* 276, 123282. doi:10.1016/j.jclepro.2020.123282

Sapir, E. (1944). Grading, A study in semantics. *Philos. Sci.* 11, 93–116. doi:10.1086/286828

Schuetz, S., and Venkatesh, V. (2020). Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *J. Assoc. Inf. Syst.* 21, 460–482. doi:10.17705/1jais.00608

Sinha, A., Mishra, S., Sharif, A., and Yarovaya, L. (2021). Does green financing help to improve environmental and social responsibility? Designing SDG framework through advanced quantile modelling. *J. Environ. Manage.* 292, 112751. doi:10.1016/j.jenvman.2021.112751

Song, W., and Yu, H. (2018). Green innovation strategy and green innovation: The roles of green creativity and green organizational identity. *Corp. Soc. Responsib. Environ. Manag.* 25, 135–150. doi:10.1002/csr.1445

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *J. Bus. Econ. Stat.* 20, 518–529. doi:10.1198/073500102288618658

Subramaniam, M., and Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Acad. Manag. J.* 48, 450–463. doi:10.5465/AMJ.2005.17407911

Sukma, N., and Leelasantitham, A. (2022a). A community sustainability ecosystem modeling for water supply business in Thailand. *Front. Environ. Sci.* 10, 940955. doi:10.3389/fenvs.2022.940955

Sukma, N., and Leelasantitham, A. (2022b). From conceptual model to conceptual framework: A sustainable business framework for community water supply businesses. *Front. Environ. Sci.* 10, 1013153. doi:10.3389/fenvs.2022.1013153

Tian, H., Li, Y., and Zhang, Y. (2022). Digital and intelligent empowerment: Can big data capability drive green process innovation of manufacturing enterprises? *J. Clean. Prod.* 377, 134261. doi:10.1016/j.jclepro.2022.134261

Tong, T. W., He, W., He, Z. L., and Lu, J. (2014). Patent regime shift and firm innovation: Evidence from the second amendment to China's patent law. *Acad. Manag. Proc.* 2014, 14174. doi:10.5465/ambpp.2014.14174abstract

Wang, F., Sun, Z., and Feng, H. (2022a). Can media attention promote green innovation of Chinese enterprises? Regulatory effect of environmental regulation and green finance. *Sustainability* 14, 11091. doi:10.3390/su141711091

Wang, K., and Zhang, X. (2021). The effect of media coverage on disciplining firms' pollution behaviors: Evidence from Chinese heavy polluting listed companies. *J. Clean. Prod.* 280, 123035. doi:10.1016/j.jclepro.2020.123035

Wang, L., Zeng, T., and Li, C. (2022b). Behavior decision of top management team and enterprise green technology innovation. *J. Clean. Prod.* 367, 133120. doi:10.1016/j.jclepro.2022.133120

Wei, Z., and Sun, L. (2021). How to leverage manufacturing digitalization for green process innovation: An information processing perspective. *Ind. Manag. Data Syst.* 121, 1026–1044. doi:10.1108/IMDS-08-2020-0459

Wen, H., Lee, C. C., and Song, Z. (2021). Digitalization and environment: How does ICT affect enterprise environmental performance? *Environ. Sci. Pollut. Res.* 28, 54826–54841. doi:10.1007/s11356-021-14474-5

Wen, H., Zhong, Q., and Lee, C. C. (2022). Digitalization, competition strategy and corporate innovation: Evidence from Chinese manufacturing listed companies. *Int. Rev. Financ. Anal.* 82, 102166. doi:10.1016/j.irfa.2022.102166

Wernerfelt, B. (1984). A resource-based view of the firm. *Strateg. Manag. J.* 5, 171–180. doi:10.1002/smj.4250050207

Wiersema, M. F., and Bantel, K. A. (1992). Top management team demography and corporate strategic change. *Acad. Manag. J.* 35, 91–121. doi:10.5465/256474

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT press.

Wu, G., Xu, Q., Niu, X., and Tao, L. (2022). How does government policy improve green technology innovation: An empirical study in China. *Front. Environ. Sci.* 9, 799794. doi:10.3389/FENVS.2021.799794

Wu, J., and Hua, X. (2021). Top management team attention and firm green innovation strategy: Empirical evidence from listed Chinese manufacturing companies. *First Sci. Sci. Manag. S.and Trans.* 42, 122–142.

Yao, Y., Ivanovski, K., Inekwe, J., and Smyth, R. (2019). Human capital and energy consumption: Evidence from OECD countries. *Energy Econ.* 84, 104534. doi:10.1016/j.eneco.2019.104534

Yong, J. Y., Yusliza, M.-Y., Ramayah, T., and Fawehinmi, O. (2019). Nexus between green intellectual capital and green human resource management. *J. Clean. Prod.* 215, 364–374. doi:10.1016/j.jclepro.2018.12.306

Youndt, M. A., Subramaniam, M., and Snell, S. A. (2004). Intellectual capital profiles: An examination of investments and returns. *J. Manag. Stud.* 41, 335–361. doi:10.1111/j.1467-6486.2004.00435.x

Zahid, M. M., Ali, B., Ahmad, M. S., Thurasamy, R., and Amin, N. (2018). Factors affecting purchase intention and social media publicity of green products: The mediating role of concern for consequences. *Corp. Soc. Responsib. Environ. Manag.* 25, 225–236. doi:10.1002/csr.1450

Zhang, C., Chen, P., and Hao, Y. (2022). The impact of digital transformation on corporate sustainability-new evidence from Chinese listed companies. *Front. Environ. Sci.* 10, 1047418. doi:10.3389/fenvs.2022.1047418

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 23 February 2023
DOI 10.3389/fenvs.2023.1120806

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Shujahat Haider Hashmi,
Bahria University, Pakistan
Edmund Udemba,
Gelişim Üniversitesi, Türkiye
Ирина Белик,
Ural Federal University, Russia

*CORRESPONDENCE
Quan Su,
suquanspring@foxmail.com
Xiaohong Wang,
wongxh@lzu.edu.cn
Min Fan,
1160529881@qq.com

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 10 December 2022
ACCEPTED 07 February 2023
PUBLISHED 23 February 2023

CITATION
Fan Y, Su Q, Wang X and Fan M (2023), Digitalization and green innovation of enterprises: Empirical evidence from China.
Front. Environ. Sci. 11:1120806.
doi: 10.3389/fenvs.2023.1120806

Digitalization and green innovation of enterprises: Empirical evidence from China

Yaojun Fan[1], Quan Su[1]*, Xiaohong Wang[2]* and Min Fan[2]*

[1]Chinese International College, Dhurakij Pundit University Bangkok Thailand, [2]School of Economics, Lanzhou University, Lanzhou, China

With the acceleration of the digital technology construction process, digitalization has given impetus to the transformation and upgrading of China's economy and micro businesses. China's social and economic sectors have begun to integrate and develop in-depth with digital technology. Whether the digitalization of enterprises can drive their green innovation is an urgent question to be explored. The aim of our study is to answer this question and investigate whether digitalization has finally affected corporate green innovation. On the basis of theoretical discussion, the data of 3,547 Chinese listed companies from 2014 to 2019 were selected as samples. The fixed effect model was used to empirically test the relationship between digitization and green innovation, and then the intermediary effect model was used to analyze the influence mechanism. Research has found that digitalization is genuinely driving green innovation in business. After the robustness test, the conclusion remains the same. In order to deepen the understanding of the impact of digitalization on the green innovation of enterprises, this study additionally analyzed the impact mechanism. We find that digitization can promote corporate green innovation by easing corporate financing constraints and enhancing corporate awareness of fulfilling social responsibility. Moreover, we also find that the impact of digitalization on firm performance is more obvious in the samples with high level of internal control, state-owned enterprises and senior executives with IT background. The findings of this study enrich the related theories of digitalization and sustainability and provide empirical evidence for the positive externalities of digitalization.

KEYWORDS

digitization, green innovation, financing constraints, corporate social responsibility, internal control level

1 Introduction

Based on past experience, sacrificing the environment in economic development is frequently a favorable option in the short term, especially when developing countries are seeking to quickly catch up with developed countries. After years of environmental destruction by the world's nations, the planet's environment is getting worse. When humans realized the catastrophic destruction caused by environmental degradation, they began to reflect and devote themselves to protecting the environment. China is one of them. China's greening achievements have attracted worldwide attention in recent years. In recent years, China has vigorously advocated green innovation strategy, taking green innovation as the fundamental strategy to solve environmental problems (Jin et al., 2022). The high-quality development of the economy and society is the theme of the development of the era. Countries around the world increasingly attach importance to the performance of enterprises in environmental, social and governance (Hu et al., 2022). Deepening the green innovation driven strategy and promoting the greening of traditional industries will inevitably require enterprises to take green as the guidance, technology as the support and innovation as the driving force (Wang et al., 2022). The World Commission on Environment and Development stated in Our Common Future that sustainable development should be "development that meets the needs of the present without jeopardizing the ability of future generations to meet their own needs. Green innovation contributes to the creation of a favorable living environment for future generations and is an important force for sustainable development. Green technology innovation featuring high efficiency, low carbon and recycling is an important driving force in transforming economic development patterns and achieving green and sustainable development. It is also an inevitable choice for the development of human society (Ngo and O'Cass, 2009) and an important support for China to achieve "carbon peak" and "carbon neutrality" (Song et al., 2022).

In addition, today's wave of digital development is sweeping the world, information technology and the real industry are accelerating their integration, and the current generation of digital technologies such as artificial intelligence, blockchain, cloud computing and their continuous penetration into enterprises have promoted the manufacturing industry to undergo profound changes in all aspects of the value creation process (Jin et al., 2022). Increasingly, enterprises are using emerging digital technologies for digital transformation and raising the level of digitalization in their enterprises. Enterprise digitalization refers to the process in which enterprises apply a variety of digital technologies to products, operations, management, strategic thinking, business models and other aspects in the innovation process to improve enterprise performance and competitiveness and achieve enterprise shift (Fichman et al., 2014). The gradual integration of digital technology and business model will form a digital industrial chain and industrial cluster, injecting fresh vitality into enterprises (Zuo and Chen, 2021; Zhou et al., 2022). Moreover, digitalization is becoming the leading force driving innovation and transformation (Wang et al., 2022). Digital technology has changed the combination mode of innovation elements, reduced innovation transaction and contract costs, cognitive differences, etc., so as to improve the innovation capability of enterprises (Wang et al., 2018), which together with the level of internal governance affects the future of enterprises. Digital technology also plays a crucial role in green development. The application of digital technologies such as precise collection and visualization analysis of carbon emission data by enterprises can accelerate emission reduction at the supply end, reduce carbon emissions at the consumption end, and realize energy conservation and emission reduction in urban living scenes (Shen et al., 2022), especially for state-owned enterprises. According to the data of the World Economic Forum, by 2030, all industries will benefit from information and communication technology (ICT) to reduce carbon emissions by 12.1 billion tons. Digitalization has become an essential hand to drive industrial optimization and upgrading and achieve green, high-quality development. In the process of promoting green innovation and realizing green development, digital technology is indispensable (Jin et al., 2022).

There are two main types of literature related to this research topic. One is to study the impact of digitalization on R&D efficiency, and the other is to study the positive signal effect of digitalization on reducing internal costs and freeing up external signals. According to the former group, digitalization of enterprises can enhance their capacity for technological innovation by improving the level of internal human capital, reducing R&D costs and promoting improved R&D input-output efficiency. However, it is difficult to promote the "quality improvement" of technological innovation due to the constraints of "double arbitrage" and "same-group effect" of enterprises (Smith et al., 2017; Matray, 2021). In addition, the latter group believes that the application of the Internet of Things and digital platforms in innovation can help smes reduce resource use and waste, develop cost-effective business models and gain competitive advantages (Yousaf et al.). The digitalization of enterprises reduces the cost of information analysis and process optimization, effectively improves the utilization of resources of enterprises to achieve a higher level of innovation output performance. This positive signal is an important factor to attract external investors. The relief of financing pressure will further promote enterprises to be more willing to assume social responsibility and take more promising green innovation activities (Hoenig and Henkel, 2015; Shen and Tan, 2022), especially for enterprises with information technology background. There have also been several studies on the relationship between digitalization and green technology innovation, but there is no consensus. Some studies believe that the application of digital technology by enterprises can highlight their competitive advantages in green innovation (EI-Kassar and Singh, 2019) and have a positive impact on the quality and quantity of green innovation (Xiao et al., 2022), but unfortunately they did not make a more specific analysis of the impact mechanism between the two. Another part of the research argues that advances in digital technology will drive businesses to re-purchase production equipment. However, in the transition phase of enterprise digital transformation, in order to rapidly increase production, enterprises will increase the exploitation of resources and energy consumption, which may reduce the green innovation activities of enterprises (Li et al., 2021). Both positive and negative views on the impact of digitalization on green innovation are lacking in in-depth analysis. Therefore, the research purpose of this paper is to supplement the shortcomings of existing studies on the basis of existing studies, explore the important factors to promote enterprise green innovation, and provide certain enlightenment for promoting enterprise digitalization. In this study, we carried out a theoretical analysis of the impact of digitalization on corporate green innovation and proposed research hypotheses that digitalization can promote corporate green innovation and promote corporate green innovation by easing financing constraints and improving corporate social responsibility awareness, and then conducted empirical tests on these hypotheses. In contrast to the existing studies, the contribution of this study is the following. First, this study examines the impact of digitization on green innovation, which enriches the theoretical system of related research. Second, this study provides a detailed analysis of the specific ways in which digitalization affects green innovation and expands and deepens the research system on the impact of digitalization on green innovation. Third, based on the perspective of internal corporate control, enterprise nature and executive information technology background, this study deepens the understanding of the impact of digitalization on green innovation by analyzing whether the impact of digitalization on green innovation varies across different groups.

2 Literature and theoretical reviews

2.1 Digitalization and green innovation

China leads the world in carbon emissions and its environment is in dire need of improvement. Udemba et al. (2022a) argue that China has the capacity to achieve its climate and sustainable development goals by developing policies around the energy sector and strengthening technology through strong institutions. In fact, in addition to urbanization, entrepreneurial activity (Udemba et al., 2022b), foreign direct investment (FDI), and institutional factors (Udemba et al., 2022a), the presence of digital factors also provides a powerful force for solving environmental problems. With the increase of resource and environmental pressure, the rise of labor costs and the intensification of industry competition, traditional enterprises will only gain the upper hand in the rapidly advancing digital trend by further accelerating the construction of digital infrastructure and increasing the investment in digital technology (Liu et al., 2022). Digitalization can use the new generation of information technology to promote industrial change, improve industrial operation efficiency, and build a modern economic system (Li et al., 2022a). Green innovation is an innovation activity in which enterprises use innovative technology, innovative management and alternative methods to achieve dual objectives of economic performance and environmental performance with the purpose of improving resource utilization and reducing energy consumption (Xiao et al., 2021a). According to sustainable development theory and environmental Kuznets curve theory, digital development is an essential new driving force for today's social and economic growth, while green innovation is regarded as an influential starting point for reducing environmental pollution (Philip et al., 2022). Digital transformation needs to "feed back" green technology innovation, so as to improve the quality of overall green economic development. In fact, the promotion of digital technology facilitates enterprises to obtain customers' consumption habits and preferences by means of the Internet of Things, huge data, etc., so as to achieve accurate identification of market demands (Bajari et al., 2019), and transform enterprises' green innovation from experience-driven to data-driven, laying an intellectual foundation for the improvement of innovation quality. For enterprises, green innovation output capacity is a measure of the contribution of innovation achievements to the enterprise economy and technology through the implementation of green development strategies (Pan and Wang, 2022). The application of digital technology can also reduce the marginal transaction costs of enterprises, and easily form the effects of economies of scale and network economy. It can not only stimulate the green consumption of customers (Wang and Li, 2021), but also bring more invisible resources to enterprises and improve their economic benefits. In addition, according to the legitimacy theory, in the process of digital transformation, enterprises can make use of the leading advantages of digital technology to achieve the strategic goals of resource conservation and environmental protection, and create a good green image with a higher level of green innovation (Xie et al., 2016). Choosing green innovation is a smart choice for corporate management at this time. Based on resource-based and dynamic capabilities theories, the digitalization of enterprises not only brings various advantages of external resources to enterprises, but also brings a new ability to reconfigure internal and external resources. With the help of digital technology, enterprises can also efficiently allocate resource elements, obtain a lot of external information and knowledge, increase the knowledge reserve of green technology innovation, and promote green technology innovation (Zhang and Tang, 2018).

Based on the above analysis, we propose the following hypothesis H_1:

H_1: Digitalization can promote green innovation of enterprises.

2.2 Digitalization, financing constraints and green innovation

With the dual attributes of environmental protection and innovation, green innovation is bound to face more R&D costs and higher risks, as well as lower return rates and greater uncertainty in returns. There is a serious phenomenon of information asymmetry, thus the enthusiasm of investors is low (Doran and Ryan, 2012; Liu et al., 2022). Studies have shown that when enterprises face serious financing constraints, they will actively reduce investment in green technology innovation (Yang and Xi, 2019). Information asymmetry often leaves investors, as vulnerable parties to the information, bogged down in issues of adverse selection and moral hazard. Whether or not to effectively solve the problem of information asymmetry caused by it is the key for enterprises to obtain effective support from investors on green innovation resources (Roca et al., 2017; Shen et al., 2022). Digital technology helps reduce the cost of information acquisition and communication. The government, external regulatory authorities and potential investors can timely obtain enterprise information, break the physical limit of "time and space", invisibly expand the scale of enterprise information networks, effectively reduce pollution under reporting and concealment, and reduce information asymmetry (Li et al., 2022b). Sufficient information enables companies to continuously secure investor support for innovation activities, alleviates financing constraints faced by corporate activities or green innovation activities, and promotes corporate active participation in environmental governance. The positive "exposure effect" generated attracts investors' attention, thus bringing additional market resources for enterprise green innovation, which is ultimately reflected in the improvement of enterprise green R&D innovation level (Biondi et al., 2002).

Based on the above analysis, we propose the following hypothesis H_2:

H_2: Digitalization can promote green innovation of enterprises by easing financing constraints.

2.3 Digitization, corporate social responsibility and green innovation

At the end of the last century, Ramirez, (1999) put forward the concept of "value co-production", pointing out that value is not created by a single entity, but by consumers and enterprises. Under the background of the digital era, to improve the low-carbon circular economy system and promote green development, manufacturing enterprises should attach importance to environmental protection policies, adopt green technologies to establish a green image, and bring customers, suppliers and other stakeholders into the process of creating green value (Li, 2022). Digital transformation will drive the transformation of enterprises into serve-based enterprises and encourage them to assume more social responsibilities (Zhao and Huang, 2022). The fulfillment of corporate social responsibility, including a series of organizational activities and strategic measures, is essentially a behavioral choice based on its own development strategy (Shen et al., 2022). According to the stakeholder theory, the combination of "contracts" concluded by different stakeholders constitutes an enterprise. In the process of obtaining economic resources from the "contract" subjects, enterprises need to return benefits to various stakeholders by fulfilling their social responsibilities (Huang and Kung, 2010). Corporate social responsibility has something in common with the concept of sustainable development. Corporate social responsibility includes environmental responsibility, that is, the responsibility to protect the ecological environment, which coincides with the concept of sustainable development. Active performance of social responsibility, help enterprises to obtain a wide range of social recognition and acceptance, constantly open up development space, pay attention to the protection of ecological environment, achieve external economy, promote sustainable development. The digital transformation of enterprises is based on digital technology to realize value co creation for all stakeholders, thus bringing fresh impetus for enterprises to fulfill their social responsibilities (Shang and Wu, 2022). Enterprise digitalization can also profoundly engage all aspects of CSR, strengthen the willingness and motivation of enterprises to fulfill CSR, and ultimately improve CSR performance. The performance of corporate social responsibility can promote green product and process innovation (Xiao et al., 2021b). Excellent performance of social responsibility generally means that enterprise management can coordinate the relationship between economic benefits, environmental protection and resource consumption, thus improving the level of green innovation of enterprises (Gu and Gao, 2022). The higher the level of social responsibility fulfilled, the higher the company considers the interests of its stakeholders and the more harmonious the relationship with them, the higher the company's image and social standing. The enterprise can obtain further resources from stakeholders for green technology innovation, and the enterprise will be more successful (Yang et al., 2022). Cox and Wicks (2011) found that enterprises with higher charitable donations have higher investment in environmental protection and better environmental performance.

Based on the above analysis, we propose the following hypothesis H_3:

H_3: Digitalization can promote green innovation of enterprises by improving corporate social responsibility.

3 Data and methodology

3.1 Research design

Drawing on previous research, considering that the factors of company and year may affect the regression results, we build the following model (1) to test the relationship between digitalization and enterprise green innovation.

$$gre_{i,t} = \alpha_0 + \alpha_1 \mathrm{num}_{i,t} + \delta X + \varphi_i + \omega_t + \varepsilon_{i,t} \quad (1)$$

In model (1), the subscript i is industry, t is year. The dependent variable gre is enterprise green innovation, the independent variable num is enterprise digitalization level, and X represents control variables. φ means industry fixed effects and ω means time fixed effects.

We used the econometric software Stata 17.0 for our empirical analysis. The Stata commands used in this study include asdoc, reghdfe, and ivreghdfe.

3.2 Variable selection

3.2.1 Dependent variable

As it takes a certain amount of time for patent application to be granted, it may have an impact on enterprises during the application process, so patent application data will be more reliable and timely than the amount granted. Referring to the research practice of Li and Zheng (2016), we adopted the number of green patent applications of listed companies (including invention patents and utility model patent applications) as the proxy variable of green innovation of enterprises, which is recorded as gre. As the green patent data has a typical "right biased" feature, we add one to it and take the natural logarithm. The greater the greener, the higher the level of green innovation in the business. In addition, we tested the robustness with the number of green patents granted by listed companies (gre2).

3.2.2 Independent variable

The previous studies mainly used the virtual variable of whether the enterprise has conducted digital transformation as the digital proxy variable (He and Hongxia, 2019), which could not measure the extent of the enterprise's digital transformation. The extent to which an enterprise attaches importance to a specific strategic orientation can frequently be reflected by the frequency of the keywords involved in the strategy in the annual report (Wang et al., 2022). Drawing on the research of Pan and Wang, (2022), we use the word frequency of the words related to "enterprise digitalization" in the annual report to measure enterprise digitalization. When we digitize computing enterprises, we cover five categories of words, namely, artificial intelligence, blockchain, cloud computing, big data and digital technology applications, which are consistent with previous research (Wu et al., 2021).

3.2.3 Mediating variables

Following the theoretical analysis in, we choose financing constraints and CSR as intermediary variables. For the measurement of financing constraints, Kaplan andZingles, (1997) qualitatively divided the degree of enterprise financing constraints according to the financial situation of enterprises in a limited sample in 1997, and then described the quantitative relationship between the degree of financing constraints and the variables reflecting the characteristics of enterprises. Drawing on the research of Ju et al. (2013), We use the SA index, which is constructed by using the firm size (SI) and firm age (A), two variables that have little change over time and have strong externalities, as the proxy variables of financing constraints (SA). Where SA = −0.737 × SI+0.043 × SI2-0.040 × A. SI is the natural logarithm of the total assets of the enterprise, A is the listed years of the enterprise, and SA is a

TABLE 1 Variable definitions.

Variable	Symbol	Definition	Unit
Enterprise green innovation	gre	Ln (total green patent applications+1)	%
digitization	num	Calculated	single digits
Financing constraints	SA	−0.737 × SI+0.043 × SI2-0.040 × A	single digits
Corporate Social Responsibility	csr	Total score of social responsibility of Hexun	single digits
Fixed assets ratio	fix	Total fixed assets ÷ total assets	%
financial leverage	lev	Total liabilities ÷ total assets	%
Proportion of independent directors	boa	Number of independent directors ÷ Number of directors	%
Cash flow level	cash	Cash flow from operating activities ÷ total assets	%
Net profit rate of total assets	roa	Enterprise net profit ÷ total assets	%
Shareholding ratio of the largest shareholder	first	Shares held by the largest shareholder/total shares	%

negative value. Take the absolute value of the SA index. If the absolute value is larger, the financing constraint is larger. The reason why we choose SA index is that SA index does not contain endogenous financing variables and is easy to calculate.

Using the research of Zhao (2022) for reference, we use the web crawler method to capture the total social responsibility scores of listed companies over the years from the social responsibility report database of Hexun listed companies as the proxy variable of corporate social responsibility. The total score for social responsibility is the sum of the sub-scores for shareholder responsibility, environmental responsibility, employee responsibility, supplier, customer and consumer interest responsibility, and social responsibility.

3.2.4 Control variables

Drawing on the existing literature (Jin et al., 2022; Xiao et al., 2022), the sustainable development capability of enterprises, such as green innovation, is influenced by many factors, such as basic organizational characteristics, organizational resources and R&D capability. We selected the company level factors such as fixed asset ratio (fix), financial leverage (lev), proportion of independent directors (boa), cash flow level (cash), total asset net profit rate (roa), and the first largest shareholder's shareholding ratio (first) as the control variables of the model to exclude the impact of heterogeneous factors on enterprise performance.

The variable definition table is shown in Table 1.

3.3 Data sources

To test the theoretical hypothesis, we validate the relationship between digitalization and corporate green innovation using data from 2014 to 2020 for A-share listed companies in mainland China. Given the difficulty of obtaining complete data for non-listed companies, and the advantages of listed companies such as significant digitalization and service characteristics and transparent data information, listed companies were selected for this study. In addition, given the particularities of financial companies, we also excluded listed companies in the financial sector. The following conditions shall be followed for screening. First, ST, * ST and PT samples shall be removed (ST sample refers to listed companies with negative net profits for two consecutive accounting years, * ST sample refers to listed companies with losses of 3 years, and PT sample refers to listed companies waiting for delisting). Second, financial and insurance samples were not included. Third, missing observations of the main studied variables are eliminated. After the screening described above, After the above screening, we finally get 19,158 observations. To avoid the effect of extreme values, we shrink the tails of the continuous variables by 1 percent. Data were taken from the CSMRA and CNRDS databases (CSMRA refers to Guotai'an Database, https://cn.gtadata.com/, and CNRDS refers to China Research Data Service Platform, https://www.cnrds.com/Home/Login) and STATA 17.0 was used for data processing.

4 Empirical results

4.1 Descriptive statistics

Table 2 lists the descriptive statistical results for the main variables. The average value of enterprise green innovation (gre) is 0.4840, and the standard deviation is 0.8990. The average value of digital (num) is 3.0250, the maximum value is 5.8550, and the minimum value is 0, indicating that there is still much room for Chinese enterprises to improve their digitalization. In addition, we did a multicollinearity test. We found that the VIF value of each variable was less than 2, indicating that there was no multicollinearity between variables.

4.2 Regression results

In order to reduce the interference caused by heteroscedasticity and residual autocorrelation, we have adopted clustering robust standard error for regression. Table 3 shows benchmark regression results for the impact of digitalization on corporate green

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
gre	19,158	0.4840	0.8990	0.0000	4.0070
num	19,158	3.0250	1.2410	0.0000	5.8550
fix	19,158	0.2050	0.1590	0.0020	0.6930
lev	19,158	0.4300	0.2040	0.0620	0.9120
boa	19,158	0.3800	0.0650	0.2500	0.6000
cash	19,158	0.1480	0.1110	0.0090	0.5520
roa	19,158	0.0300	0.0740	−0.3630	0.1910
first	19,158	33.5450	14.5790	8.4480	72.8800

innovation. Column (1) is the result without adding control variables under the condition of controlling industry fixed effect and year fixed effect. The coefficient of ϕ is 0.1076 and is significant at the 1% level. Column (2) also adds control variables, and the coefficient of num is 0.0935, which is significant at the 1% level. The results show that the coefficient of num is significantly positive in columns (1) and (2), indicating that higher digitalization can promote the level of green innovation of Chinese A-share listed companies. The research hypothesis H_1 is verified. This research conclusion is consistent with the existing research conclusions (Jin et al., 2022; Shen et al., 2022).

4.3 Robustness checks

4.3.1 Replace the dependent variable

Furthermore, drawing on the research of Qi et al. (2018), we selected green patent licensing (gre2) as an indicator to measure green innovation of enterprises for robustness test. The regression results are shown in column (1) of Table 4. The coefficient of ϕ is 0.0323 and is significantly positive at the 1% level. This suggests that digitalization can effectively drive green innovation in enterprises, which is in line with previous conclusions.

4.3.2 Replace the independent variable

In order to avoid the instability of the results due to the numerical level of the measurements performed by the methods described above. Drawing on the work of He Fan et al. The

TABLE 3 Benchmark regression.

	(1)	(2)
	gre	gre
num	0.1076***	0.0935***
	(0.0062)	(0.0062)
fix		0.0879*
		(0.0509)
lev		0.7049***
		(0.0356)
boa		−0.1090
		(0.0912)
cash		0.2626***
		(0.0608)
roa		1.1959***
		(0.0890)
first		0.0013***
		(0.0004)
_cons	0.1589***	−0.1978***
	(0.0197)	(0.0474)
Control	NO	YES
Industry_FE	YES	YES
Year_FE	YES	YES
Obs	19,158	19,158
r2_a	0.1608	0.1817

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

TABLE 4 Robustness test 1

	(1)	(2)
	gre2	gre
Num	0.0323***	
	(0.0040)	
Fix	0.0338	−0.0879
	(0.0332)	(0.0575)
lev	0.3124***	0.7457***
	(0.0233)	(0.0403)
boa	0.0086	−0.1950*
	(0.0602)	(0.1024)
cash	0.0694*	0.2710***
	(0.0401)	(0.0690)
roa	0.3255***	1.2728***
	(0.0599)	(0.0987)
first	0.0008***	0.0015***
	(0.0003)	(0.0005)
num2		2.0246***
		(0.5298)
_cons	−0.1268***	0.1045**
	(0.0311)	(0.0492)
Control	YES	YES
Industry_FE	YES	YES
Year_FE	YES	YES
Obs	15,843	15,047
r2_a	0.1162	0.1708

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

regression results are shown in column (2) of Table 4. The coefficient for number two is 2.0246, which is significantly positive at the 1% level. This still suggests that digitalization can drive green innovation in companies, which is nearly the same as the baseline regression results.

4.3.3 Regression of instrumental variable

Given the impact of digital transformation on corporate green innovation, there may be an endogenous problem of cause and effect inversion, where companies with stronger green innovation capabilities are more motivated to conduct digital transformation activities. Drawing on the research of Jin et al. (2022), we use the 2SLS method to regress the mean digital level (mnum) of peers and other enterprises in the same province as a digital tool variable. The regression results for the instrumental variables are shown in Table 5. The results of the C-D Wald F test show that the instrumental variables satisfy the correlation property and there is no problem with the weak instrumental variables, that is, the instrumental variables are reasonably reliable. The regression results of the first stage are shown in column (1). The coefficient of mnum is 0.9793, which is significantly positive at the level of 1%. The regression results of the second stage are shown in Column (2) of Table 5. The coefficient of ϕ is 0.0777 and is significantly positive at the 1% level. This result is consistent with the research conclusion of Shen et al. (2022). It also shows that digitalization has boosted the level of green innovation in companies. Our conclusions remain valid.

5 Further analysis

5.1 Influence mechanism test

Previous analyses have shown that digitalization can significantly drive green innovation in business. Next, we will further explore the internal mechanisms of enterprise digitalization to promote its green innovation. According to the theoretical analysis, we believe that digitalization can improve the

TABLE 5 Robustness test 2

	(1)	(2)
	gre	gre
num		0.0777***
		(0.0112)
fix	−0.7459***	0.0711
	(0.0488)	(0.0519)
lev	0.4011***	0.7139***
	(0.0342)	(0.0360)
boa	0.1347	−0.1056
	(0.0879)	(0.0912)
cash	−0.0843	0.2600***
	(0.0587)	(0.0609)
roa	0.6312***	1.2142***
	(0.0857)	(0.0897)
first	0.0006	0.0013***
	(0.0004)	(0.0004)
mnum	0.9793***	
	(0.0105)	
Cragg-Donald Wald F		8,654.9770
Control	YES	YES
Industry_FE	YES	YES
Year_FE	YES	YES
Obs	19,157	19,157
r2_a		0.0355

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

level of green innovation of enterprises by easing financing constraints and enhancing corporate social responsibility awareness. Motivated by this, we develop a mediation effect model to analyze mediation effects. According to Wen and Ye, (2014) three-step method of intermediary effect model, we establish the following model:

$$gre_{i,t} = \alpha_0 + \alpha_1 \mathrm{num}_{i,t} + \delta X + \varphi_i + \omega_t + \varepsilon_{i,t} \tag{2}$$

$$middle_{i,t} = \alpha_0 + \alpha_1 \mathrm{num}_{i,t} + \delta X + \varphi_i + \omega_t + \varepsilon_{i,t} \tag{3}$$

$$gre_{i,t} = \alpha_0 + \alpha_1 \mathrm{num}_{i,t} + \alpha_2 middle_{i,t} + \delta X + \varphi_i + \omega_t + \varepsilon_{i,t} \tag{4}$$

Among them, middle represents the intermediary variable, which is represented by financing constraints (SA) and corporate social responsibility (csr). The model (2) is the same as (1).

First, the SA index is used in this paper to measure the overall financing constraints faced by enterprises. If the SA index is larger, it indicates that firms are facing greater funding constraints. The results of the intermediary effect regression are shown in Table 6. In column (1), the coefficient of num is −0.0191, which is significantly negative at the level of 1%. This suggests that digitalization can ease the constraints on corporate financing. This is consistent with the research conclusion of Wang et al. (2022). In column (2), the coefficient of num is 0.0896 and the coefficient of SA is −0.3522, both of which are significant at the level of 1%. This shows that the easing of financing constraints can promote green innovation of enterprises, which is consistent with the existing research results (Ye, 2021). Analysis of intermediary effects shows that digitalization can indeed drive green innovation in businesses by easing financing constraints. Let's say H_2 is verified.

Next, we measure corporate social responsibility (csr) with the total score of social responsibility of Hexun. The higher the score, the more CSR is achieved. In column (3), the coefficient of num is 0.6934, which is significantly positive at the 1% level. This shows that digitalization is conducive to promoting enterprises to fulfill their social responsibilities, which is consistent with Shang and Wu, (2022). In column (4), the coefficient of num is 0.0888, and the coefficient of csr is 0.0063, both of which are significantly positive at the level of 1%, indicating that the performance of corporate social responsibility can promote corporate green innovation, which is consistent with Xiao and Zeng, (2022). Analysis of intermediary

TABLE 6 Mediating effect analysis.

	(1)	(2)	(3)	(4)
	SA	gre	csr	gre
num	−0.0191***	0.0896***	0.6934***	0.0888***
	(0.0019)	(0.0066)	(0.0772)	(0.0062)
SA		−0.3522***		
		(0.0260)		
csr				0.0063***
				(0.0006)
fix	−0.0258	0.0191	−2.8449***	0.1035**
	(0.0157)	(0.0542)	(0.6314)	(0.0508)
lev	0.0271**	0.7862***	2.6957***	0.6861***
	(0.0111)	(0.0382)	(0.4413)	(0.0355)
boa	−0.2655***	−0.1427	−0.8932	−0.1071
	(0.0277)	(0.0960)	(1.1298)	(0.0909)
cash	0.0073	0.3148***	6.5062***	0.2156***
	(0.0187)	(0.0646)	(0.7554)	(0.0609)
roa	−0.0183	1.1370***	89.2878***	0.6275***
	(0.0293)	(0.1013)	(1.1033)	(0.1029)
first	−0.0020***	0.0005	0.0507***	0.0010**
	(0.0001)	(0.0005)	(0.0054)	(0.0004)
_cons	4.0503***	1.1953***	13.3824***	−0.2781***
	(0.0145)	(0.1167)	(0.5870)	(0.0479)
Control	YES	YES	YES	YES
Industry_FE	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES
Obs	17,730	17,730	19,122	19,122
r2_a	0.1453	0.1953	0.3734	0.1870

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

effects shows that digitalization can also drive green innovation in companies by raising CSR awareness. So far, we have proved our research hypothesis H_3.

5.2 Internal control level difference analysis

Internal control is an internal governance method or procedure involving all the senior management of the enterprise to ensure the safety of assets and the quality of accounting information, which affects the realization of enterprise operations and laws and regulations (Gao et al., 2022). A reasonable internal control system, on the one hand, can enhance an enterprise's ability to respond to environmental uncertainties. On the other hand, it can also consolidate the owner's supervision of the management, send a positive signal to external investors (Yan and Yang, 2022), and have an influential impact on enterprise digitalization and green innovation. Referring to the research of Zeng et al. (2022), we take the internal control index in Dibo's internal control and risk management database as the proxy variable of the enterprise's internal control level. The higher the index value, the higher the level of internal control in the business. In addition, we consider firms with an internal control index greater than the industry median as firms with elevated internal control levels, otherwise, we treat them as firms with low internal control levels and perform group regression. The regression results are shown in columns (1) and (2) of Table 7. It can be seen that digitalization has an impact coefficient of 0.1003 on green innovation in companies with higher levels of internal control, which is

TABLE 7 Heterogeneity analysis1.

	(1)	(2)	(3)	(4)
	gre	gre	gre	gre
num	0.1003***	0.0790***	0.0960***	0.0873***
	(0.0096)	(0.0080)	(0.0119)	(0.0072)
fix	0.0690	0.1307**	0.0983	0.0170
	(0.0806)	(0.0638)	(0.0845)	(0.0660)
lev	0.9927***	0.4810***	0.4209***	0.6872***
	(0.0579)	(0.0442)	(0.0659)	(0.0439)
boa	−0.2272*	−0.0295	0.5351***	−0.2550**
	(0.1362)	(0.1202)	(0.1646)	(0.1088)
cash	0.3230***	0.1757**	−0.0314	0.2716***
	(0.0905)	(0.0808)	(0.1178)	(0.0706)
roa	1.8168***	0.7653***	1.6544***	1.1398***
	(0.2116)	(0.0997)	(0.2092)	(0.0970)
first	0.0006	0.0014**	0.0015*	0.0006
	(0.0007)	(0.0006)	(0.0008)	(0.0005)
_cons	−0.2729***	−0.1186*	−0.2820***	−0.0837
	(0.0733)	(0.0617)	(0.0853)	(0.0570)
Control	YES	YES	YES	YES
Industry_FE	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES
Obs	9,577	9,569	6,636	12,102
r2_a	0.2057	0.1588	0.2358	0.1852

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

significant at the level of 1 percent. Digitalization has an impact coefficient of 0.0790 on green innovation in companies with low levels of internal control, which is significant at the 1 percent level. The quality of corporate development will be affected by the internal environment of the company. The higher the level of internal control, the better digitalization will work, ensuring the smooth development of green innovation activities and improving the impact of digitalization on corporate green innovation, which is conducive to corporate development. This is consistent with Gao et al. (2022).

5.3 Enterprise nature difference analysis

Differences in business objectives and risk control between SOEs and non-SOEs will have an impact on corporate activities and, therefore, corporate green innovation. Like most scholars, this study also analyzes the effect of differences in the nature of the business on the conclusions of the study. We regressed the samples of state-owned enterprises and non-state-owned enterprises, respectively, and the regression results are shown in columns (3) and (4) of Table 7. It can be seen that the impact of digitalization on the green innovation of SOEs has a coefficient of 0.0960, which is significantly positive at the 1 percent level. The coefficient of influence of digitalization on green innovation in non-state-owned enterprises is 0.0873, which is significantly positive at the 1 percent level. This shows that improving the level of digitalization in SOEs can effectively increase the level of green innovation in enterprises. In contrast to non-state-owned enterprises, the business objective of state-owned enterprises does not lie in their own profits, but in promoting the maximization of social and national interests. As a result, green development has been given more importance by SOEs.

5.4 Information technology background difference

As enterprise action guides, senior executives play a decisive role in the development of corporate strategic social responsibility and green innovation activities (Xiao et al., 2021a). The heterogeneity of information technology backgrounds of senior executives means that they have different cognitive bases for digitalization, as well as

TABLE 8 Heterogeneity analysis2.

	(1)	(2)
	gre	gre
num	0.1554***	0.0834***
	(0.0302)	(0.0063)
fix	0.3304	0.0772
	(0.2640)	(0.0511)
lev	1.2571***	0.6568***
	(0.1576)	(0.0361)
boa	−0.2917	−0.0681
	(0.3858)	(0.0929)
cash	0.5603**	0.2415***
	(0.2354)	(0.0625)
roa	2.0398***	1.1049***
	(0.3747)	(0.0907)
first	−0.0065***	0.0020***
	(0.0020)	(0.0004)
_cons	−0.2543	−0.1998***
	(0.2181)	(0.0480)
Control	YES	YES
Industry_FE	YES	YES
Year_FE	YES	YES
Obs	1,636	17,516
r2_a	0.2059	0.1758

Note: *, ** and *** denote significance at the significance level of 10%, 5% and 1%, respectively.

different identification capabilities for digital opportunities. Using the research of Zhao and Huang, (2022) for reference, we establish a dummy variable (Dceo) for senior executives' information technology background. Dceo has a value of one if the executive has an IT background and 0 otherwise. Further, we conducted group regression according to the information technology background of senior executives, and the regression results are shown in columns (1) and (2) of Table 8. It can be seen that digitalization has an impact coefficient of 0.1554 on corporate green innovation among companies with information technology background, which is significantly positive at the level of 1 percent. Among companies without an IT background, the impact of digitalization on corporate green innovation was 0.0834, which is significantly positive at the 1% level. This suggests that the digitalization of companies with IT backgrounds for their executives can boost the level of green innovation compared to companies without IT backgrounds for their executives. The information technology background of an executive can enhance the likelihood of applying information technology to business operations and management, as well as the quality of its application, thus enhancing the impact of digitalization on the company's green innovation.

5.5 Evaluate and discuss together

Based on the perspective of endogenous innovation, this paper summarizes the green innovation performance of enterprises by the number of patents, and tests the effect of digitalization on green innovation. Here we will discuss more.

Social media influencers also play a role in the process of enterprise digitization. For enterprises with high degree of social network embeddedness, "data-driven" enables enterprises to better carry out green innovation activities. Especially for start-ups, social media influencers and social platforms can provide them with huge information and technology resources for green development. This study does not consider the green innovation of smes, but for smes, there is a lack of long-term vision. Small and medium-sized enterprises tend to pay special attention to short-term interests, and do not have a clear strategic planning and design for long-term interests, nor do they have implementation of organizational and management measures, which are exactly the constraints to the implementation of green innovation. In addition, countries around the world have recognized that green development is the trend of world development, and bilateral trade contracts and agreements on green economy and green policies have begun to appear on the world stage. On 18 October 2022, Australia and Singapore announced the signing of the Singapore-Australia Green Economy Agreement (GEA). By combining trade, economic and environmental goals, the agreement provides a major boost to the world's green economy by facilitating bilateral trade in green products and extensive cooperation between emerging growth sectors to promote common rules and standards for trade and environmental sustainability, enabling both countries to jointly transition to a zero-carbon economy. The future of green innovation is bright.

6 Conclusion and policy recommendation

With the rapid development of information technology, the development of enterprises will inevitably be affected by digitalization. In this context, this study explores the impact of digitalization on the green innovation of enterprises and their internal mechanisms in a multidimensional way. Based on existing research, we have incorporated financing constraints, corporate social responsibility, internal control levels, and the information technology background of executives into the research system, expanding the accumulated literature in the related field. Based on a detailed theoretical analysis, we systematically investigate the impact of digitalization on corporate green innovation, using Chinese A-share listed companies from 2014 to 2019 as a sample. Research has found that digitalization can indeed drive green innovation in companies. This conclusion remains valid after robustness and endogenous tests. In the subsequent intermediary effect analysis, we demonstrate that digitalization can promote green innovation in businesses by easing financing constraints and enhancing corporate social responsibility awareness. In addition, we found that the impact of digitalization on corporate green innovation is more pronounced among companies with high levels of internal control, state-owned enterprises, and executives with information technology backgrounds.

In contrast to existing research, we also support the idea that digitization can drive green innovation in companies. However, we demonstrate this using relatively new data and methods. In particular, we empirically demonstrate that digitization can drive corporate green innovation by easing financing constraints and enhancing corporate social responsibility awareness. In addition, we innovatively explore the impact of the level of internal control on the outcome of the study.

Based on our conclusions, we believe that enterprises should not hesitate to implement their digital strategies and continuously improve their digital levels. Indeed, it can be found from our study that easing of financing constraints and increased awareness of CSR are also crucial. Therefore, the government should attach importance to the improvement of enterprise financing environment, and enterprises without political connection should take the initiative to establish a "pro-clear relationship between government and business" with the government to obtain government support and alleviate the predicament of resource constraints. In addition, enterprises should attach importance to the fulfillment of social responsibility, regard corporate social responsibility as a necessary strategic measure to integrate corporate economic and social attributes, and promote the integration of corporate social responsibility and sustainable development cognitive orientation into the internal strategic management and innovation management system, so as to better realize the responsibility embedding in the process of corporate technological innovation. Based on our heterogeneity analysis, we believe that while the nature of the enterprise is difficult to modify, the level of internal control of the enterprise can be changed in a short period of time. Businesses should regularly promote the improvement of their internal control levels.

However, this study is not without limitations. This paper focuses only on the Chinese case and lacks empirical analysis of other countries. The specific impact coefficient of digitalization on green innovation of listed companies calculated in this paper is 0.0935. However, there are a variety of unlisted companies in China, each with a different situation. It is difficult for unlisted companies to make specific development plans based on this figure. This study lacks a more in-depth and concrete theoretical justification.

In the future, researchers should consider additional countries and more samples, and should construct new metrics to measure non-listed companies whose data is difficult to obtain but should emerge. Researchers should construct a more specific theoretical model to discuss the impact of digital images on green innovation in business. In the future, researchers should also consider the long-term impact of digitalization on green innovation in business.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YF: software, validation, investigation, data curation, manuscript revision financial support; QS: validation, investigation; supervision; financial support, manuscript revision XW: Conceptualization, funding acquisition and writing and horbar; original draft. MF: Methodology, writing and horbar; original draft, resources, supervision, software. Manuscript revision.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Bajari, P., Chernozhukov, V., Hortagcsu, A., and Suzuki, J. (2019). The impact of big data on firm performance: An empirical investigation. *AEA Pap. Proc.* 109, 33–37. doi:10.1257/pandp.20191000

Biondi, V., Iraldo, F., and Meredith, S. (2002). Achieving sustainability through environmental innovation: The role of SMEs. *International Journal of Technology Management*24 (5/6), 612.

Cox, P., and Wicks, P. C. (2011). Institutional interest in corporate responsibility: portfolio evidence and ethical explanation. *J. Bus. Ethics* 103, 143–165. doi:10.1007/s10551-011-0859-0

Doran, J., and Ryan, G. (2012). Regulation and firm perception, eco-innovation and firm performance. *Eur. J. Innovation Manag.* 15 (4), 421–441. doi:10.1108/14601061211272367

El-Kassar, A. N., and Singh, S. K.,(2019),"Green innovation and organizational performance:the influence of big data and the moderating role of management commitment and HR practices",*Technol. Forecast. Soc. Change*,144(C):483–498. doi:10.1016/j.techfore.2017.12.016

Fan, H., and Liu, H. (2019). Evaluation of performance improvement effect of digital transformation of real enterprises from the perspective of digital economy. *Reform* (4), 137–148.

Fichman, R., Santos, D., Brian, L., and Zheng, Z. (2014). Digital innovation as a fundamental and powerful concept in the information systems curriculum. *MIS Q.* 2 (38), 329–343. doi:10.25300/misq/2014/38.2.01

Gao, K., Zhao, H., and Wang, L. (2022). East China economic management (02), 119–128. doi:10.19629/j.cnki.34-1014/f.210713001

Gu, H. F., and Gao, H. H. (2022). A study on the impact of digital finance development on corporate green innovation. *Statistics and Information Forum* (11), 77–93.

He, F., and Hongxia, L. (2019). Assessment of the performance enhancement effect of digital change in real enterprises from the perspective of digital economy. *Reform* (04), 137–148.

Hoenig, D., and Henkel, J.,2015,"Quality Signals?The role of Patents,Alliances,and team experience in venture capital financing",*Res. Policy*,44(5):1049–1064. doi:10.1016/j.respol.2014.11.011

Hu, J., Han, Y., and Zhong, Y. (2022). How the digital transformation of enterprises affects ESG performance - evidence from Chinese listed companies industrial economic review. doi:10.19313/j.cnki.cn10-1223/f.20221104.001

Huang, C. L., and Kung, F. H. (2010). Drivers of environmental disclosure and stakeholder expectation:Evidence from Taiwan. *J. Bus. Ethics* 96 (3), 435–451. doi:10.1007/s10551-010-0476-3

Jin, Y., Wen, W., and He, Y. (2022). The impact of digital transformation on green innovation of enterprises - based on empirical evidence of listed companies in China's manufacturing industry. *Finance and Trade Research* 33 (07), 69–83. doi:10.19337/j.cnki.34-1093/f.2022.07.006

Ju, X., Lu, D., and Yu, Y. (2013). Financing constraints, Working capital management and corporate innovation sustainability. *Econ. Res. J.* 48 (01), 4–16.

Kaplan, S. L., and Zingales, L. (1997). Do investment cash flow sensitivities provide useful measures of financing constraints? *Q. J. Econ.* 112, 169–215. doi:10.1162/003355397555163

Li, H. (2022). *Research on the impact of digital innovation on green Innovation performance in manufacturing Industry (Master Dissertation*. Harbin: Harbin University of Science and Technology.

Li, J., Chen, L., Chen, Y., and He, Y. (2022a). Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. *Manag. Decis. Econ.* 43 (3), 616–629. doi:10.1002/mde.3406

Li, J., Hu, S., Qi, X., Zhou, T., and Lu, Z. (2022b). Analysis of the impact of corporate digital transformation on performance *Investment and Entrepreneurship* (13), 48–52.

Li, W., and Zheng, M. (2016). Substantial innovation or strategic innovation? - the impact of macro industrial policies on micro enterprise innovation. *Econ. Res.* 4, 60–73.

Li, X. Y., Liu, J., and Ni, P. J. (2021). The impact of the digital economy on CO2 emissions:A theoretical and empirical analysis. *Sustainability* 13 (13), 7267.

Liu, D., Bai, F., and Dong, K. (2022). Research on the impact mechanism of digital transformation on enterprise performance Finance and Accounting Communication (16), 120–124. doi:10.16144/j.cnki.issn1002-8072.2022.16.010

Liu, G. Z., and Liu, J. (2022). The theory and demonstration of digital finance enabling green innovation - empirical evidence from prefecture level cities Wuhan Finance (09), 50–60.

Matray, A. (2021). The local innovation spillovers of listed firms. *J. Financial Econ.* 141 (2), 395–412. doi:10.1016/j.jfineco.2021.04.009

Mubarak, M. F., Tiwari, S., Petraite, M., Mubarik, M., and Raja Mohd Rasi, R. Z. (2021). How industry 4.0 technologies and open innovation can improve green innovation performance? *Manag. Environ. Qual.* 32 (5), 1007–1022. doi:10.1108/meq-11-2020-0266

Ngo, L. V., and O'Cass, A. (2009). Creating value offerings via operant resource-basedcapabilities. *Ind. Mark. Manag.* 38 (1), 45–59. doi:10.1016/j.indmarman.2007.11.002

Pan, H. B., and Gao, J. F. (2022). Digital transformation and corporate innovation - Empirical evidence based on annual reports of Chinese listed companies. *Journal of Central South University (Social Science Edition)* (05), 107–121.

Pan, J., and Wang, F. (2022) How does digital empowerment affect the green transformation of enterprises—analysis of the dual impact of green innovation capability and organizational inertia. *Journal of Nanjing University of Technology (Social Science Edition)* (04), 89–100+116.

Philip, L. D., Emir, F., and Udemba, E. N. (2022). Investigating possibility of achieving sustainable development goals through renewable energy, technological innovation, and entrepreneur: A study of global best practice policies. *Environ. Sci. Pollut. Res. Int.* 29 (40), 60302–60313. doi:10.1007/s11356-022-20099-z

Qi, S. Z., Lin, D., and Cui, J. (2018). Can environmental equity trading market induce green innovation?—Evidence based on data on green patents of listed companies in China. *Econ. Res.* 12, 159–177.

Ramirez, R. (1999). Value coproduction: Intellectual origins and implications for practice and research. *Strategic Manag. J.* 20 (1), 49–65. doi:10.1002/(sici)1097-0266(199901)20:1<49::aid-smj20>3.0.co;2-2

Roca, J. B., Vaishnav, P., Morgan, M. G., Mendonca, J., and Fuchs, E. (2017). When risks cannot Be seen:regulating uncertainty in emerging technologies. *Res. Policy* 46 (7), 1215–1233. doi:10.1016/j.respol.2017.05.010

Shang, H., and Wu, T. (2022). Corporate digital transformation, social responsibility and corporate value. *Technology Economics* (07), 159–168.

Shen, M. H., and Tan, W. J. (2022). Digitalization and corporate green innovation performance—Identifying the dual effect based on incremental and qualitative improvement. *Southern Economics* (09), 118–138. doi:10.19592/j.cnki.scje.391819

Shen, M. H., Zhang, W. B., and Tan, W. J. (2022). Does digital transformation enhance corporate social responsibility fulfillment?. *Western Forum*, 63–80.

Smith, C., Smith, J. B., and Shaw, E.,2017,"Embracing digital networks:entrepreneurs' social capital online",*J. Bus. Ventur.*,32(1):18–34. doi:10.1016/j.jbusvent.2016.10.003

Song, D. Y., Zhu, W. B., and Ding, H. (2022). Can corporate digitalization promote green technology innovation?—An examination of listed companies in the heavy pollution industry. *Financial Studies* (04), 34–48. doi:10.16538/j.cnki.jfe.20211218.304

Udemba, E. N., Emir, F., and Philip, L. D. (2022a). Mitigating poor environmental quality with technology, renewable and entrepreneur policies: A symmetric and asymmetric approaches. *Renew. Energy* 189, 997–1006.

Udemba, E. N., Philip, L. D., and Emir, F. (2022b). Performance and sustainability of environment under entrepreneurial activities, urbanization and renewable energy policies: A dual study of Malaysian climate goal. *PSN Glob. Warming Clim. Change (Topic).*

Udemba, E. N., and Tosun, M. S. (2022). Moderating effect of institutional policies on energy and technology towards a better environment quality: A two dimensional approach to China's sustainable development. *Technol. Forecast. Soc. Change* 183, 121964. doi:10.1016/j.techfore.2022.121964

Wang, F. Z., Liu, X. L., Zhang, L., and Cheng, W. (2022). Does digitalization promote green technology innovation of resource-based enterprises *Sci. Sci. Res.* (02), 332–344. doi:10.16192/j.cnki.1003-2053.20210824.001

Wang, J., Guo, S., and Zhang, L. (2018). Research on the impact of the Internet on enterprise innovation performance and its mechanism - based on the interpretation of open innovation Nankai Economic Research (06), 170–190. doi:10.14116/j.nkes.2018.06.10

Wang, J. Y., Sun, T., Li, P., and Gong, Y. (2019) Scientific decision-making (11), 1–23.

Wang, M., and Li, Y. (2021). The balance and stability of the green technology innovation system involving multiple entities China Management. *Science* (3), 59–70.

Wang, Z., and Buaisheng (2019). Corporate social responsibility, innovation capability and internationalization strategy—The moderating role of executive compensation incentives. *Manag. Rev.* (03), 193–202.

Wen, Z. L., and Ye, B. (2014). Analyses of mediating effects: The development of methods and models. *Adv. Psychol. Sci.* 22 (05), 731–745. doi:10.3724/sp.j.1042.2014.00731

Wu, F., Hu, H., Lin, H., Ren, X., et al. (2021). Digital transformation of enterprises and capital market performance - empirical evidence from stock liquidity Management World, (7): 130–144+10. doi:10.19744/j.cnki.11-1235/f.2021.0097

Xiao, H., Yang, Z., and Ling, H. C. (2022). Does corporate social responsibility have green innovation effect? *Trends Econ.* (08), 117–132.

Xiao, J., and Zeng, P. (2022). Can digitization "increase the quality and quantity" of corporate green innovation?—A resource-based perspective *Scientific Research* 3 (10), 57–70.

Xiao, X. H., Pan, Y., and Wang, Z. (2021b). Does corporate social responsibility promote corporate green innovation Economic longitude and latitude (03), 114–123. doi:10.15931/j.cnki.1006-1096.20210324.001

Xiao, X. H., Pan, Y., and Wang, Z. (2021a). Does corporate social responsibility promote corporate green innovation? *Econ. Latit.* 38.03, 114–123. doi:10.15931/j.cnki.1006-1096.20210324.001

Xie, X. M., Huo, J. G., Qi, G. Y., and Zhu, K. X. G.,2016,"Green process innovation and financial performance in emerging economies:moderating effects of absorptive capacity and green subsidies",*IEEE Trans. Eng. Manag.*,63(1):101–112. doi:10.1109/tem.2015.2507585

Yan, H., and Yang, H. (2022). Environmental uncertainty, internal control quality and firm performance: Evidence from the special equipment manufacturing industry. *Bus. Account.* (10), 25–29.

Yang, G. Z., and Xi, Y. (2019). Empirical study on financing constraints of enterprises' green technology innovation activities. *Ind. Technol. Econ.* 11, 70–76.

Yang, H., Shi, X., and Wang, S. (2022). The impact of heterogeneous corporate social responsibility on green technology innovation. *Shandong Social Science* (02), 165–175.

Ye, C. H. (2021). Financing constraints, government subsidies and green innovation of enterprises Statistics and Decision Making (21), 184–188. doi:10.13546/j.cnki.tjyjc.2021.21.038

Yousaf, Z., Radulescu, M., Sinisi, C. I., Luminita, S., and Loredana, M. P. (2021). Towards sustainable digital innovation of SMEs from the developing countries in the context of the digital economy and frugal environment. *Sustainability* 13 (10), 57–75.

Zeng, J. Z., Liu, G. D., and Pang, R. (2022). CEO Financial Expertise, Internal Control and Corporate Performance—Empirical Evidence Based on Chinese Listed Companies. *Int. Financial Res.* (05), 87–96.

Zhang, L. P., and Tang, Z. W. (2018). The impact of enterprise information technology application on Open Innovation:From the perspective of transaction cost. *Sci. &Technological Prog. Policy* 35 (20), 79–87.

Zhao, C. (2022). Research on the impact of digital transformation on corporate social responsibility. *Contemporary Economic Science* (02), 109–116.

Zhao, C. (2022). Research on the impact of digital transformation on corporate social responsibility Contemporary Economic Science (02), 109–116.

Zhao, L., and Huang, H. (2022). Research on the impact of directors' information technology background on the effectiveness of internal control in the digital age. *Journal of Yunnan University of Finance and Economics* (05), 80–101. doi:10.16537/j.cnki.jynufe.000787

Zhou, X., Han, L., and Xiao, X. (2022) The impact of digital economy on sustainable green innovation under the "double carbon" target—a mediating perspective based on digital transformation. *Securities Market Herald* (11), 2–12.

Zuo, P., and Chen, J. (2021). Digital economy and economic growth from the perspective of high-quality development. *Res. Financial Issues* (9), 19–27.

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 March 2023
DOI 10.3389/fenvs.2023.1138200

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Kai Liu,
Shandong Normal University, China
Remus Cretan,
West University of Timișoara, Romania
Jaroslaw Nazarczuk,
University of Warmia and Mazury in Olsztyn, Poland

*CORRESPONDENCE
Xingxing Niu,
2021212839@nwnu.edu.cn
Weijing Ma,
maweijing@lzu.edu.cn

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management, a section of the journal Frontiers in Environmental Science

RECEIVED 05 January 2023
ACCEPTED 07 March 2023
PUBLISHED 20 March 2023

CITATION
Ma Z, Niu X, Ma W, Kang Y and Xie W (2023), Interregional and intersectoral interaction of digital economy in China. *Front. Environ. Sci.* 11:1138200.
doi: 10.3389/fenvs.2023.1138200

Interregional and intersectoral interaction of digital economy in China

Zhong Ma[1,2], Xingxing Niu[1,2]*, Weijing Ma[3]*, Yanxia Kang[1,2] and Weiwei Xie[1,2]

[1]College of Geography and Environmental Science, Northwest Normal University, Lanzhou, China, [2]Key Laboratory of Resource Environment and Sustainable Development of Oasis, Gansu Province, Lanzhou, China, [3]College of Earth and Environmental Sciences, Lanzhou University, Lanzhou, China

With the continuous advancement of the integration of the world's digital economy, the economic development of various regions has become increasingly interdependent. However, the interregional interactions of digital industries have yet to be further elucidated. Here, based on the Multi-Regional Input-Output model, we take China, for example, and analyze the impact of digital industries on the economy from the industrial and regional. At the industry level, we discuss the economic spillover relationship between the digital industry and the three traditional industries, and analyzes the spatial and temporal differentiation in the inter-industry spillover status of China's 30 provinces; at the regional level, we discuss the digital industrial economic spillover links and spillover states. The results show that: 1) The self-generating ability within the digital industry sector is the most significant factor influencing the industrial growth of China's digital economy, followed by the interrelated effect between industry sectors, while the inter-industry feedback effect has a weak impact on the economic system. 2) There is a clear gap in the economic spillover capacity of the digital industry in 30 provinces, and the overall performance is decreasing in the eastern, central and western regions. 3) The intra-regional multiplier effect of digital industry shows a slowly decreasing trend, and the intra-regional digital economic spillover-feedback effect shows a growing trend. At the same time, the inter-regional digital economy interaction tends to decay in distance, indicating that regional accessibility has a significant impact on the inter-regional spillover effect.

KEYWORDS

digital industry, spillover effect, multiplier effect, feedback effect, MRIO model, China

1 Introduction

With the technology advancements such as the Internet, big data, cloud computing, artificial intelligence, and blockchain, the world economy is gradually transforming into digitalization (Liu et al., 2021a; Liu et al., 2021b). Digital economy have become the precursors for the current world scientific and technological and industrial revolution (Latif, et al., 2018), as well as the key forces for restructuring the world's factor resources, reshaping the worldwide economic structure, and altering the global competition landscape (Jiang and Jia, 2022). The concept of "digital economy" was first proposed by Bowman (Bowman, 1996), and since then, it has rapidly become popular worldwide. Major western developed countries have stepped up the strategic layout of the application of the new generation of information technology to seize the opportunity of digital economy development. In the 1990s, the United States took the lead in seizing the opportunity of the digital revolution and seizing the commanding heights of the digital economy with infrastructure construction, which laid a solid foundation for the economic prosperity of the United States for more than a decade (Oliner and Sichel, 2000; Stiroh, 2002; Jorgenson and Vu, 2016). By giving play to the active leading role of the government, Europe, Japan, and other regions have introduced a series of digital economy development strategies (Jiang and Jia, 2022), which have produced great results in vigorously promoting the digital revolution (Bunje et al., 2022; Kurniawan, et al., 2022). In the context of the current intensifying downward pressure on the global economy, the digital economy is bucking the trend (Bulturbayevich et al., 2020), and has become a key tool for countries to stabilize economic growth and achieve economic recovery (Xue et al., 2022). Especially under the outbreak of COVID-19, the global industrial chain, supply chain and value chain are facing the challenge of being reshaped (Sun and Wang, 2021; Wang and Zhang, 2021). The resilience of digital technology has made the international community aware of the critical role of the digital economy in restoring the economy (Popkova et al., 2022; Wang et al., 2022). It is also an enlightening path for strategic measures to realize the new development pattern of "dual circulation" (Bressanelli et al., 2018).

As the development of China's digital economy started late compared with developed countries, the construction of digital technology infrastructure lags behind, and there is still a considerable gap between China and developed countries in terms of basic theories, core algorithms, key equipment, *etc.*, making the import and export trade deficit of digital products is huge and heavily dependent on imports, resulting in a series of problems in the development of China's internal digital economy. Because China is a vast country, the balance of regional development is a key topic at present.

From the spatial perspective of economic development, the economic growth of a region is affected by the following three effects: intra-regional multiplier effect (ME), inter-regional spillover effect (SE), and inter-regional feedback effect (FE) (Round, 1985). The intra-regional multiplier effect refers to the output growth brought about by the interaction of various industrial sectors in region a; the inter-regional spillover effect refers to the one-way effect of the output growth of one region on the economic development of another region. The feedback effect represents the effect of the final output change of one region on other regions and then on the region itself through economic circulation. If the study of the multiplier effect is the economic development of a single region, then the research content of interregional spillover and feedback effect, especially the spillover effect, is more concerned with the development of the multi-regional economy.

The mainstream approaches to study spillover feedback effects include spatial econometric models, life cycle assessment (LCA), general and partial equilibrium models (GEM), and multi-regional input-output models (MRIO) (Ning et al., 2019). Although MRIO has a time lag due to the need to compile input-output tables, the preferred analytical method to study inter-regional industrial linkages is the multi-regional input-output model, which represents the interdependence and mutual influence relationships among sectors in complex economies in a systematic and quantitative way, and the spillover feedback effects can be effectively quantified by MRIO, which is the reason why this paper chooses to use MRIO to measure This is the reason why we choose to use MRIO to measure the spillover feedback effect.

The inter-regional spillovers and feedback effects produced by inter-regional trade play an increasingly important role in regional economic growth and inter-regional economic exchanges. Considering that regional spillovers are closely related to regional economic integration, it is necessary to measure the digital economy at the regional and industrial levels, especially in a vast developing country like China. Spillover effects, as an important factor in regional economic development, have been widely used not only to study economic aspects, but also to study environmental issues in recent years. For example, at the regional level, Zhang (2017) analyzed the spillover-feedback effects of carbon emissions in three regional levels of China. Ning et al. (2019) examine the feedback and spillover impacts of carbon emissions among China's eight regions. Hu et al. (2019) assessed the multiplier, spillover and feedback effects of water, carbon and land footprint. At the level of China's capital city agglomeration, Li et al. (2018) measured the spillover and feedback effects of economy and CO_2 emissions. Chen, et al. (2021) Measured spillover-feedback effect of virtual water transfers in urban agglomerations. At the national level, Wang et al. (2021) calculated the status of inter-regional carbon emissions along the Belt and Road. Zhang and Zhang (2018) explore the relationship between China, EU and US CO_2 emissions from regional and sectoral levels by calculating carbon spillover-feedback effects.

The digital economy can improve the efficiency of industrial innovation through spatial spillover effects (Liu et al., 2022; Zhang et al., 2022), promote industrial transformation (Xiao, 2020; Singh et al., 2021), expand the level of industrial collaboration (Lioutas et al., 2021; Su et al., 2021), which in turn drives the economic development of neighboring regions (Ma and Zhu, 2022). With the growing momentum of the digital economy, digital technology and traditional industries will be deeply integrated and become the power source and core driving force of economic growth (Pradhan et al., 2019). As a technology-intensive activity, the digital economy has become inseparable from high-quality development. It is an indispensable and vital force in China for social development (Song et al., 2021),technological progress (Ding et al., 2021), poverty eradication (Lv et al., 2022), expanding the labor market (Simionescu, 2022), and expanding regional economic integration (Gong, 2022). Therefore, research on the digital economy has direct relevance for improving China's overall national power and promoting high-quality and stable economic development (Bahrini and Qaffas, 2019). Although the spillover effects of the digital economy have been confirmed (Liu, et al., 2022; Zhang, et al., 2022), however, most studies focus on the overall effect, and few studies quantify the spillover effects of the digital economy in detail, ignoring heterogeneity and inter-city or regional heterogeneity and spatial spillover effects, which may lead to biased findings.

Through sorting and summarizing the existing literature, we found that, at present, most of the studies on digital economy are focused on measuring the scale or added value of digital economy, and relatively few of them study the effect of digital economy and

TABLE 1 Interregional input-output table for three region.

<table>
<tr><th colspan="3">Output</th><th colspan="3">Intermediate input</th><th colspan="3">Final demand</th><th rowspan="4">Export</th><th rowspan="4">Total output</th></tr>
<tr><th colspan="3"></th><th>Region</th><th>Region</th><th>Region</th><th>Region</th><th>Region</th><th>Region</th></tr>
<tr><th colspan="3">Input</th><th>a</th><th>b</th><th>c</th><th>a</th><th>b</th><th>c</th></tr>
<tr><th colspan="3"></th><th>1 . . . n</th><th>1 . . . n</th><th>1 . . . n</th><th></th><th></th><th></th></tr>
<tr><td rowspan="4">Inter-mediate input</td><td>region a</td><td>1 . . . n</td><td colspan="3" rowspan="3">$X_{a...b}^{1...n}$</td><td colspan="3" rowspan="3">$F_{a...b}^{1...n}$</td><td rowspan="3">$EX_{a...b}^{1...n}$</td><td rowspan="3">$X_{a...b}^{1...n}$</td></tr>
<tr><td>region b</td><td>1 . . . n</td></tr>
<tr><td>region c</td><td>1 . . . n</td></tr>
<tr><td colspan="2">Import</td><td colspan="3">$IM_{a...b}^{1...n}$</td><td colspan="5" rowspan="3"></td></tr>
<tr><td colspan="3">Total added value</td><td colspan="3">$V_{a...b}^{1...n}$</td></tr>
<tr><td colspan="3">Total input</td><td colspan="3">$X_{a...b}^{1...n}$</td></tr>
</table>

various industries in the national economy. In addition, most scholars analyze the development level of digital economy by constructing an index system, and only a few scholars use the input-output method to construct an economic model to study the impact of digitalization level. Compared with the existing literature, the contribution of this paper is mainly reflected in three aspects:

First, this study focuses on the internal structure of the digital economy industry and analyzes the inter-industry association patterns between the digital economy industry and the traditional three major industries (primary industry, secondary industry, and tertiary industry) and their macroeconomic spillover effects using an input-output model; Second, this paper analyzes the spatial variability of inter-industry spillover effects of the digital economy in China's 30 provinces. Finally, this paper takes into account the inter-regional spatial spillover and uses a multi-regional input-output model to analyze mutual spillover effects among the eight regions in China.

The research purpose of this article is to use overflow feedback effects to evaluate the scale of China's digital economy development, and analyze the association of digital industries between eight regions and the two -way impact between target areas. Based on this, we will explore how the digital industry contributes to the region and whether it has promoted the economic development between regional. It will provide a reference for the accuracy and scientificity of quantitative research on China's digital economy industry, enrich the research content of the digital economy industry to a certain extent, and provide a new basis for existing research.

2 Methodology

2.1 Multi-region input-output model

Multi-region Input-Output Model (MRIO) is able to measure the interaction between different regions, and plays a unique role in the fields of industrial linkage and cross-regional accounting. It is a practical model for analyzing the interaction and interdependence between different sectors in different regions by linking various regional input-output models.

On this Table 1, the equilibrium output relationship of the three regions is expressed by formula (1) as:

$$\begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} = \begin{bmatrix} A^{aa} & A^{ab} & A^{ac} \\ A^{ba} & A^{bb} & A^{bc} \\ A^{ac} & A^{bc} & A^{cc} \end{bmatrix} \begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} + \begin{bmatrix} Y^a \\ Y^b \\ Y^c \end{bmatrix} \tag{1}$$

Then, Eq. 1 can be divided into:

$$\begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} = \begin{bmatrix} (I - A^{aa})^{-1} & 0 & 0 \\ 0 & \left(I - A^{bb}\right)^{-1} & 0 \\ 0 & 0 & (I - A^{cc})^{-1} \end{bmatrix} \times \left(\begin{bmatrix} 0 & A^{ab} & A^{ac} \\ A^{ba} & 0 & A^{bc} \\ A^{ca} & A^{cb} & 0 \end{bmatrix} \begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} + \begin{bmatrix} Y^a \\ Y^b \\ Y^c \end{bmatrix} \right) \tag{2}$$

Define $B^{rr} = (I - A^{rr})^{-1}, S^{rs} = B^{rr} A^{rs}$, Eq. 2 can be expressed as:

$$\begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} = \begin{bmatrix} 0 & S^{ab} & S^{ac} \\ S^{ba} & 0 & S^{bc} \\ S^{ca} & S^{cb} & 0 \end{bmatrix} \begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} + \begin{bmatrix} B^{aa} & 0 & 0 \\ 0 & B^{bb} & 0 \\ 0 & 0 & B^{cc} \end{bmatrix} \begin{bmatrix} Y^a \\ Y^b \\ Y^c \end{bmatrix} \tag{3}$$

Define

$$F^{aa} = \left[I - \left(S^{ab} + S^{ac} S^{cb}\right)\left(I - S^{ac} S^{cb}\right)^{-1} \left(S^{ba} + S^{bc} S^{cb}\right) - S^{ac} S^{ca} \right]^{-1} \tag{4}$$

$$K^{ac} = \left[S^{ab} + \left(S^{ac} + S^{ac} S^{cb}\right)\left(I - S^{bc} S^{cb}\right)^{-1} S^{bc} \right] \tag{5}$$

$$U^{ab} = \left(S^{ab} + S^{ac} S^{cb}\right)\left(I - S^{bc} S^{cb}\right)^{-1} \tag{6}$$

Similarly, the expressions of $F^{bb}, F^{cc}, K^{ac}, K^{ba}, U^{ab}, U^{ca}$ can be defined. Equation 3 can be further decomposed into:

$$\begin{bmatrix} X^a \\ X^b \\ X^c \end{bmatrix} = \begin{bmatrix} F^{aa} & 0 & 0 \\ 0 & F^{bb} & 0 \\ 0 & 0 & F^{cc} \end{bmatrix} \begin{bmatrix} I & U^{ab} & K^{ac} \\ K^{ba} & I & U^{bc} \\ U^{ca} & K^{cb} & I \end{bmatrix} \begin{bmatrix} B^{aa} & 0 & 0 \\ 0 & B^{bb} & 0 \\ 0 & 0 & B^{cc} \end{bmatrix} \begin{bmatrix} Y^a \\ Y^b \\ Y^c \end{bmatrix} \tag{7}$$

According to Eq. 7, the inter-region Leontief inverse matrix can be decomposed into:

$$L = \begin{bmatrix} L^{aa} & L^{ab} & L^{ac} \\ L^{ba} & L^{bb} & L^{bc} \\ L^{ca} & L^{cb} & L^{cc} \end{bmatrix} = \begin{bmatrix} F^{aa}B^{aa} & F^{aa}U^{ab}B^{bb} & F^{aa}K^{ac}B^{cc} \\ F^{bb}K^{ba}B^{aa} & F^{bb}B^{bb} & F^{bb}U^{bc}B^{cc} \\ F^{cc}U^{ca}B^{aa} & F^{cc}K^{cb}B^{bb} & F^{cc}B^{cc} \end{bmatrix} \tag{8}$$

2.2 Multiplier, spillover and feedback effects in MRIO

The term "feedback effect" was first coined by Miller (1963), who first proposed two regional input-output models to measure the economy feedback effects, but did not explicitly introduce the concept of spillover effects. Pyatt and Round (1979) and Stone (1985) proposed the concept of spillover effects based on the social accounting matrix (SAM) and analyzed it. Round (1985) proposed a decomposition model based on the above to measure spillover-feedback effects in more detail and extended a SAM-based three-region model. Since then, spillover-feedback effect models have been widely used to analyze inter-regional economic linkages and interactions.

For closed three-region, according to the multi-regional input-output model, the change in economy caused by each unit of the final demand of region a can be expressed as follows:

$$\begin{aligned} &\left[(e)^T, (e)^T, (e)^T,\right]\left[L^{ab}, L^{ba}, L^{ca},\right]^T \\ &\quad = (e)^T F^{aa}B^{aa} + (e)^T F^{bb}K^{ba}B^{aa} + (e)^T F^{cc}U^{ca}B^{aa} \\ &\quad = (e)^T B^{aa} + (e)^T K^{ba}B^{aa} + (e)^T U^{ca}B^{aa} \\ &+ (e)^T (F^{aa} - I)B^{aa} + (e)^T \left(F^{ba} - I\right)K^{ba}B^{aa} + (e)^T \left(F^{bb} - I\right)U^{ca}B^{aa} \end{aligned} \tag{9}$$

where $(e)^T$ denotes the unit inverse matrix. Then, the multiplier effect, spillover effect, and feedback effect are as follows:

1) Intraregional multiplier effect of the region a

$$ME^{aa} = (e)^T B^{aa} \tag{10}$$

Equation 10 denotes the intra-regional multiplier of region a, which represents the economic changes caused by the own inter-industry structure within region a.

2) Interregional spillover effect of the region a

$$SE = (e)^T K^{b^a} B^{aa} + (e)^T U^{ca} B^{aa} \tag{11}$$

where denotes the effect of changes in final demand for a on total output of b, Similarly, $(e)^T U^{ca}B^{aa}$ denotes the effect of a change in final demand in a on the total output of c.

3) feedback effect of the region a

$$\begin{aligned} FE^{aa} &= (e)^T (F^{aa} - I)B^{aa} + (e)^T \left(F^{b^b} - I\right)K^{b^a}B^{aa} \\ &\quad + (e)^T (F^{cc} - I)U^{ca}B^{aa} \end{aligned} \tag{12}$$

Where $(e)^T (F^{aa} - I)B^{aa}$ denotes region a's own economic changes caused by feedback effects, $(e)^T (F^{b^b} - I)K^{b^a}B^{aa}$ denotes the final demand of region a affecting the change in output of region b, which in turn affects the output of region a, $(e)^T (F^{cc} - I)U^{ca}B^{aa}$ represents the same meaning.

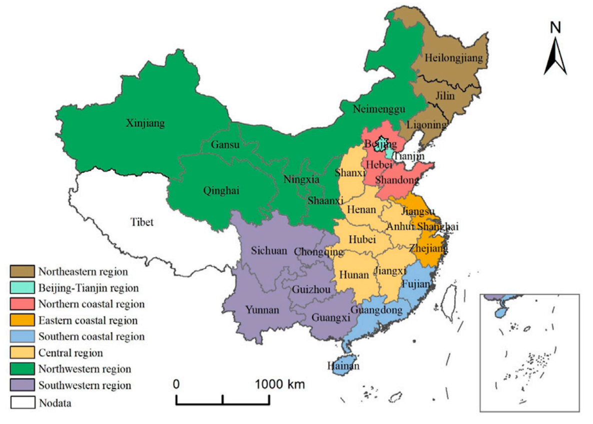


FIGURE 1
The eight regions of China.

2.2 Data sources

China's inter-regional input-output tables of 42 sectors in 2012 and 2017 were obtained from the China Carbon Accounting Database (CEADs) (Zheng, et al., 2020), and provincial input-output tables were published by the National Bureau of Statistics. In this paper, we divide China into eight regions, based on interregional input-output tables for China in 1997, 2002 and 2007 (Figure 1). At the same time, we define the digital industry macroscopically and merge digital manufacturing and digital services into a hybrid industry, which is the object of this research. In the industry-level analysis section, we divided the industries into four industries: primary industry, secondary industry, tertiary industry, and digital industry.

3 Results

3.1 Intra- and inter-industrial effect intensity at industrial level

3.1.1 Intra-industry effect intensity decomposition analysis

The intra-industrial multiplier and feedback effect, and inter-industrial spillover effect intensities of four industrial (primary, secondary, tertiary and digital industry) in three time periods (2007, 2012 and 2017) are presented in Figure 2. In these three time periods, the secondary industry has the maximum value of the intra-industrial multiplier and feedback effect intensities, and the digital industry has the peak of the inter-industrial spillover effect intensities; in contrast, the spillover effect intensity of the primary industry surpasses the tertiary industry only in 2012 and 2017, and the primary industry holds the lowest value of the three types of effects in the rest of the time. This phenomenon implies that the internal correlation mechanism of digital industry exceeds the primary and secondary industries. As an emerging industry, it has a vital role in driving the national economy.

From the perspective of the time dynamic evolution trend, the digital industrial total effect intensity (the sum of the intra-industrial

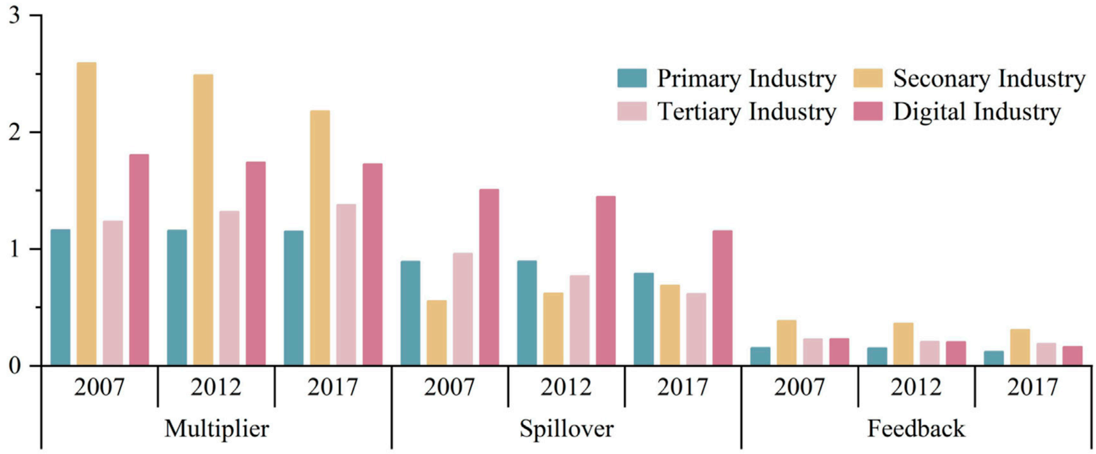


FIGURE 2
The effect intensities of the intra-industry of four industries.

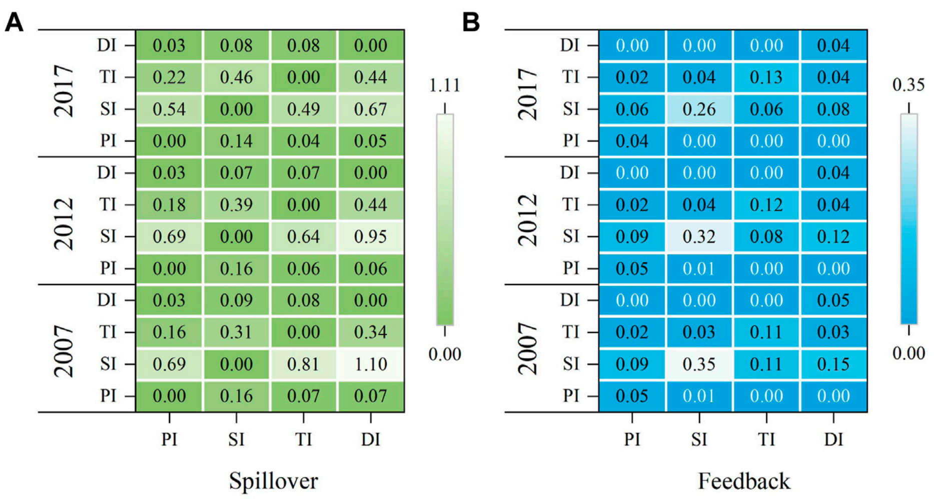


FIGURE 3
The inter-industrial mutual spillover **(A)** and feedback **(B)** effect intensities of four industries.

multiplier and feedback effect intensities, and the inter-industrial spillover effect intensities) showed a downward trend. The reason for this fluctuation may be related to the fact that China's economy has entered a new routine and high-quality development stage of medium and low-speed growth, which has caused a more significant impact on the original extensive industrial development mode. The driving effect of the digital industry on the growth of the national economy depends not only on the endogenous development of the digital industry but also on the smoothness of the interaction mechanism with other industries. For the three major traditional industries, their total effect intensities are similar to the changing trend of the digital, and all show a downward trend, indicating that industrial systems are interdependent in the impact of the national economic system. After the stage of high-quality development, China's economy as a whole has entered a state of medium-low growth, resulting in a weakening of the effects of the inter-industry correlation mechanism and fluctuations in its endogenous development momentum.

3.1.2 Inter-industrial spillover-feedback effect intensity

The inter-industrial mutual spillover-feedback effect intensities of four industries and three time periods are appeared in Figure 3. Frist, for the inter-industrial mutual spillover effect intensities aspect, from the perspective of one industrial demand, the secondary industry has the crest value of spillover effect intensities (2.61, 2.28 and 1.70, respectively), and the digital industry has the least value of intensities (0.20, 0.17 and 0.19, respectively) in these time periods. At the same time, except for the tertiary industry, where the intensity of effects rises by 27.80%,

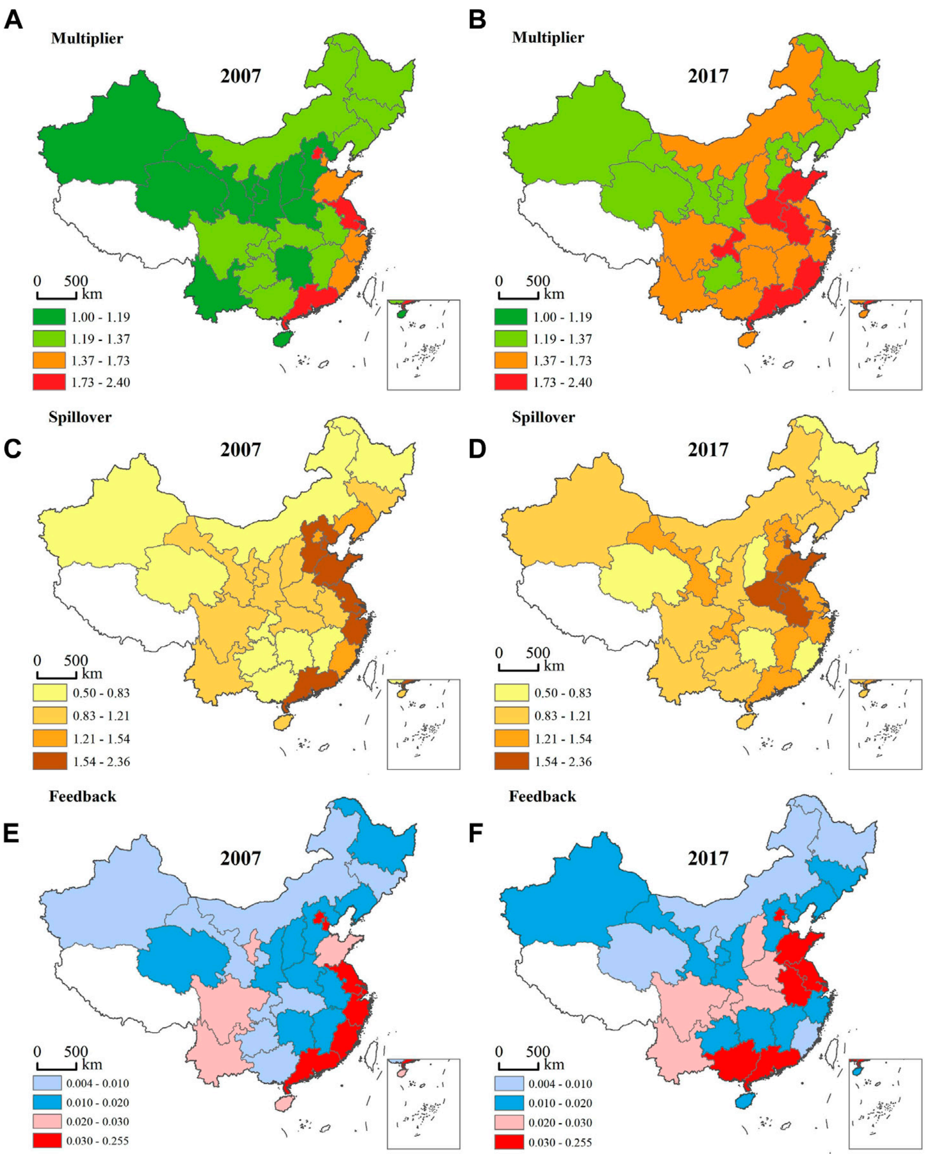


FIGURE 4
The spatiotemporal pattern of the multiplier, spillover, and feedback effect intensities of China's digital industry in 2007(left) and 2017(right).

the effect intensity of the rest of the industries showed a decreasing trend (26.03%, 53.19%, and 5.36%, respectively). From the perspective of one industrial supply, the results are just the opposite of the demand, with the largest values for the digital industry (1.51, 1.45 and 1.15, respectively), and the smallest values for the secondary industry (0.56, 0.62, 0.69, respectively). Similarly, except for the intensity of the effect of the secondary industry increased by 19.18%, while the remaining industries showed a decreasing trend (12.68%, 55.83% and 30.56%, respectively). Second, for the inter-industrial mutual feedback effect intensities aspect, from the perspective of feedback effect intensities of one industry *via* other industries back to itself, the digital industry has the crest value of intensities (0.18, 0.16 and 0.12, respectively). On the time scale, the tertiary industry has increased by 27.18%, while the remaining industries have all decreased. From the perspective of feedback effect intensities of other industries *via* the industry back to other industries, the largest values for the secondary industry (0.35, 0.29 and 0.20, respectively). The value of the secondary industry has increased by 24.04%, while the remaining industries has a decreasing trend.

At the same time, we find that in the structure of inter-industrial mutual spillover-feedback effects, the intensity of the effects of both digital and primary industries is relatively small. Therefore, in the future, the in-depth integration of the digital industry and the primary industry should be further promoted, making it a powerful starting point for the rural revitalization strategy, promoting the integrated development of the rural digital industry and various industries, enriching the rural economic format, and enhancing the coordination of urban and rural development.

3.2 Spatiotemporal variability of effect intensity in 30 Chinese provinces

3.2.1 Spatial variability of intra-industrial effect intensity

The measurement results of the intra-provincial multiplier, spillover, and feedback effect intensities for 30 provinces in China in 2007 and 2017 was presented in Figure 4. Due to the obvious differences in the level of economic development, industrial structure, and the degree of development of the digital industry in various provinces in China, there are also heterogeneities in the intra-provincial multiplier, spillover, and feedback effect intensities of the digital industry. Taking 2017 as an example, Shandong's total effect has the highest value, and the spillover effect intensity reached 2.36, which exceeded the multiplier effect intensity. This result shows that the relationship between industries in Shandong is close, the degree of integration between industries is high, and the growth of digital industries can be cross-transmitted through spillover effects to form the growth of multiple industries. The top ten provinces, except for Anhui and Chongqing, are from the eastern region; The bottom 10 are from the central and western regions. This result shows that the digital industry in the eastern region has improved in scale and efficiency; on the other hand, it has also formed a close connection with other industries. However, the digital industry in the central and western regions has not yet formed a more mature industrial interaction than in the eastern region. Generally, the intensity of the three effects in the developed coastal provinces is stronger than that of economically backward provinces. In the future, the internal structure of the digital industry needs to be further optimized to enhance the resilience of development and cope with the strong impact of the adjustment of the international economic and trade pattern.

After nearly a decade of development, the effect intensity of digital industries in the central and western regions has increased significantly, such as Chongqing, Henan, and.

Anhui. This result is closely related to China's implementation of the strategic guidance of the "Rise of Central China" and the "China Western Development." However, the intensity of the effect in the more economically developed provinces in the coastal region all declined to varying degrees, and this result does not seem to match their economic status. Nevertheless, if we look at the reasons, part of the reason is that with the development of the economy, the economic connection between such regions and the outside world is strengthened, and it is no longer limited to the region itself. The intermediate products of the digital industry required by the inter-region begin to be provided by other regions, and the region is also started supplying intermediate goods to other regions. After taking this factor into account, this result can be reasonably explained to a certain extent. In general, the regions with higher intensity of the effect of digital industry are still concentrated in the southeast of the Hu Huanyong line, and have not yet broken through the line constraint, but show the trend of stronger in the east and gradual release of development potential in the middle and west.

3.2.2 Spatial variability of inter-industry effect intensity

The decomposition results of the intensity of spillover effects of digital industries in 30 Chinese provinces are displayed in Figure 5. In 2017, the intensity of spillover effects between digital and secondary industries was higher than that between digital and primary and tertiary industries in 26 provinces. This result is in line with the average level of spillover effect intensity of digital industries in China. However, the intensity of spillover effects between the digital industry and the tertiary industry in Beijing is twice as strong as that of the secondary industry, which also implies that the degree of integration between the digital industry and the tertiary industry in Beijing is much better than that with the secondary industry. The spillover structure of digital industries was adjusted between 2007 and 2017. The spillover intensity between digital and secondary industries in some developed coastal provinces showed a decreasing trend, such as Guangdong, Zhejiang, Anhui, and Fujian; on the contrary, the intensity of spillover effects between digital industries and both secondary and tertiary industries in inland regions increased. This phenomenon presents that the demand for secondary industries in the eastern coastal provinces is no longer limited to the domestic market, and the spillover effects of digital industries to other industries in the inland regions are more coordinated.

3.3 Intra- and inter-regional effect intensities at regional level

3.3.1 Intra-regional digital economic multiplier effect

The intra-regional multiplier and inter-regional spillover-feedback effects in eight regions (NE, BT, NC, SC, CT, NW and SW) and two periods (2012 and 2017) are presented in Figure 6. Regions SC and EC had larger intra-regional multiplier; NW, NC and CT had larger inter-regional spillover-feedback; In contrast, NW had the smallest intra-regional multiplier effects; SC had the smallest inter-regional spillover-feedback. By and large, all of the intra-regional multiplier effects moved towards a decline over the long haul; inter-regional spillover-feedback effects trended towards an increase. This tendency also indicates that the inter-regional linkage status shows a positive trend and the economic exchanges between regions are no longer confined to the intra-region. Regional markets are gradually opening up, and economic interactions are becoming frequent.

3.3.2 Real inter-regional economic spillover of digital industry

The inter-regional spillover intensities of the digital industry across the 2 years are shown in Table 2. Taking the results in 2017 as an example, NC, CT, and NW were the regions with higher intensity of spillover effects; from a region's demand side, CT, EC, and NC were the regions with higher intensity. Inversely, regions BT and NW had the smallest in demand aspect; regions SC and EC had the smallest in supply aspect. According to the viewpoint of time aspect, the inter-regional spillover intensities of digital industry in the eight region in demand and supply level is to keep growing. Specifically, from 2012 to 2017, the region SC, NW and CT in demand level increased by 156.49%, 60.43% and 54.22%, respectively, and similarly, from 2012 to 2017, the proportions in region NW, CT, BT in supply level were 57.00%, 48.51% and 45.29%, respectively.

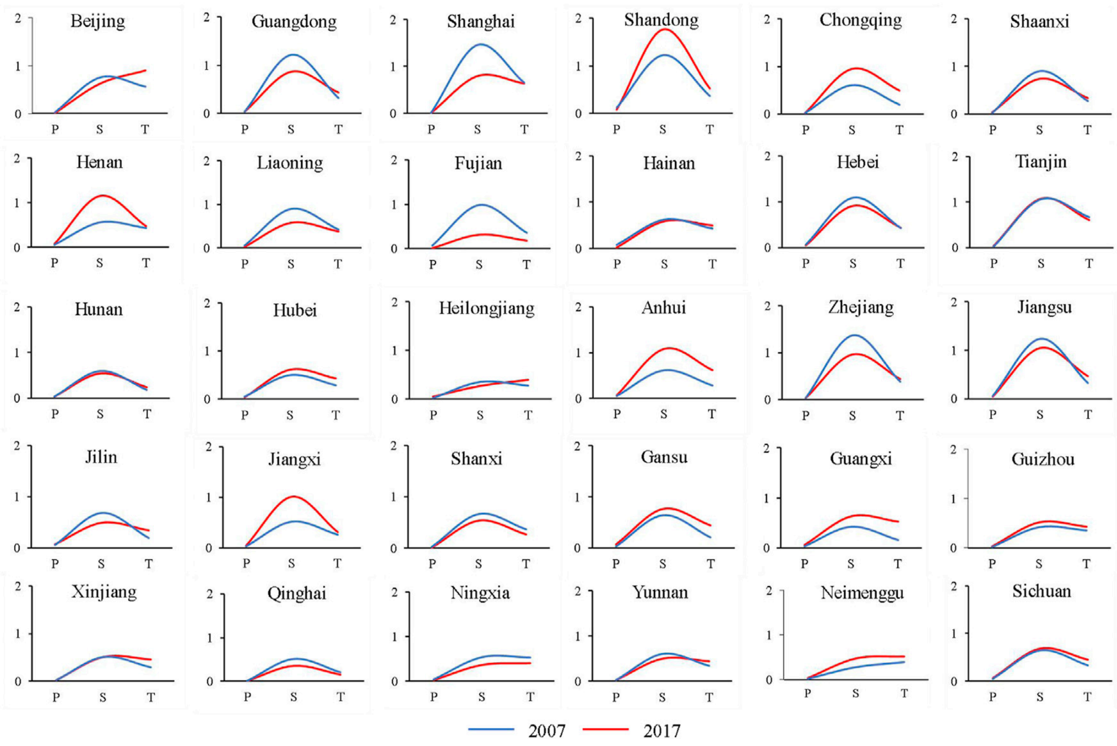


FIGURE 5
Spillover effects of digital industries on traditional tertiary industries by province. Note: "P" denotes the spillover effect of the digital industry on the primary industry; "S" denotes the spillover effect of the digital industry on the secondary industry; "T" denotes the spillover effect of the digital industry on the tertiary industry.

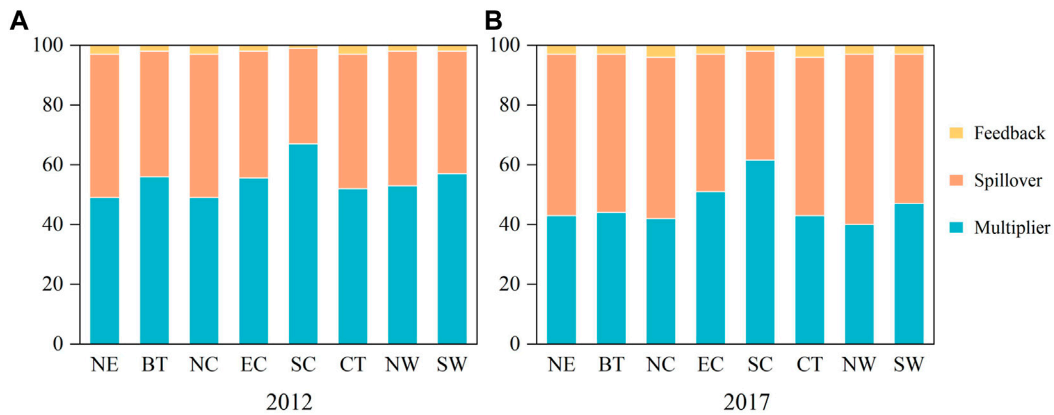


FIGURE 6
Ratio of digital industry spillover-feedback to total effect in eight regions of China. Note: NE-Northeast BT-Beijing-Tianjin NC-Northern coastal EC-Eastern coastal SC-Southern coastal CT-Central region NE-Northwest SE-Southwest.

Therefore, the improvement of the regions is gradually relying on inter-regional interactions and linkages, which indicates that the level of regional integration is being strengthened.

The eight inter-regional mutual economic spillover in two time periods are shown in Figure 7. Overall, whether in 2012 or 2017, BT, EC and SC were digital economic spillover flow export areas while NC, EC, and CT were net economic spillover flow import areas. However, in 2017, BT and SW transform from digital economic spillover flow import areas to economic spillover flow import areas than 2012, and the structure of inter-regional digital economic spillovers is also more balanced. Because, under the strategic guidance of the "Rise of Central China" and the "China Western Development", the role of the central region in "connecting the east and connecting

TABLE 2 The effect intensities of digital industry's intra and interregional economic multipliers in China.

Time	Region	Intra-regional multiplier	Inter-regional spillover								Feedback
			NE	BT	NC	EC	SC	CT	NW	SW	
2012	NE	1.143	0.000	0.041	0.029	0.040	0.020	0.032	0.039	0.030	0.063
	BT	1.298	0.047	0.000	0.033	0.036	0.036	0.039	0.049	0.031	0.038
	NC	1.584	0.083	0.118	0.000	0.093	0.077	0.083	0.093	0.067	0.101
	EC	1.310	0.149	0.181	0.065	0.000	0.145	0.129	0.181	0.128	0.055
	SC	1.402	0.046	0.058	0.017	0.043	0.000	0.042	0.057	0.044	0.029
	CT	1.200	0.088	0.115	0.060	0.115	0.074	0.000	0.113	0.087	0.060
	NW	1.118	0.035	0.042	0.038	0.043	0.021	0.039	0.000	0.031	0.037
	SW	1.413	0.043	0.050	0.030	0.046	0.045	0.041	0.060	0.000	0.054
2017	NE	1.030	0.000	0.053	0.028	0.033	0.020	0.039	0.058	0.039	0.061
	BT	1.169	0.041	0.000	0.029	0.027	0.019	0.043	0.042	0.036	0.067
	NC	1.361	0.066	0.101	0.000	0.062	0.038	0.065	0.092	0.059	0.145
	EC	1.259	0.142	0.264	0.101	0.000	0.113	0.176	0.181	0.158	0.072
	SC	1.322	0.101	0.236	0.080	0.112	0.000	0.162	0.144	0.177	0.045
	CT	1.237	0.139	0.190	0.104	0.134	0.112	0.000	0.216	0.157	0.117
	NW	1.022	0.044	0.057	0.036	0.039	0.025	0.056	0.000	0.049	0.071
	SW	1.275	0.062	0.079	0.039	0.048	0.052	0.066	0.093	0.000	0.078

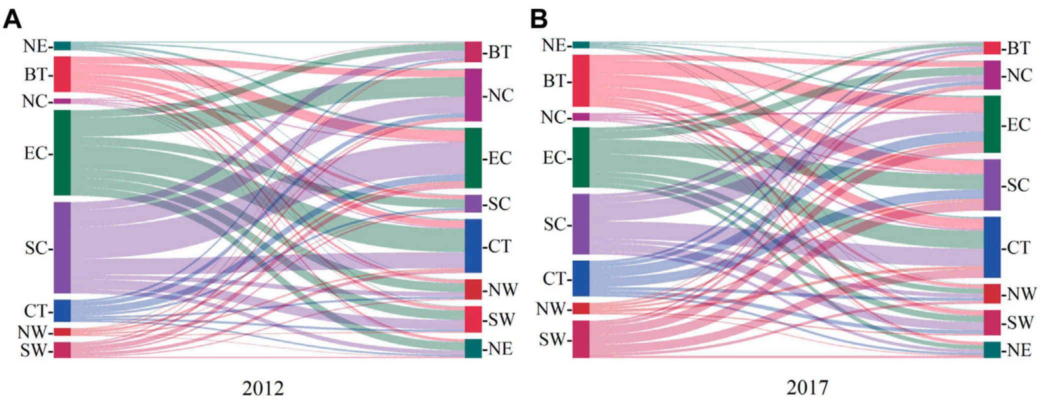


FIGURE 7
Mutual economic spillover of digital industries in eight regions of China. Note: "NE-" indicates the direction in which the northeast region overflows, "-NE" indicates the direction in which other regions spill into the northeast, and the rest have similar meanings.

the west" is becoming more and more apparent. On the whole, it can be seen that spatial accessibility significantly impacts the inter-regional digital economic spillover. This influence is reflected in two aspects. First, the economic spillover between neighboring regions is more pronounced. Second, the region with low transportation costs is more significant. For example, the inter-regional economic spillover with maritime transport conditions is more significant, even if they are not adjacent.

3.3.3 Inter-regional digital economic feedback effect intensities

The intra-regional and the inter-regional digital economic feedback effect intensities are respectively shown in Table 2 and Figure 8. Taking an example 2017, at the intra-region level, regions NC and CT had the largest intra-regional feedback effect intensity; Region SC and NE had the smallest intra-regional feedback effect intensities. Except for the region NE, the remaining seven regions show an increasing trend over time.

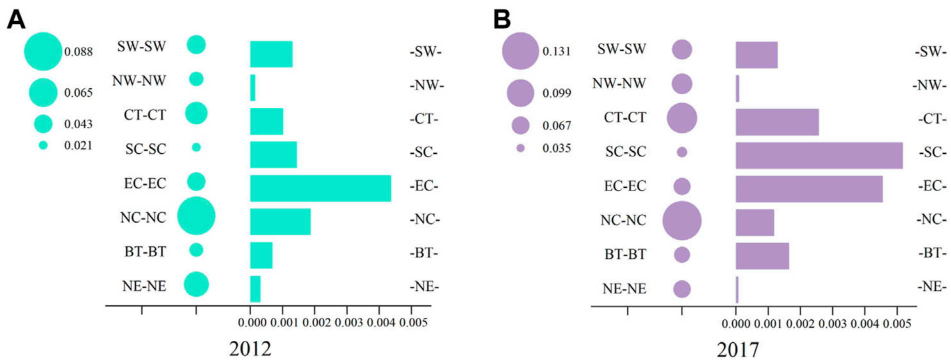


FIGURE 8
The inter-regional digital economic feedback effect intensities from one region's own reaction and other regions' own reaction. Note: "NE-NE" refers to the feedback effect intensities from one region's own reaction, and "-NE-" refers to the feedback effect intensities from other regions' own reaction, and the rest have similar meanings.

The region CT, NW and BT in increased by 96.02%, 95.28% and 78.24% from 2012 to 2017, respectively. From the standpoint of interregional feedback effect intensities of one region *via* other regions back to itself, the peak and least values are region NC and region SC in 2012 and 2017. From the standpoint of interregional feedback effect intensities of other regions *via* the region back to other regions, the peak and least values are region SC and region NE in 2017. In terms of time, all eight regions maintain an upward trend in one region *via* other regions back to itself aspect, and the region NW, CT and BT increasing by 104.87%, 95.26% and 68.54%; however, in other regions *via* the region back to other regions aspect, the trend stays up in some areas and down in others, the region SC, CT, BT and EC respectively increasing by 261.40%, 154.48%, 141.74% and 4.28%, the region NE NC NW SW decreasing by 81.88%, 37.54%, 38.45% and 1.97% respectively.

4 Discussions

4.1 Potential uses of the results

The experience of developed countries shows that the more developed the economy is, the more significant the resource allocation efficiency of digital industry is, and the closer the industrial relationship between digital industry and other industries is. At present, the intra-industry multiplier effect of China's digital economy is stronger than the inter-industry spillover effect, and economic growth is mainly achieved through self-circulation. Therefore, it is necessary to further optimize the economic structure of the digital industry, focus on the coordinated development of the digital industry and the traditional industry, establish and improve the industrial system, so that it can bring greater economic growth momentum by improving labor productivity and promoting industrial technological innovation. In addition, China is in the critical period of industrial restructuring and supply-side reform, and is facing strong transformation needs. The digital industry needs innovation at the technical and model levels to promote the vertical development of the digital industrial chain and improve the modernization level of the industrial chain, in order to play a role in promoting the real economy.

The spatial variability of China's digital industries effect intensities is excellent. To a certain extent, it also reflects the problem of unbalanced regional economic development. The effect intensity is related not only to the digital industry itself but also to the local industrial structure. The digital industries in the eastern region have a strong spillover effect. The digital industries in the central and western regions are in a rapid expansion stage, and there is no mature industrial interactive relationship with basic industries. For the eastern region, we should start with the optimization of industrial structure and industrial integration, encourage the model innovation of the digital industry, promote the integration of traditional industries and digital industries in industrial chain and industrial agglomeration, so that the digital industry can lead and drive the optimization and upgrading of the traditional industry structure, enhance the enhancement Sustainable development capabilities in the region. For the central and western regions, it should be placed in the first place in the development of the market, developing a digital industry with local characteristics according to local conditions, promoting the optimization and upgrading of the industrial structure, and the transformation of economic growth methods.

China's regional digital industry development is very uncoordinated. The provinces with more developed digital industries do not show a higher degree of internal openness, and most of the digital industries are dominated by internal circulation, and the external export of digital industries in each region is significantly insufficient. For regions with backward economic development, the low level of digital industry development directly restricts the local economic growth rate, and the intra-regional circulation of digital industry in developed regions not only aggravates the unevenness of China's regional development, but also fails to achieve the optimal allocation of resources. If this gap is to be narrowed, the interaction between regions needs to be strengthened, with strength leading to weakness. Therefore, more support should be given to the central and western regions in terms of policies and financial resources, and the mining of digital resources in the central and western regions should be expanded. At the same time, the central and western regions should also firmly grasp the strategic opportunities, strengthen regional cooperation with the eastern region, and learn from the advanced experience of digital industry development in the eastern region. Further breaking the market barriers between regions and promoting the economic development of China's three growth poles, will bring a vital source of power to China's overall economic growth, especially in the central and western regions.

4.2 The limitation and future prospects

In this paper, the spillover-feedback effects of the digital industry with other industries are measured in detail, but the internal mechanism and the influencing factors are not analyzed in depth. In the current study, the research on the spillover-feedback effects of industries exists more in the description of the current situation, and the research on the internal mechanism and influencing factors needs to be studied more deeply with the help of other modeling tools other than input-output models.

Second, this paper analyzes the spatially differentiated characteristics of the spillover-feedback effects of digital industries in 30 Chinese provinces, but the specific reasons for the differences in these characteristics are not further analyzed; whether the spatially differentiated characteristics affect the regional economy or the development of the regional economy affects the characteristics are questions worth further study in the future, which will provide a stronger explanation for understanding the promotion of digital industries to economic growth.

Finally, this paper finds through research that the spillover effect of China's inter-regional digital industry is weak, and how to transform the current inter-industry spillover within the digital industry region into inter-regional spillover is a topic of great practical significance.

5 Conclusion

Based on the input-output model, this study analyzes the dynamic evolution characteristics of digital industry linkages at the industry level and compares the interactions between digital industry and the three major industries; at the provincial level, it shows the spatial and temporal differences and characteristics of digital industry linkages among 30 provinces in China and clarifies the different positions of digital industry in the economic development of each province; at the regional level, it analyzes the inter-regional spillover of digital industry and, as a result, the following important findings are obtained.

First, the autogenous capacity within the digital industry sector is the biggest factor affecting China's digital economy industry, followed by the mutual spillover between industry sectors, while the feedback effect of industry has a weaker impact on the economic system. The spillover effect of the digital industry is the highest among the four industries, and the multiplier and spillover effects of the industries are also relatively balanced, while the secondary and tertiary industries rely more on their own endogenous multiplier effects, although this structural difference is gradually converging, and the mutual spillover between industries is becoming more and more significant.

Secondly, the differentiation of the industrial association structure of digital industry in each province is outstanding, and the degree of industrial integration in economically developed provinces is higher and is generally stronger than that in economically backward provinces. However, the regional differences are gradually narrowing, because the degree of industrial integration within the economically backward provinces is supported by policies showing a gradual upward trend, while the economically developed is subject to the impact of foreign markets showing a downward trend.

Third, overall, it seems that the external supply of digital industry in each region is very low, and the vast majority of digital products in each region of China are circulated internally within the region, with relatively weak inter-regional exchanges, and the external export of digital industry in each region is obviously insufficient. The intra-regional digital industry is most closely connected within the northern coastal region, and the northeastern region is the weakest. At the same time, the coastal region shows a decreasing trend, while the inland region shows an increasing trend; the inter-regional spillover is the highest in the Beijing-Tianjin region, the lowest in the eastern coastal region. The inter-regional spillover and feedback effect in the inland region keep increasing, but the coastal region shows a decreasing trend.

In summary, the development of the digital economy in the less developed regions of China, such as the Northeast, Northwest, and Southwest China, is increasingly being influenced by other regions; in contrast, the ability of coastal regions to drive digital economic growth in other regions of China is weakening. It further indicates that with the deepening integration of different regional markets, the development of China's regional economy has gradually shifted from relying on local final products to relying on external regional final products, and the inter-regional spillover has become an important driving force source for China's regional economic development that cannot be ignored.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

ZM, conceptualization, methodology, software, visualization; XN, data curation, methodology, software, visualization, writing-original draft; WM, conceptualization, methodology, supervision, writing- reviewing and editing; YK, methodology, software, visualization; WX, methodology, software, visualization.

Funding

This work was supported by the National Natural Science Foundation of China (grant number 42201302) and the "Double First-Class" University Construction Project of Lanzhou University (grant number 561120213).

Acknowledgments

The author is grateful for the data support from the China Carbon Accounting Database (CEADs) and the National Bureau of Statistics and the very valuable comments from the anonymous referees.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Bahrini, R., and Qaffas, A. A. (2019). Impact of information and communication technology on economic growth: Evidence from developing countries. *Economies* 7, 21. doi:10.3390/economies7010021

Bowman, J. P. (1996). *The digital economy: Promise and peril in the age of networked intelligence*. USA Academy of Management Perspectives. doi:10.1016/S0099-1333(96)90098-1

Bressanelli, G., Adrodegari, F., Perona, M., and Saccani, N. (2018). Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability* 10, 639. doi:10.3390/su10030639

Bulturbayevich, M. B., and Jurayevich, M. B.Law and Education (2020). The impact of the digital economy on economic growth. *Int. J. Bus.* 1, 4–7. doi:10.56442/ijble.v1i1.2

Bunje, M. Y., Abendin, S., and Wang, Y. (2022). The multidimensional effect of financial development on trade in Africa: The role of the digital economy. *Telecommun. Policy* 46, 102444. doi:10.1016/j.telpol.2022.102444

Chen, Y., Huang, K., Hu, J., Yu, Y., Wu, L., and Hu, T. (2021). Understanding the two-way virtual water transfer in urban agglomeration: A new perspective from spillover-feedback effects. *J. Clean. Prod.* 310, 127495. doi:10.1016/j.jclepro.2021.127495

Ding, C., Liu, C., Zheng, C., and Li, F. (2021). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. *Sustainability* 14, 216. doi:10.3390/su14010216

Gong, Q. H. a. Y., and Gong, Y. (2022). The impact of the quality of digital economy development on manufacturing in the yangtze river delta city cluster. *J. Econ. Finance Account. Stud.* 4, 52–63. doi:10.32996/jefas.2022.4.3.6

Hu, J., Huang, K., Ridoutt, B. G., Yu, Y., and Xu, M. (2019). Measuring integrated environmental footprint transfers in China: A new perspective on spillover-feedback effects. *J. Clean. Prod.* 241, 118375. doi:10.1016/j.jclepro.2019.118375

Jiang, M., and Jia, P. (2022). Does the level of digitalized service drive the global export of digital service trade? Evidence from global perspective. *Telematics Inf.* 72, 101853. doi:10.1016/j.tele.2022.101853

Jorgenson, D. W., and Vu, K. M. (2016). The ICT revolution, world economic growth, and policy issues. *Telecommun. Policy* 40, 383–397. doi:10.1016/j.telpol.2016.01.002

Kurniawan, T. A., Maiurova, A., Kustikova, M., Bykovskaia, E., Othman, M. H. D., and Goh, H. H. (2022). Accelerating sustainability transition in st. Petersburg (Russia) through digitalization-based circular economy in waste recycling industry: A strategy to promote carbon neutrality in era of industry 4.0. *J. Clean. Prod.* 363, 132452. doi:10.1016/j.jclepro.2022.132452

Latif, Z., mengke, Y., DanishLatif, S., Ximei, L., Pathan, Z. H., Salam, S., et al. (2018). The dynamics of ICT, foreign direct investment, globalization and economic growth: Panel estimation robust to heterogeneity and cross-sectional dependence. *Telematics Inf.* 35, 318–328. doi:10.1016/j.tele.2017.12.006

Li, Y., Luo, E., Zhang, H., Tian, X., and Liu, T. (2018). Measuring interregional spillover and feedback effects of economy and CO2 emissions: A case study of the capital city agglomeration in China. *Resour. Conservation Recycl.* 139, 104–113. doi:10.1016/j.resconrec.2018.07.021

Lioutas, E. D., Charatsari, C., and De Rosa, M. (2021). Digitalization of agriculture: A way to solve the food problem or a trolley dilemma? *Technol. Soc.* 67, 101744. doi:10.1016/j.techsoc.2021.101744

Liu, X., Latif, Z., DanishLatif, S., and Mahmood, N. (2021a). The corruption-emissions nexus: Do information and communication technologies make a difference? *Util. Policy* 72, 101244. doi:10.1016/j.jup.2021.101244

Liu, X., Latif, Z., Xiong, D., Yang, M., Latif, S., and Wara, K. U. (2021b). The nexus among globalization, ICT and economic growth: An empirical analysis. *J. Inf. Process. Syst.* 17, 1044–1056. doi:10.3745/JIPS.04.0227

Liu, L., Ding, T., and Wang, H. (2022). Digital economy, technological innovation and green high-quality development of industry: A study case of China. *Sustainability* 14, 11078. doi:10.3390/su141711078

Lv, C., Song, J., and Lee, C.-C. (2022). Can digital finance narrow the regional disparities in the quality of economic growth? Evidence from China. *Econ. Analysis Policy* 76, 502–521. doi:10.1016/j.eap.2022.08.022

Ma, D., and Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* 145, 801–813. doi:10.1016/j.jbusres.2022.03.041

Miller, R. (1963). Comments on the "General Equilibrium" model of professor moses. *Metroeconomica* 15, 82–88. doi:10.1111/j.1467-999X.1963.tb00301.x

Ning, Y., Miao, L., Ding, T., and Zhang, B. (2019). Carbon emission spillover and feedback effects in China based on a multiregional input-output model. *Resour. Conservation Recycl.* 141, 211–218. doi:10.1016/j.resconrec.2018.10.022

Oliner, S. D., and Sichel, D. E. (2000). The resurgence of growth in the late 1990s: Is information technology the story? Economic perspectives. *J. Econ. Perspect.* 14, 3–22. doi:10.1257/jep.14.4.3

Popkova, E. G., De Bernardi, P., Tyurina, Y. G., and Sergi, B. S. (2022). A theory of digital technology advancement to address the grand challenges of sustainable development. *Technol. Soc.* 68, 101831. doi:10.1016/j.techsoc.2021.101831

Pradhan, R. P., Arvin, M. B., Nair, M., Bennett, S. E., and Bahmani, S. (2019). Short-term and long-term dynamics of venture capital and economic growth in a digital economy: A study of European countries. *Technol. Soc.* 57, 125–134. doi:10.1016/j.techsoc.2018.11.002

Pyatt, G., and Round, J. (1979). Accounting and fixed price multipliers in a social accounting matrix framework. *Econ. J.* 89, 850–873. doi:10.2307/2231503

Round, J. I. (1985). Decomposing multipliers for economic systems involving regional and world trade. *Econ. J.* 95, 383–399. doi:10.2307/2233216

Simionescu, M. (2022). The insertion of economic cybernetics students on the Romanian labor market in the context of digital economy and COVID-19 pandemic. *Mathematics* 10, 222. doi:10.3390/math10020222

Singh, S., Sharma, M., and Dhir, S. (2021). Modeling the effects of digital transformation in Indian manufacturing industry. *Technol. Soc.* 67, 101763. doi:10.1016/j.techsoc.2021.101763

Song, M., Zheng, C., and Wang, J. (2021). The role of digital economy in China's sustainable development in a post-pandemic environment. *Enterp. Inf. Manag.* 35, 58–77. doi:10.1108/JEIM-03-2021-0153

Stiroh, K. J. (2002). Information technology and the US productivity revival: What do the industry data say? *Am. Econ. Rev.* 92, 1559–1576. doi:10.1257/000282802762024638

Stone, R. J. S. (1985). The disaggregation of the household sector in the national accounts. *Social accounting matrices: A basis for planning*, 145–185.

Su, J., Su, K., and Wang, S. (2021). Does the digital economy promote industrial structural upgrading?—a test of mediating effects based on heterogeneous technological innovation. *Sustainability* 13, 10105. doi:10.3390/su131810105

Sun, L., and Wang, Y. (2021). Global economic performance and natural resources commodity prices volatility: Evidence from pre and post COVID-19 era. *Resour. Policy* 74, 102393. doi:10.1016/j.resourpol.2021.102393

Wang, Q., and Zhang, F. (2021). What does the China's economic recovery after COVID-19 pandemic mean for the economic growth and energy consumption of other countries? *J. Clean. Prod.* 295, 126265. doi:10.1016/j.jclepro.2021.126265

Wang, J., Dong, K., Dong, X., and Jiang, Q. (2021). Research on the carbon emission effect of the seven regions along the Belt and road—Based on the spillover and feedback effects model. *J. Clean. Prod.* 319, 128758. doi:10.1016/j.jclepro.2021.128758

Wang, X., Wang, L., Zhang, X., and Fan, F. (2022). The spatiotemporal evolution of COVID-19 in China and its impact on urban economic resilience. *China Econ. Rev.* 74, 101806. doi:10.1016/j.chieco.2022.101806

Xiao, X.-Y. (2020). Research on the integration of digital economy and real economy to promote high-quality economic development. Proceeding of the 2020 Management Science Informatization and Economic Innovation Development Conference (MSIEID). December 2020, Guangzhou, China. IEEE, 8–11.

Xue, Y., Tang, C., Wu, H., Liu, J., and Hao, Y. (2022). The emerging driving force of energy consumption in China: Does digital economy development matter? *Energy Policy* 165, 112997. doi:10.1016/j.enpol.2022.112997

Zhang, Y.-J., and Zhang, K.-B. (2018). The linkage of CO2 emissions for China, EU, and USA: Evidence from the regional and sectoral analyses. *Environ. Sci. Pollut. Res.* 25, 20179–20192. doi:10.1007/s11356-018-1965-7

Zhang, W., Zhang, T., Li, H., and Zhang, H. (2022). Dynamic spillover capacity of R&D and digital investments in China's manufacturing industry under long-term technological progress based on the industry chain perspective. *Technol. Soc.* 71, 102129. doi:10.1016/j.techsoc.2022.102129

Zhang, Y. (2017). Interregional carbon emission spillover–feedback effects in China. *Energy Policy* 100, 138–148. doi:10.1016/j.enpol.2016.10.012

Zheng, H., Zhang, Z., Wei, W., Song, M., Dietzenbacher, E., Wang, X., et al. (2020). Regional determinants of China's consumption-based emissions in the economic transition. *Environ. Res. Lett.* 15, 074001. doi:10.1088/1748-9326/ab794f

TYPE Original Research
PUBLISHED 18 April 2023
DOI 10.3389/fenvs.2023.1166080

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Institute of Economics Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Ekaterina Wegner-Kozlova,
Institute of Economics of the Ural Branch of the Russian Academy of Sciences, Russia
Francisco Diniz,
University of Trás-os-Montes and Alto Douro, Portugal
Otilia Manta,
Romanian Academy, Romania
Karl Weinmayer,
MODUL University Vienna, Austria

*CORRESPONDENCE
Yuying Gao,
gyy3990@pdsu.edu.cn

RECEIVED 14 February 2023
ACCEPTED 03 April 2023
PUBLISHED 18 April 2023

CITATION
Chen L, Mao C and Gao Y (2023), Executive compensation stickiness and ESG performance: The role of digital transformation.
Front. Environ. Sci. 11:1166080.
doi: 10.3389/fenvs.2023.1166080

Executive compensation stickiness and ESG performance: The role of digital transformation

Lifeng Chen[1], Chuanmei Mao[1] and Yuying Gao[2]*

[1]School of Business, Hangzhou City University, Hangzhou, Zhejiang, China, [2]School of Economics and Management, Pingdingshan University, Pingdingshan, Henan, China

A growing number of institutional investors have realized that environmental, social, and governance (ESG) performance has become financial in the long run, but the implementation of ESG approaches at the enterprise's executive level remains insufficient. Furthermore, urgent attention needs to be paid to the full application of digital solutions for resource allocation and sustainable development. We have directed this research interest toward searching for potential approaches to sustainable digital transformation for the environment. Encouraged by the asymmetric effect between executive compensation stickiness (ECS) and ESG goals, executives are more willing to improve the ESG indices by digital transformation (DT) activities. This study employs 18,098 observations from Chinese A-share listed companies to examine the impact of ECS on ESG indicators. Our results show that ECS can significantly improve the ESG scores, whereas DT played a partial mediating role within this promotion. We further examined this relationship by the bootstrap and Sobel methods and found that all empirical results are robust and credible. Our findings provide more practical enlightenment at the management aspect for improving environmental performance through digital transformation.

KEYWORDS

executive compensation stickiness, ESG performance, digital transformation, bootstrap, Sobel

1 Introduction

The world has witnessed many changes associated with industrial development and technological transformation. Since Agenda 2030's Sustainable Development Goals (SDGs), proposed by the United Nations 2015, emphasize the role of digital technology in the enhancement of sustainability, digital transformation (DT) has become a necessary prerequisite for achieving SDCs (Camodeca and Alex, 2021). Digital transformation is not only a technological change but also highly related to the value proposition, business model, production process, and employment style in the long run (Matt et al., 2015). Here, the environmental, social, and governance (ESG) concept is a productive solution to accelerate the transition to a more sustainable future by a digital informational approach. Nowadays, ESG is receiving much attention from businesses, investors, and regulators due to the global ESG investment market's rapid growth (Zheng et al., 2022). So, investors have started to give more importance to investigating the link behind non-financial information. ESG scores and ratings can be used to evaluate a firm's commitment to sustainable business practices. However, the validity of ESG performance is still debatable in the current literature, with most of these studies concentrating on the effects of ESG performance in developed economies (Khan, 2022). Nevertheless, there is a lack of studies investigating the function of ESG performance and its connection to digital transformation in emerging economies. Addressing the significance of integrating sustainability strategies into digital transformation roadmaps entails thinking beyond profit and placing social and environmental considerations on the same footing with financial objectives.

Since China's manufacturing industries and economic volume reached first and second in the world, respectively, in 2010, how to maintain the stability of China's economy has become the major developmental strategy of China. In the new stage of high-quality economic development, efficient and equitable development has also become the main objective for all enterprises in China. In this context, the management of organizational elements for successful digital transformation and green governance has therefore become a key research topic. Owing to the characteristics of long periodicity, high uncertainty, and strong professionalism, digital technology-driven transformation is not limited to the implementation and operation of new technologies. Today's digital transformations must be purpose-driven, offering value to all stakeholders as a prerequisite for organizational success. There are increasing interests in how ESG and DT criteria can integrate into the executive compensation contract, while executives are assumed to have the main responsibility for daily operations and management. Traditional agency theory emphasizes the role of pay-for-performance to align the interests of management and shareholders (Jensen and Murphy, 1990; Core et al., 1999), controlling executive compensation by earning management (Ali et al., 2022). Meanwhile, the literature on executive compensation is more concerned with pay-arrangement features rather than effective incentives, reflecting a "rent seeking" effect (Blanchard et al., 1994; Yermack, 1997; Bertrand and Mullainathan, 2001). Furthermore, executive compensation and corporate performance present a "downward stickiness" impact, where executive compensation does not decrease to the same extent as the firm's performance declines (Adut et al., 2003; Garvey and Milbourn, 2006; Jackson et al., 2008; Gao et al., 2011). With the continuous improvement in the compensation contract, executive compensation stickiness (ECS) is proposed to effectively measure the marginal administrative expenses with corporate performance (Lin et al., 2013; Cordeiro et al., 2016.; Luo et al., 2016; Zhang and Gao, 2017). However, the existing literature on ECS is more focused on corporate performance with less consideration of the multi-dimensional mechanisms, including environmental and social aspects. Moreover, the importance of digital transformation on corporate governance and green indicators is also unclear. This paper aims to narrow this research gap between ECS and ESG indicators in view of digital transformation, addressing an empirical approach that contributes to harmonious and sustainable development.

The rest of this paper is organized as follows: Section 2 explains the literature review and hypothesis development; Section 3 presents the methodology, which includes sample selection and data sources, the definition of all variables, model construction, and hypothesis development; Section 4 demonstrates the empirical findings based on several regression analyses and robustness tests, including Sobel, bootstrap, replacing variable, and endogeneity approaches; Section 5 concludes the study with a summary of our findings, policy enlightenment, and limitations with regard to future prospects.

2 Hypothesis development

2.1 ECS and ESG performance

Investment on environmental and social responsibilities would waste administrative resources, increase extra expenses, and bring more negative management factors that damage shareholders' interests (Garcia & Orsato, 2020). Moreover, performance-based payments may induce a lower level of motivation in managers for long-term investment (Cheng, 2004), so they may pursue short-term accounting performance and abandon the ESG developmental strategy in consideration of managers' interests. However, with the continuous improvement in the compensation contract, enterprises have experienced asymmetric changes between managers' compensation and stakeholders' response (Jackson et al., 2008). Particularly, for institutional investors who are more focused on the long-term interests and their participation in corporate governance, this information asymmetry between executive compensation and the governance layer can also be reduced (Hong, 2022). When executives' performance declines, those shareholders generally have a "failure tolerance" mentality, imposing more pressure on senior executives (Lai and Leng, 2021). The existence of institutional investors has inhibited executive compensation stickiness (ECS) (Yi et al., 2010), and this fact has been widely accepted in the field of environmental behavior research, whereby sustainable and environmentally conscious behavior could be further examined (Ali et al., 2023; Gansser and Reich, 2023). In general, institutional investors pay more attention on company's life cycle and executive compensation stickiness, pushing enterprises to improve the long-term performance including all ESG dimensions. Thus, we propose the following hypothesis:

Hypothesis 1: ECS has a positive effect on the ESG performance.

2.2 ECS and DT

Studies on digital transformation (DT) could be traced back to a dozen years, and they have attracted greater scientific interests recently. At present, digital transformation has become a "common buzzword" both in the business and academic community. Digital transformation is a comprehensive transformation process, which involves all aspects from business philosophy to corporate culture, from production to sales, and from managers to staff (Ivancic et al., 2019). Moreover, digital transformation is also a continuous process of climbing the scale of digital maturity by employing digital and other technologies along with organizational practices to create a digital culture (He and Liu, 2019). This digital maturity enables the company to provide better services, gain competitive advantages, and respond to the external environment. Meanwhile, entrepreneurial orientation further encourages managers to gain the competitive advantages of digital transformation (Sousa and Rocha, 2019; Weber et al., 2022). Ultimately, companies that succeed in employing digital transformation are generally more profitable, enjoying better returns on assets (Westerman et al., 2012), improving the operation efficiency of business structures (Ghosh et al., 2014), and reducing the tendency toward opportunism-driven earning management (Zhong et al., 2023). However, the digital scene required the necessarily matching of existing administrative architecture and management practice. Digital transformation is deemed to bring with it increasing management risks and challenges that require high levels of leadership and operating capabilities (Zeike et al., 2019). Similarly, the risk-taking characteristics of top managers favor the digital transformation process by allowing the exchange of novel ideas and initiatives on payment (Jiang et al., 2019; Porfírio et al., 2021) and reducing uncertainty in the case of ambiguous digital strategy goals (Ritala et al., 2021). In view of the traditional salary incentive mechanism, the performance-based mechanism would induce senior executives to avoid these managing risks (Manso, 2011), which is often not conducive to the process of digital transformation. Westerman et al. (2014) highlighted that firms need to build high levels of leadership and management to successfully drive the process of digital transformation. In this context, the application of ECS provides a feasible incentive design for the promotion of digital transformation of enterprises (Xu et al., 2018). Therefore, we propose the following hypothesis:

Hypothesis 2: ECS has a positive impact on DT.

2.3 Mediating roles of DT

From the perspective of resource-based theory, resource heterogeneity is the core resource of high profit (Wernerfelt, 1984), where digital technology capability belongs to the intangible resources that are hard to be imitated or replaced (Hu, 2016). Both scarcity and sustainability of digital resources are beneficial for the enterprise to obtain more competitive advantages (Wu et al., 2021), and executives tend to integrate digital transformation activities with sustainable development goals while making data-driven decisions (He and Liu, 2019). Furthermore, digital transformation can also optimize the procurement and production links among enterprises, reducing operating costs and improving corporate governance (Qi et al., 2020). In a word, enterprises often face insufficient resources and incentives for ESG practice, but this situation may change with more core resources brought by digital transformation activities, so digital transformation can reduce the total expenses of ESG performance.

Planned behavior theory proposed by Ajzen (1991) explained the psychological and social aspects of individuals' behavior. In view of the planned behavior theory, Vahid et al. (2023) examined the key managerial micro-foundations of the successful digital transformation process. Their results indicated that the executive management ability can positively impact the information acquisition process, and the managers' ability for obtaining information further enhanced their capacity to exploit new business opportunities from digital transformation. With regard to signal transmission theory, digital transformation can reduce information asymmetry and transaction costs by improving the transparency of information (Xiao et al., 2021) and reducing the interaction costs between enterprises and stakeholders (Zhong et al., 2023). So this digital information is also conducive to improving corporate governance and fulfilling social responsibilities; both are closely related to ESG scores (Qiu and Yin, 2019). Overall, digital transformation can promote the long-term value of enterprises, providing more practical approaches for both ECS and ESG indices. Based on the aforementioned discussion, we propose the following hypothesis.

Hypothesis 3: DT plays a mediating role within the impact of ECS on ESG performance.

2.4 Research framework

Based on the aforementioned theoretical analyses, this study constructs the research framework as shown in Figure 1.

3 Research design

3.1 Variable definition

3.1.1 Dependent variables

In line with the studies of Staiger and Stock, (1997), Xie and Lv (2022), and Gao et al. (2021), this paper uses the Hua Zheng ESG scores as the proxy index of ESG performance. The scope of the Hua Zheng ESG index covers all A-share listed companies in China, assigning ESG ratings at the nine levels ranging from AAA to C (i.e., the ESG score is 1 if the rating is C, the ESG score is 2 if the rating is CC, and the ESG score is 9 if the rating is AAA), where a higher ESG rating indicates a better ESG performance of the enterprise in this scoring system.

3.1.2 Mediator variables

Referring to the practice of Zhao et al. (2021), Wu et al. (2021), and Tu and Yan (2022), we adopt the method of text frequency analysis to construct the digital transformation (DT) score. A higher DT score also reflects a higher degree of digital transformation of an enterprise, and the calculating steps of the DT score are as follows: (1) DT dictionary is first constructed from five dimensions of artificial intelligence, big data, cloud computing, block chain, and technology application; (2) conducting the word frequency analysis of companies based on the DT dictionary by Python software; and (3) obtaining the total DT frequency by the summation of each company and taking the natural logarithm value after adding the word frequency by 1.

3.1.3 Independent variables

Executive compensation stickiness (ECS) is the difference between executive compensation sensitivity when the company's performance increases and decreases (Bu & Wen, 2013). According to the studies by Xu et al. (2018) and Hong (2022), we calculated the mean values of executive compensation and the company's performance sensitivity when the company's performance increases and decreases to acquire the total score of ECS.

3.1.4 Control variables

Referring to previous research studies, this paper introduces the following control variables into our empirical models including total assets (SIZE), total debt (LEV), net income (ROA), fixed assets (FIXED), asset growth (GROW), net profit (LOSS), board directors (BOARD), independent board (INDEP), market value (TOBIN), enterprise nature (SOE), and firms' age (AGE). All data of this study are collected from the RESSET database (RESSET), Wind China financial database (WIND), and China Stock Market & Accounting Research (CSMAR) database. Table 1 reports the specific definition of variables.

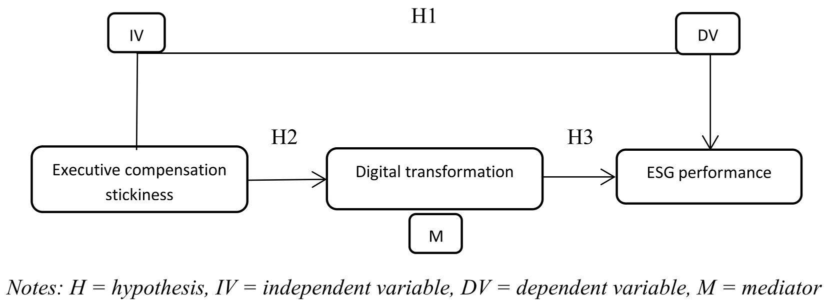


FIGURE 1
Research framework. Notes: H, hypothesis; IV, independent variable; DV, dependent variable; M, mediator.

TABLE 1 Variable definition.

Variable classification	Symbol	Definition
Dependent variable	ESG	Environmental, social, and governance performance
Independent variable	ECS	Executive compensation stickiness
Mediating variable	DT	Degree of digital transformation
Control variables	SIZE	Natural logarithm of the total assets
	LEV	Ratio of total debt to total assets
	ROA	Ratio of net income to total assets
	FIXED	Ratio of fixed assets to total assets
	GROW	Ratio of assets growth in the current year to total assets
	LOSS	Take 1 if net profit for the current year is less than 0; otherwise, take 0
	BOARD	Natural logarithm of numbers of board directors
	INDEP	Natural logarithm of numbers of independent board directors
	TOBIN	Ratio of market price to book values
	SOE	State-owned enterprises = 1; else = 0
	AGE	Natural logarithm of the number of years from the issue year

3.2 Model construction

The following mediating models of the "causal step approach" are adopted to verify our hypotheses H1, H2, and H3, and the model constructions are shown as

$$\mathrm{ESG}_{i,t} = \beta_0 + \beta_1 ECS_{i,t} + \sum Controls_{i,t} + \varepsilon_{i,t}, \quad (1)$$

$$\mathrm{DT}_{i,t} = \beta_0 + \beta_1 ECS_{i,t} + \sum Controls_{i,t} + \varepsilon_{i,t}, \quad (2)$$

$$\mathrm{ESG}_{i,t} = \beta_0 + \beta_1 ECS_{i,t} + \beta_2 DT_{i,t} + \sum Controls_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where "β" represents the estimated coefficient of variables, "$Controls_{i,t}$" represents all control variables, "$\varepsilon_{i,t}$" represents the error term, "t" denotes the year fixed effect, and "i" denotes the individual fixed effect. Model (1) examines H1, which is the impact of ECS on ESG performance. Model (2) examines H2, which is the impact of ECS on DT. Model (3) examines H3, which is the intermediary role of DT.

3.3 Sample selection and descriptive statistics

Our panel data on A-share listed enterprises were selected from the Shanghai and Shenzhen Stock Exchange; data collection began in 2010 because of the abnormal variation caused by the global financial crisis. In order to guarantee the validity of the empirical results, samples with the following characteristics are excluded: (1) samples with ST or ST* treated, (2) samples of the financial industry, and (3) samples with missing variables. Furthermore, we winsorize all continuous variables at the 1% and 99% quantiles to exclude the influence of outliers. Finally, 18,098 observations scanned from 2010 to 2020 were acquired for empirical regression. The descriptive statistics of all variables are shown in Table 2. Table 2 shows that the dependent variable ESG has a mean value of 6.537 and a variance of 1.117, indicating that there is some variation in the ESG performance between firms. The

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	S. D	Min	Max
ESG	18,098	6.537	1.117	3.000	9.000
ECS	18,098	2.703	8.237	−12.013	60.018
DT	18,098	0.094	0.221	0.000	1.000
SIZE	18,098	22.332	1.259	19.525	26.398
LEV	18,098	0.443	0.199	0.027	0.925
ROA	18,098	0.035	0.058	−0.398	0.244
FIXED	18,098	0.227	0.166	0.0015	0.736
GROW	18,098	0.161	0.437	−0.660	4.330
LOSS	18,098	0.092	0.289	0.000	1.000
BOARD	18,098	2.140	0.200	0.000	2.708
INDEP	18,098	0.374	0.053	0.000	0.600
TOBIN	18,098	1.926	1.289	0.000	17.728
SOE	18,098	0.402	0.490	0.000	1.000
AGE	18,098	2.904	0.310	1.386	3.555

independent variable ECS has a mean value of 2.703 and a variance of 8.237, with a minimum value of −12.013 and a maximum value of 60.018, indicating that there are large differences in executive compensation stickiness among the sample firms. The intermediate variable DT, with a mean value of 0.094, a variance of 0.221, a minimum value of 0, and a maximum value of 1.000, indicates that the overall level of digital transformation in the sample companies is low. The means and variances of the control variables are within reasonable limits, and there are no outliers affecting the statistical results.

4 Empirical results

4.1. Correlation analyses

All correlation coefficients of variables are reported in Table 3, and the highest coefficient among them is 0.498, implying that there is no multicollinearity issue in our empirical regression. The results of the correlation coefficient also demonstrate a basic positive association between ECS, DT, and ESG.

4.2 Main tests

We conduct the Hausman test on models (1)–(3) before the regression analysis, and our results show that the p-value is 0.000, where the random effect model with a null hypothesis is rejected. Thus, the fixed effects (FE) model is chosen as the benchmark test with all equations. Table 2 shows that Model (1) examines the relationship between ECS and ESG. The coefficient of ECS on ESG is significant and positive, indicating that the executive compensation stickiness of enterprises can improve their ESG performance, so H1 has been supported. Similarly, the positive relationship between ECS and DT has been examined in Model (2), implying that ECS is the driving factor to optimize the ESG performance, so H2 is also verified. Model (3) introduces the impact of DT, illustrating a joint impact of ECS and DT on ESG. Both regression coefficient of ECS and DT on ESG in Model 3 are still significantly positive, but the coefficient of ECS ($\beta = 0.054$) is decreased by 0.014 in comparison with the coefficient of ECS ($\beta = 0.068$) in Model 1. The decline and the significance of ECS and DT indicate that DT plays an intermediary role between the ECS and ESG performance of enterprises, as shown in Table 4. So, H3 has been verified by mediation after controlling the influence of DT, implying that the digital transformation of enterprise plays a partial mediating effect between the ECS and ESG performance.

These findings indicate that better executive compensation systems can improve the development of enterprises (Zhang and Gao, 2017; Hong, 2022) both from the perspective of digital transformation and ESG ratings. Our results also show that digital transformation has a mediation effect within executive compensation stickiness, promoting ESG indicators (consistent with the findings of Zhao et al., 2021; Camodeca and Alex, 2021; Porfírio et al., 2021). This may be because executive compensation stickiness can strengthen the relationship between enterprises and stakeholders through digital transformation activities, improving performance in terms of environment, society, and governance, to realize the non-economic value creation from the digital transformation progress. All these findings provide more managerial implications at the executive level toward searching for approaches to sustainable digital transformation for the environment.

4.3 Robustness analyses

4.3.1 Sobel test

This paper conducts the Sobel test to verify the mediating effect of digital transformation. Table 5 shows that the Z value of the Sobel test is 26.91 and the p-value is less than 0.05. So the mediating effect of DT has been further verified, and displaying ECS can positively affect ESG performance through the path of digital transformation.

4.3.2 Bootstrap test

In order to make interval estimation, the bootstrap test has become a necessary methodology in mediation effect verification, and the Sobel test is supplemented in this paper. The 95% confidence intervals of indirect effects in Table 6 do not contain “0,” indicating the mediating effect of DT is valid. Thus, our H3 is verified again by both the Sobel and bootstrap approaches, and all results are stable and reliable.

4.3.3 Replacing variables

Referring to the methods of Xu et al. (2018) and Hong (2022), we choose the total remuneration of the top three executives (TRTs) as the substitution variable of ECS. The regression results are shown in Table 7, where TRTs can still positively promote ESG performance with a mediating effect for DT.

10.3389/fenvs.2023.1166080

TABLE 3 Correlation analyses.

	ESG	ECS	DT	SIZE	LEV	ROA	FIXED	GROWTH	LOSS	BOARD	INDEP	TOBIN	SOE	AGE
ESG	1													
ECS	0.639***	1												
DT	0.644***	0.872***	1											
SIZE	0.361***	0.284	0.329***	1										
LEV	0.109***	0.123**	0.118***	0.4979***	1									
ROA	0.107*	0.062	0.073**	0.008***	−0.286***	1								
FIXED	0.017**	−0.067***	−0.039*	0.101***	0.054	−0.020***	1							
GROW	−0.024*	−0.017**	−0.313***	0.028***	0.042***	−0.215***	−0.057***	1						
LOSS	−0.102*	−0.069**	−0.065	−0.055*	0.137***	−0.634***	0.026***	−0.162***	1					
BOARD	0.144**	0.072	0.085	0.264***	0.156***	0.036***	0.157	−0.007	−0.031***	1				
INDEP	−0.0043*	0.0095	0.013	0.0072***	−0.015**	−0.025	−0.045	−0.003	0.010	−0.515***	1			
TOBIN	−0.102**	−0.081	−0.087**	−0.423***	−0.296***	0.142***	−0.088***	0.019	0.003	−0.132***	0.038	1		
SOE	0.268*	0.127***	0.119	0.314***	0.255***	−0.043***	0.208***	−0.063***	−0.008	0.259***	−0.058***	−0.145***	1	
AGE	0.070***	0.082***	0.095***	0.146***	0.117***	−0.048***	−0.036***	−0.052***	0.032***	0.010***	−0.014***	−0.041***	0.133	1

Notes: The t-statistics in parentheses;*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

TABLE 4 Regression analyses.

	M1	M2	M3
Variable	ESG	DT	ESG
ECS	0.068***	0.021***	0.054***
	(7.94)	(7.09)	(5.42)
DT			0.682***
			(11.56)
SIZE	0.091***	0.070***	0.086***
	(6.58)	(3.68)	(6.26)
LEV	−0.389***	−0.012*	−0.381***
	(−7.05)	(−1.66)	(−6.93)
ROA	0.280**	0.038**	0.254*
	(2.09)	(2.05)	(1.91)
FIXED	0.151**	0.007	0.146**
	(2.14)	(0.7)	(2.08)
GROW	0.002	0.069***	0.003
	(−0.16)	(−4.36)	(0.24)
LOSS	−0.012	−0.013	−0.013*
	(−0.52)	(−0.44)	(−0.57)
BOARD	−0.118**	−0.009	−0.124**
	(-2.17)	(−1.16)	(−2.29)
INDEP	−0.304*	−0.004	−0.306*
	(−1.85)	(0.18)	(-1.87)
TOBIN	−0.005	−0.002	−0.005
	(−0.89)	(0.29)	(−0.92)
SOE	−0.044	−0.003	−0.004
	(−0.12)	(−0.06)	(−0.11)
AGE	−0.199***	−0.034***	−0.223***
	(-5.02)	(6.33)	(−5.63)
Cons	5.401***	−0.235***	5.561***
	(18.78)	(-5.97)	(19.39)
Year fix	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes
Obs	18,098	18,098	18,098
$AdjR^2$	0.285	0.263	0.287

Notes: The t-statistics in parentheses;*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

4.3.4 Endogeneity analyses

Considering the endogenous problems such as measurement errors and missing variables, we refer to the method of Liu (2022) and Zheng et al. (2022), employing the average number of DT in the industry and year as the instrumental variable; thus, the instrumental values of IV_DT are obtained, and the calculation formula is as follows:

TABLE 5 Sobel test results.

	Obs	Coef	Std. Err	Z	P>|Z|
Sobel	18,098	0.034	0.002	26.91	0
Goodman-1 (Aroian)	18,098	0.034	0.002	26.91	0
Goodman-2	18,098	0.034	0.002	26.91	0
Proportion of the total effect that is mediated: 0.44					
Ratio of indirect to direct effects: 0.79					

$$IV\_DT_{y,i} = \left(\sum_{1}^{n} DT_{y,i}\right) \Big/ n. \tag{4}$$

Table 8 shows the regression results of the two-stage least squares (2SLS) method by instrumental variables, and the coefficient of first-stage regression of instrumental variables in column (1) is 0.605, so IV_DT passes the significance test at the 1% level. Meanwhile, the Kleibergen–Paap rk LM statistic of 50.03 corresponds to a p-value of 0, indicating that the instrumental variable is identifiable. Moreover, the Cragg–Donald Wald F-statistic of 316.32 is much greater than the Stock–Yogo critical judgment value of 16.38 at the 10% level, so there is no weak instrumental variable issue. The regression coefficients of DT on ESG in columns (2)–(3) are significantly positive at the 1% level, both with and without controlling the impact of ECS. Based on the instrumental variable test, we further estimated dynamic panel data estimation by a two-step generalized method of moment (GMM) regression, and the robustness results of columns (4)–(5) are still consistent with the main test. In general, both results of 2SLS and GMM regression are highly consistent with the baseline regression results of Model 3, further verifying and highlighting the partial mediating effect of digital transformation of listed companies.

5 Discussion

5.1 Practical implication

The previous literature has considered drivers and barriers to digital innovation in the construction industry, including technical and non-technical factors. Since enterprises incline to integrate digital technologies, such as information and communication, into the collaborative transformation of processes, models, and organizations (Wimelius et al., 2021), digital transformation progression offers substantial opportunities to accelerate this technical transition to the new era of the industrial internet of things (IIoT) (Chen et al., 2021). As the digital economy quickly expands, the emphasis has sometimes been on the need to understand the technology being adopted, but evidence suggests that digital transformation is less about technology and more about the transformation process. The indices of digitization and ESG would, therefore, be included in the assessment requirements of enterprise platforms to reduce the negative impact of incentive dislocation (Zhong et al., 2023). In this context, the management of organizational incentives for successful digital transformation and sustainability should be a key research agenda.

TABLE 6 Bootstrap test results.

	Obs	Coef	Std. Err	z	P>|z|	95% conf. interval
Indirect effect	18,098	0.034	0.001	25.86	0	(0.032, 0.037)
Direct effect	18,098	0.043	0.003	16.22	0	(0.038, 0.049)

Notes: Sampling number = 1,000.

TABLE 7 Results of the replacing variable.

Variable	M1	M2	M3
	ESG	DT	ESG
TRT	0.027***	0.035**	0.019**
	(3.16)	(2.00)	(2.51)
DT			2.372***
			(5.83)
Controls	Yes	Yes	Yes
Year fix	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes
Obs	18,098	18,098	18,098
AdjR^2	0.153	0.227	0.235

Notes: The t-statistics in parentheses;*p < 0.1, **p < 0.05, and ***p < 0.01.

From the perspective of enterprises, corporate responses rely upon managers' insistence regarding the material benefits of adjusting to and scoring high on ESG ratings and their alignment with corporate sustainability (Chen et al., 2022). Corporate sustainability is a strategic approach, aiming to create stakeholder values as critical for creating goodwill for businesses, enhancing opportunities, and managing the risks due to economic, social, and environmental developments. Therefore, investors are trying to chart the course of the future through ESG orientation, and ESG considerations should be integrated into the company's overall digital strategy. This may involve identifying digital opportunities that align with ESG priorities, such as developing products or services that help customers reduce their carbon footprint or using digital platforms to engage with stakeholders on social issues. Considering that digital transformation is also a key aspect of an organization's survival strategy, enterprise management and leadership has become particularly important if the change has to be successful. Moreover, executives may need to conduct their digital transformation activities with sustainability goals if their decisions are made by digital information. Enterprises would find it easier to realize resource integration and evoke the internal governance vitality by digital transformation, thus improving the information transparency and total ESG performance. Additionally, integrating quantitative data on ESG performance as a part of bonus evaluation systems can further promote the enthusiasm of senior executives, and the management committee should also support the senior executives with a long-term perspective. In general, successful digital transformation and ESG performance should therefore focus on executive compensation stickiness.

From the perspective of the government, China's government should give priority to the impact on the environmental quality, while introducing external capital that would promote the transformation of domestic resources into green and low-carbon industries (Chen et al., 2023). Digital transformation in the industry is part of the overall digitalization process, but it accounts for the greatest impact on the environmental quality. The government should provide more environmentally friendly policies to support the green-oriented market and improve the protection of green products. Government and social organizations could establish an official ESG quality evaluation system and information-release mechanism to reward or punish enterprises in view of ESG indices. Relevant departments can also improve the administrative procedure of digital transformation, and assist enterprises to avoid potential risks within the process. In the context of better environment and digital transformation policy, new business models of green transformation would continue to emerge. Finally, it is important to consider the broader societal impact of digital transformation. This may involve assessing the impact of digital technologies on labor markets, the environment, and social inequality. Governments should take steps to mitigate any negative impacts and ensure that digital transformation is aligned with broader societal goals.

5.2 Future research

As this study's limitation and future direction, we focused on Chinese listed firms, so future studies can extend the analysis to non-listed firms (i.e., unicorn enterprises or family businesses). Moreover, there should be a clear focus on identifying the indicators that may hamper or promote the integration of digital progression and SDGs. Future works can introduce specific key performance algorithms of digitalization as an enabler to achieve the SDGs and assess the impact of digital transformation on sustainability performance in a broader context (i.e., AI-driven alternative digitalization ratings). Additionally, there are now many providers of ESG scores and ratings, but there is ongoing debate about the reliability and comparability of these ratings. Future researchers are encouraged to explore how different providers rate companies differently and what factors contribute to these variations, investigating how investors use ESG ratings and how effective these ratings are in predicting green performance. Furthermore, digital transformation mediates the positive association of ECS and ESG, so future studies may consider other potential driving factors of ESG (i.e., CEO characteristics and investors' reactions) for Chinese or overseas enterprises. Finally, future researchers can alter the model to consider the present pandemic scenario and empirically investigate how COVID-19 affects the impact of ECS on ESG performance.

TABLE 8 GMM and 2SLS test.

	2SLS 1st stage	2SLS 2nd stage	2SLS 2nd stage	GMM	GMM
	DT	ESG	ESG	ESG	ESG
IV_DT	0.605***				
	(78.49)				
ECS			0.075***		0.366*
			(7.40)		(1.87)
DT		2.713***	1.826***	0.947**	0.829**
		(8.42)	(6.61)	(2.38)	(2.01)
Controls	Yes	Yes	Yes	Yes	Yes
Year fix	Yes	Yes	Yes	Yes	Yes
Industry fix	Yes	Yes	Yes	Yes	Yes
Obs	17,875	17,875	17,875	14,550	14,550
Kleibergen–Paap rk LM	50.03				
Cragg–Donald Wald F	316.32				
Kleibergen–Paap Wald rk F	56.15				
AR(1)				0.000	0.000
AR(2)				0.129	0.148
Hansen				1.000	1.000

Notes: The t-statistics in parentheses;*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

6 Conclusion

This paper employs 18,098 samples from Chinese A-share listed companies to examine the impact mechanism of executive compensation stickiness on environmental, social, and governance performance. Our empirical results show that executive compensation stickiness can positively impact ESG indicators, and digital transformation plays a partial mediating role within this positive relationship. Based on the "causal step approach," we further examine the mediating effect of digital transformation by bootstrap and Sobel methods, and all empirical results are robust and credible. Our personal scientific contributions involve the dual mediating verification by Sobel and bootstrap approaches and the GMM method based on the weak instrumental variable test of 2SLS first-order regression. The results are appropriate and in agreement with the research tools used, respectively, and emphasize the innovative elements of an applied scientific nature. However, this study contributes to the current literature on developed and emerging economies about corporate government and sustainable development. Our framework provides further theoretical and empirical support for the prior research on the efficacy of digital transformation and ESG practices. The authors hope that this empirical study can guide academicians intending to further excavate this relatively uncharted area, and corporate bodies and top managers who seek some guidelines to formulate an effective payment plan.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

LC and YG contributed to the conception and design of the study. CM organized the database. LC performed the statistical analysis. CM wrote the first draft of the manuscript. LC and YG wrote sections of the manuscript. All authors contributed to manuscript revision, and read and approved the submitted version.

Funding

This work was supported by the Scientific Research Foundation of Hangzhou City University (J202310) and the Key Project of Henan Higher Education (23B630013).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Adut, D., Cready, W., and Lopez, T. (2003). Restructuring charges and CEO cash compensation: A reexamination. *Account. Rev.* 78 (1), 169–192. doi:10.2308/accr.2003.78.1.169

Ajzen, I. (1991). The theory of planned behaviour: Reactions and reflections. *Organ. Behav. Hum. Decis. Process.* 50 (2), 1113–1127. doi:10.1080/08870446.2011.613995

Ali, S., Jiang, J., Hedvicakova, M., and Murtaza, G. (2022). Does doard diversity reduce the probability of financial distress? Evidence from Chinese firms. *Front. Psychol.* 13, 976345. doi:10.3389/fpsyg.2022.976345

Ali, S., Jiang, J., Rehman, R. u., and Khan, M. K. (2023). Tournament incentives and environmental performance: The role of green innovation. *Environ. Sci. Pollut. Res.* 30, 17670–17680. doi:10.1007/s11356-022-23406-w

Bertrand, M., and Mullainathan, S. (2001). Are CEOs rewarded for luck? The ones without principals are. *Q. J. Econ.* 116 (3), 901–932. doi:10.1162/00335530152466269

Blanchard, O., Lopezde Silanes, F., and Shleifer, A. (1994). What do firms do with cash windfalls? *J. Financial Econ.* 36 (3), 337–360. doi:10.1016/0304-405X(94)90009-4

Bu, D. L., and Wen, C. H. (2013). Does executive compensation stickiness increase corporate investment? *J. Finance Econ.* 39 (6), 63–72. doi:10.16538/j.cnki.jfe.2013.06.006

Camodeca, R., and Alex, A. (2021). Digital transformation and convergence toward the 2030 agenda's sustainability development goals: Evidence from Italian listed firms. *Sustainability* 13, 11831. doi:10.3390/su132111831

Chen, L. F., Guo, F. X., and Huang, L. Y. (2023). Impact of foreign direct investment on green innovation: Evidence from China's provincial panel data. *Sustainability* 15, 3318. doi:10.3390/su15043318

Chen, L. F., Wang, Y. W., and Jin, S. Y. (2022). How green credit guidelines policy affect the green innovation in China. *Environ. Eng. Manag. J.* 21 (3), 469–481. doi:10.30638/eemj.2022.044

Chen, L. F., Ye, Z. X., and Jin, S. Y. (2021). A security, privacy and trust methodology for IIoT. *Tech. Gaz.* 28 (3), 898–906. doi:10.17559/TV-20210122095638

Cheng, S. (2004). R&D expenditures and CEO compensation. *Account. Rev.* 79 (2), 305–328. doi:10.2308/accr.2004.79.2.305

Cordeiro, J., He, L., Conyon, M., and Shaw, T. (2016). Chinese executive compensation: The role of asymmetric performance benchmarks. *Eur. J. Finance* 22 (4-6), 484–505. doi:10.1080/1351847X.2013.769892

Core, J., Holthausen, R., and Larcker, D. (1999). Corporate governance, chief executive officer compensation, and firm performance. *J. Financial Econ.* 51 (3), 371–406. doi:10.1016/S0304-405X(98)00058-0

Gansser, O. A., and Reich, C. S. (2023). Influence of the new ecological paradigm (NEP) and environmental concerns on pro-environmental behavioral intention based on the theory of planned behavior (TPB). *J. Clean. Prod.* 382, 134629. doi:10.1016/j.jclepro.2022.134629

Gao, J. Y., Chu, D. X., Lian, Y. H., and Zheng, J. (2021). Can ESG performance improve the investment efficiency of enterprises? *Secur. Mark. Her.* 22 (11), 24–72.

Gao, W. L., Luo, H., and Cheng, P. X. (2011). Managerial power and stickiness of executive compensation. *Econ. Surv.* (06), 82–86. doi:10.3969/j.issn.1006-1096.2011.06.017

Garcia, A., and Orsato, R. (2020). Testing the institutional difference hypothesis: A study about environmental, social, governance, and financial performance. *Bus. Strategy Environ.* 29 (8), 3261–3272. doi:10.1002/bse.2570

Garvey, G., and Milbourn, T. (2006). Asymmetric benchmarking in compensation: Executives are rewarded for good luck but not penalized for bad. *J. Financial Econ.* 82 (1), 197–225. doi:10.1016/j.jfineco.2004.01.006

Ghosh, K., Khuntia, J., Chawla, S., and Deng, X. (2014). Media reinforcement for psychological empowerment in chronic disease management. *Commun. Assoc. Inf. Syst.* 34, 22. doi:10.17705/1CAIS.03422

He, F., and Liu, H. X. (2019). Evaluation of the performance improvement effect of digital transformation of real enterprises from the perspective of digital economy. *Reform* (04), 137–148. CNKI:SUN:REFO.0.2019-04-012.

Hong, Y. Z. (2022). Research on institutional investors and executive compensation stickiness based on fixed effect model: A case study of Chinese listed companies. *Math. Problems Eng.* 13, 1402891–1402913. doi:10.1155/2022/1402891

Hu, S. J. (2016). Research on the influencing factors of the willingness of enterprise big data analysis technology based on the concept of resource infrastructure. *Inf. Sci.* 34 (5), 148–152. doi:10.13833/j.cnki.is.2016.05.029

Ivancic, L., Vuksic, V. B., and Spremic, M. (2019). Mastering the digital transformation process: Business practices and lessons learned. *Technol. Innov. Manag. Rev.* 9 (2), 36–50. doi:10.22215/timreview/1217

Jackson, S., Lopez, T., and Reitenga, A. (2008). Accounting fundamentals and CEO bonus compensation. *J. Account. Public Policy* 27 (5), 374–393. doi:10.1016/j.jaccpubpol.2008.07.006

Jensen, M., and Murphy, K. (1990). Performance pay and top management incentives. *J. Political Econ.* 98 (2), 225–264. doi:10.1086/261677

Jiang, F., Wang, G., and Jiang, X. (2019). Entrepreneurial orientation and organizational knowledge creation: A configurational approach. *Asia Pac. J. Manag.* 36 (4), 1193–1219. doi:10.1007/s10490-018-9609-5

Khan, M. A. (2022). ESG disclosure and firm performance: A bibliometric and meta analysis. *Res. Int. Bus. Finance* 61, 101668. doi:10.1016/j.ribaf.2022.101668

Lai, D., and Leng, J. (2021). Stickiness of executive compensation, institutional investor holding and innovation investment efficiency. *Friends Account.* (08), 121–127. doi:10.3969/j.issn.1004-5937.2022.06.002

Lin, D., Kuo, H. C., and Wang, L. H. (2013). Chief executive compensation: An empirical study of fat cat CEOs. *Int. J. Bus. Finance Res.* 7 (2), 27–42.

Liu, Y. X. (2022). Digital economy empowers high-quality development of enterprises—empirical evidence based on total factor productivity of enterprises. *Reform* (9), 35–53.

Luo, Z. Y., Zhan, Q. L., and Duan, S. (2016). Internal control quality and corporate executive compensation contract. *China Soft Sci.* (02), 169–178. doi:10.3969/j.issn.1002-9753.2016.02.014

Manso, G. (2011). Motivating innovation. *J. Finance (New York)* 66 (5), 1823–1860. doi:10.1111/j.1540-6261.2011.01688.x

Matt, C., Hess, T., and Benlian, A. (2015). Digital transformation strategies. *Bus. Inf. Syst. Eng.* 57 (5), 339–343. doi:10.1007/s12599-015-0401-5

Porfírio, J. A., Carrilho, T., Felício, J. A., and Jardim, J. (2021). Leadership characteristics and digital transformation. *J. Bus. Res.* 124, 610–619. doi:10.1016/j.jbusres.2020.10.058

Qi, H. J., Cao, X. Q., and Liu, Y. X. (2020). The impact of the digital economy on corporate governance: Based on the perspective of information asymmetry and the irrational behavior of managers. *Reform* (04), 50–64. CNKI:SUN:REFO.0.2020-04-005.

Qiu, M. Y., and Yin, H. (2019). ESG performance and financing cost of enterprises in the context of ecological civilization construction. *J. Quantitative Tech. Econ.* 36 (03), 108–123. doi:10.13653/j.cnki.jqte.2019.03.007

Ritala, P., Baiyere, A., Hughes, M., and Kraus, S. (2021). Digital strategy implementation: The role of individual entrepreneurial orientation and relational capital. *Technol. Forecast. Soc. Change* 171, 120961. doi:10.1016/j.techfore.2021.120961

Sousa, M. J., and Rocha, A. (2019). Skills for disruptive digital business. *J. Bus. Res.* 94, 257–263. doi:10.1016/j.jbusres.2017.12.051

Staiger, D., and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica* 65 (3), 557–586. doi:10.2307/2171753

Tu, X. Y., and Yan, X. L. (2022). Digital transformation, knowledge spillover and enterprise total factor productivity-Empirical evidence from manufacturing listed companies. *Industrial Econ. Res. J.* 02, 43–56. doi:10.13269/j.cnki.ier.2022.02.010

United Nations (2015). *The 2030 agenda for sustainable development*. Paris, France: United Nations.

Vahid, J. S., Mazzoleni, A., Hannan, A. M., Gazi, M. A., and Alberto, M. (2023). Entrepreneurs as strategic transformation managers: Exploring micro-foundations of digital transformation in small and medium internationalisers. *J. Bus. Res.* 154, 113287. doi:10.1016/j.jbusres.2022.08.051

Weber, E., Büttgen, M., and Bartsch, S. (2022). How to take employees on the digital transformation journey: An experimental study on complementary leadership behaviors in managing organizational change. *J. Bus. Res.* 143, 225–238. doi:10.1016/j.jbusres.2022.01.036

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Manag. J.* 5 (2), 171–180. doi:10.1002/smj.4250050207

Westerman, G., Bonnet, D., and McAfee, A. (2014). *Leading digital: Turning technology into business transformation*. Brighton, Massachusetts: Harvard Business Press.

Westerman, G., Tannou, M., Bonnet, D., Ferraris, P., and McAfee, A. (2012). *The digital advantage: How digital leaders outperform their peers in every industry*. United States: MIT Center for Digital Business and Capgemini Consulting.

Wimelius, H., Mathiassen, L., Holmström, J., and Keil, M. A. (2021). A paradoxical perspective on technology renewal in digital transformation. *Inf. Syst. J.* 31, 198–225. doi:10.1111/isj.12307

Wu, F., Hu, H. Z., Lin, H. Y., and Ren, X. Y. (2021). Digital transformation of enterprises and capital market performance: Empirical evidence from stock liquidity. *Manag. World* 55 (07), 130–144. doi:10.19744/j.cnki.11-1235/f.2021.0097

Xiao, H. J., Yang, Z., and Liu, M. Y. (2021). The promotion effect of corporate digital social responsibility: The test of internal and external dual paths. *Bus. Manag. J.* 43 (11), 52–69.

Xie, H. J., and Lv, X. (2022). Responsible international investment: ESG and China OFDI. *Econ. Res. J.* (03), 83–99.

Xu, Y., Liu, Y. G., and Cai, G. L. (2018). Executive compensation stickiness and enterprise innovation. *Account. Res.* (7), 43–49. doi:10.3969/j.issn.1003-2886.2018.07.006

Yermack, D. (1997). Good timing: CEO stock option awards and company news announcements. *J. Finance (New York)* 52 (2), 449–476. doi:10.1111/j.1540-6261.1997.tb04809.x

Yi, Z. H., Li, Y. L., and Gao, W. (2010). Governance effect of heterogeneous institutional investors: Based on the perspective of executive compensation. *Statistics Decis.* (05), 122–125. doi:10.13546/j.cnki.tjyjc.2010.05.057

Zeike, S., Bradbury, K., Lindert, L., and Pfaff, H. (2019). Digital leadership skills and associations with psychological well-being. *Int. J. Environ. Res. Public Health* 16 (14), 2628–2712. doi:10.3390/ijerph16142628

Zhang, X. M., and Gao, Y. X. (2017). Social responsibility information disclosure and executive compensation stickiness. *Soft Sci.* 31 (11), 134–138. doi:10.13956/j.ss.1001-8409.2017.11.29

Zhao, C. Y., Wang, W. C., and Li, X. S. (2021). How does digital transformation affect the overall factor productivity of enterprises? *Finance Trade Econ.* (07), 114–129. doi:10.19795/j.cnki.cn11-1166/f.20210705.001

Zheng, J. Z., Khurram, M., and Chen, L. F. (2022). Can green innovation affect ESG ratings and financial performance-evidence from Chinese GEM listed companies. *Sustainability* 14 (07), 8677. doi:10.3390/su14148677

Zhong, Y., Zhao, H., and Yin, T. (2023). Resource bundling: How does enterprise digital transformation affect enterprise ESG development? *Sustainability* 15 (2), 1319. doi:10.3390/su15021319

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 09 May 2023
DOI 10.3389/fenvs.2023.1180072

OPEN ACCESS

EDITED BY
Vikas Kumar,
Birmingham City University,
United Kingdom

REVIEWED BY
Narongsak Sukma,
Mahidol University, Thailand
Ghulam Raza Sargani,
Sichuan Agricultural University, China

*CORRESPONDENCE
Hao Dong,
yihanma20191007@163.com

RECEIVED 05 March 2023
ACCEPTED 25 April 2023
PUBLISHED 09 May 2023

CITATION
Wang B and Dong H (2023), Research on the farmers' agricultural digital service use behavior under the rural revitalization strategy—Based on the extended technology acceptance model.
Front. Environ. Sci. 11:1180072.
doi: 10.3389/fenvs.2023.1180072

Research on the farmers' agricultural digital service use behavior under the rural revitalization strategy—Based on the extended technology acceptance model

Bo Wang[1] and Hao Dong[1,2]*

[1]Institute of Land Engineering and Technology, Shaanxi Provincial Land Engineering Construction Group Co., Shaanxi, China, [2]School of Management, Xi'an Jiaotong University, Shaanxi, China

The effective use of agricultural digital services can promote the transformation of agricultural production methods and actively promote the development of agricultural economy. However, in the process of agricultural production and operation, farmers are difficult to use agricultural digital services and are still at a disadvantage in the use of information. The rapid development and promotion of agricultural digital services provide opportunities for farmers to cross the "digital divide" and obtain "data dividend." Based on the extended technology acceptance model, this paper uses the partial least squares structural equation model to empirically analyze the key influencing factors of farmers' agricultural digital service use behavior. The research shows that farmers' agricultural digital use behavior is mainly affected by two key factors: adoption intention and facility conditions. Among them, adoption intention has a more significant impact on use behavior. At the same time, adoption intention is affected by performance expectation, social influence and data quality, which is an important pre-factor affecting behavior.

KEYWORDS

agricultural digital service, extended technology acceptance model, adoption intention, PLS-SEM, facility conditions

1 Introduction

The effective use of agricultural digital services can promote the transformation of agricultural production methods and actively promote the development of agricultural economy (Qin et al., 2022). However, in the process of agricultural production and operation, farmers are difficult to use agricultural digital services and are still at a disadvantage in the use of information (Dai et al., 2023). The rapid development and promotion of agricultural digital services provide opportunities for farmers to cross the 'digital divide' and obtain 'data dividend'.

Agricultural digitalization is the strategic direction and important content of agricultural and rural modernization in the new era (Jayne et al., 2019; Steinke et al., 2020). In January 2020, China's Ministry of Agriculture and Rural Affairs and the Central Network Information Office jointly issued the "Digital Agriculture and Rural Development Plan

(2019–2025)" to fully deploy agricultural digitization. The outline of China's "14th Five-Year Plan" also clearly stated that it is necessary to accelerate the development of smart agriculture and promote the digital transformation of agricultural production, operation and management services. The Central Document No. 1 of 2022 further emphasized the development of smart agriculture and the integration of information technology and agricultural machinery and agronomy. At present, under the background of comprehensively promoting rural revitalization, following the law of modern agricultural development, China urgently needs to accelerate the development of agricultural digitalization driven by digital technology (Rotz et al., 2019; Liu et al., 2022b).

In recent years, academic research on industrial digitization has been increasing. In general, industrial digitization refers to the use of digital technology to upgrade business in traditional industries to improve production quantity and efficiency (Abbasi et al., 2022), including architecture guidance, data-driven, process integration, and ecological formation (Tseng et al., 2020). It is embodied in the form of factor digitization, process digitization and product digitization (Gao et al., 2022). Agricultural digitization refers to the digitization of agricultural elements and the management of agricultural elements by means of digitization (Remondino and Zanin, 2022). It mainly focuses on the following four aspects: First, the research perspective of agricultural digitization. Scholars have focused on the in-depth discussion of agricultural digitization from the perspectives of technology realization, technology empowerment, micro or macro economic management, and symbiotic theoretical analysis framework (Lioutas et al., 2021; Sukma and Leelasantitham, 2022b). The second is the influencing factors of agricultural digitization (Carmela Annosi et al., 2020). The imperfect agricultural digital infrastructure, the lack of agricultural digital talents, the insufficient application of supply chain digital technology, and the weak application ability of agricultural management entities have restricted the process of agricultural digitization (Liu et al., 2022a). Big data application, information infrastructure, institutional support, value-driven agricultural industry, promotion of new agricultural business entities and technology enterprises (Sukma and Leelasantitham, 2022c), and consumer demand are the key factors driving agricultural digitization (Fielke et al., 2020). The third is the promotion path of agricultural digitization. We should strengthen the basic construction of technology, organization and environmental conditions, drive agricultural modernization with precision agriculture, rely on ' block chain + Internet of Things' technology to break the drawbacks of the original agricultural industry (Sukma and Leelasantitham, 2022b), improve the application level of digital technology in the agricultural industry (Sukma and Leelasantitham, 2022a), empower the agricultural industry chain, integrate the role of resource elements in each link of the agricultural industry chain, so as to accelerate the promotion of agricultural digitization (Tang and Chen, 2022). Fourth, the practice mode of agricultural digitization. The developed country practice modes include precision agriculture mode, government-enterprise cooperation digital agriculture mode, order agriculture mode, etc (Zhang et al., 2016). The domestic practice modes are initially manifested as digital agriculture mode with unique technology and application logic, agricultural insurance decision-making mode, agricultural whole industry chain mode, intelligent agriculture mode, etc. (Balezentis et al., 2023).

The existing literature mostly conducts qualitative analysis from the importance and technical realization of agricultural digitization (Jiang et al., 2022), but there are few empirical analyses on whether farmers use agricultural digitization services. The effective use of agricultural digitization plays a positive role in realizing the strategy of rural revitalization. As the basic unit of agricultural production in China, farmers are the main body of agricultural production. In the production and operation activities of farmers, they can also embody the synergistic relationship between agricultural digitization and agricultural production decision-making. Therefore, based on the perspective of farmers, this paper reveals the important factors affecting the use behavior of agricultural digitalization. Using the classical extended technology acceptance model, based on the user's perspective, this paper explores how factors such as performance expectation, effort expectation, social impact, perceived cost, data quality and facility conditions affect the adoption intention and use behavior of agricultural digitalization services from the cognitive level of farmers. Reveal the inherent laws and basic characteristics of farmers' digital service use behavior, in order to provide targeted and operable reference for the construction of agricultural digital sharing system and the formulation of supporting policies. In short, this study aims to accomplish two main objectives.

- To explain the transmission mechanism through extended technology acceptance model influence farmers' technology adoption behavior through intrinsic perceptions.
- To test whether there is a direct effect of facility conditions on technology adoption behavior.

The structure of the article is as follows: Section 2 summarizes the theory and hypotheses; Section 3 introduces the questionnaire and data source; Section 4 presents the results of the study. Section 5 summarises the conclusions, contributions, and provides some practical implications due to empirical findings.

2 Theory and hypotheses

2.1 Extended technology acceptance model

The extended technology acceptance model (E-TAM) is a classical theoretical paradigm for explaining and predicting human behavior in the fields of economic management and social psychology (Kamal et al., 2020). The theory is developed on the basis of seven theoretical paradigms (Abdullah and Ward, 2016), including social cognitive theory (SCT), rational behavior theory (TRA), planned behavior theory (TPB), technology fit theory (TTF), innovation diffusion theory (IDT), motivation theory (MT), compound TAM and TPB model (C-TAM-TPB). Through the description of the system, Venkatesh et al. (2003) puts forward the extended technology acceptance theory (Venkatesh et al., 2003), including four core constructs: performance expectations, individual expectations of information systems to help improve their job performance (Silva et al., 2019); effort expectancy, the individual's expectation of the degree of effort to master and use information systems (Rahi et al., 2019); social influence, the recognition of this information system by people who feel important to them (Halevy et al., 2019); facility conditions, individuals believe that the existing organizations and technical facilities to support their use of this information system (Venkatesh et al., 2003).

According to the extended technology acceptance model, there is a high positive correlation between individual adoption intention and use behavior (Bock et al., 2005; Anderson and Agarwal, 2010). The stronger the individual's adoption intention, the higher the possibility of actual action (Angst and Agarwal, 2009). The three main variables of individual performance expectation, effort expectation and social impact work together on the adoption intention, and the facility conditions directly lead to the use behavior (Oliveira et al., 2016). In addition, many scholars' empirical studies have shown that data quality and perceived cost have a significant impact on the intention to use new information technology (Lai, 2004). Therefore, in this study, two variables of data quality and perceived cost are introduced in order to test the key influencing factors of agricultural digital use intention and behavior more comprehensively and reliably.

2.2 Research hypothesis

Based on the framework of Venkatesh et al., this study intends to empirically analyze the pre-influencing factors of farmers' adoption intention and use agricultural digital services (Venkatesh et al., 2003). Based on the extended technology acceptance model, farmers' adoption intention agricultural digital services will have an important impact on their use behavior. As a key influencing factor, adoption intention refers to the positive or negative behavior of farmers in the process of using agricultural digital services. Driven by positive adoption intention, farmers' agricultural digital use behavior will be more proactive (Verma and Sinha, 2018). At the same time, performance expectancy (PE) is an individual's belief that the use of new technologies will improve job performance and is regarded as the most powerful predictive tool (Brown et al., 2014). The performance expectation of farmers' digital use reflects their cognition and behavior towards agricultural digitization (Venkatesh et al., 2012). The deeper the farmers' cognition of digital performance expectations and the more positive the evaluation, the greater the possibility of using agricultural digitization (Faid et al., 2022). On the contrary, if farmers do not agree with the performance of agricultural digitization and evaluate it negatively, they are subjectively unwilling to use agricultural digitization services. Effort Expectancy refers to the time and energy that users need to pay when learning to use a new information technology system (Lutfi et al., 2022), that is, the degree of effort required to use an information system. In E-TAM, effort expectancy has a direct impact on farmers' adoption intention (Deng et al., 2010). Although the use of some rural agricultural digitization can bring changes in production and life to farmers, if there are too many and too high technical requirements for the use and acceptance of agricultural digitization platform systems and terminals, it will hinder the use of agricultural digitization for farmers with limited technical learning and use ability.

Therefore, whether the operation is simple or not is directly related to the adoption intention agricultural digitization. Social influence is the influence of groups who have used agricultural digitization on other farmers in the process of selecting and using agricultural digitization. In the process of agricultural production and management, many decisions of farmers will be influenced by the opinion leaders or authoritative people around them, such as local technical talents, large planting and breeding households, agricultural technical service personnel and their relatives and friends, etc. The adoption intention of farmers will be affected by the recommended behavior of the above people. Facility condition refers to the degree of support that the user's environment, organization and technical equipment perceived during the use of technology or services support their use of this information technology system. Venkatesh et al. (2012) have shown that users with the best Facility conditions will have a higher adoption intention and accept new technologies (Venkatesh et al., 2012). Facility condition in this study refers to farmers' perception of the facility condition required for the use of agricultural digitization and the completeness of various supporting technologies. At the same time, facility conditions provide objective conditions for the use of agricultural digitalization by farmers. Therefore, the use of agricultural digital services by farmers will also be affected by facility conditions. Based on the above analysis, this study proposes the following five hypotheses.

Hypothesis 1. (H1): Performance expectation has a significant positive impact on farmers' adoption intention agricultural digital services;

Hypothesis 2. (H2): Effort expectation has a significant negative impact on farmers' adoption intention agricultural digital services;

Hypothesis 3. (H3): Social impact has a significant positive impact on farmers' adoption intention agricultural digital services;

Hypothesis 4. (H4): Facility condition has a significant positive impact on farmers' use of agricultural digital services;

Hypothesis 5. (H5): Adoption intention has a significant positive impact on agricultural digital use behavior.

Data quality is the subjective judgment of users on the excellence or superiority of agricultural digitization, including the authenticity, scientificity, timeliness and comprehensiveness of agricultural digitization services (Zscheischler et al., 2022). Agricultural digitization is the basis of farmers' production and management. Therefore, the quality of agricultural digitization used by farmers, including weather, soil moisture, seedling condition, disaster and other data quality, is very important, which can help farmers improve the scientific nature of production decision-making and the fineness of management. Farmers' perception of the quality of agricultural digitization will affect their adoption intention, and unreliable digital services will have a negative impact on farmers and bring greater uncertainty. During the investigation, it was found that farmers were very concerned about the quality of agricultural digitization. Therefore, this study introduces data quality into the model as a key factor affecting farmers' intention to use agricultural digitization.

Perceived cost refers to all the costs perceived by individuals when purchasing products or services, including the cost of purchasing terminals and the cost of using agricultural

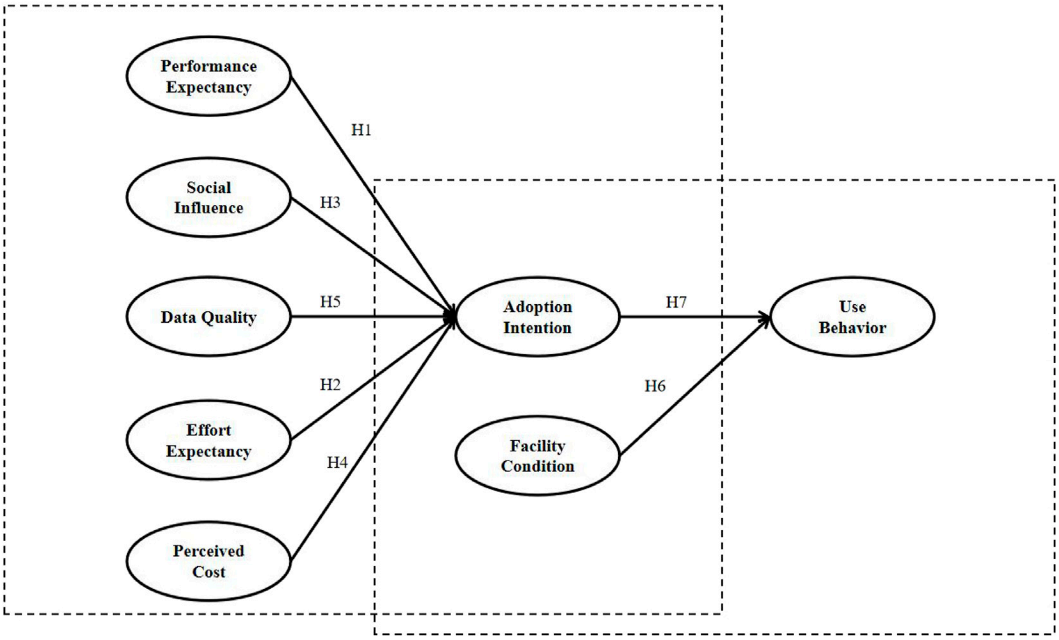


FIGURE 1
Research model.

digitization. Research shows that cost factors have a significant impact on the adoption of new technologies. Under the long-term urban-rural dual system, farmers' income is relatively low, and they are more sensitive to perceived costs when using agricultural digitization. Therefore, the cost and price structure in the use of agricultural digitization will have an impact on farmers' intention to use. As mentioned above, the perceived cost is also an important factor in the extended E-TAM. Therefore, according to the nature of agricultural digitization, from the perspective of system quality and economic characteristics, data quality and perceived cost are taken as two variables that affect the adoption intention, and the technology acceptance model is further expanded, and the analysis framework and hypothesis to be tested are proposed. See Figure 1.

Hypothesis 6. (H6): Data quality has a significant positive impact on farmers' intention to use agricultural digitization;

Hypothesis 7. (H7): Perceived cost has a significant negative impact on farmers' intention to use agricultural digitization.

3 Methodology

3.1 Data collection

As an important agricultural province in China, Shaanxi has built a "Shaanxi Agricultural Digital Platform" in recent years. The platform aims at the characteristics of large spatial and temporal variation of key factors affecting crop growth such as soil fertility, salt content, pH, groundwater and salinity in Guanzhong Plain. The Internet of Things and digital technology collaboration system can accurately collect and store data in real time, and provide solutions through data mining analysis. Therefore, this paper selects "Shaanxi Agricultural Digital Platform" as the research object and conducts field research in Shaanxi Province. The research group visited Weinan City and Baoji City in Shaanxi Province from September to October 2022. Two counties were selected from the two cities, and two villages were randomly selected from the two counties for investigation. The specific survey sample points are distributed as shown in Table 1. A total of 500 questionnaires were distributed, 482 questionnaires were collected, and 465 valid questionnaires were collected. The effective rate of the questionnaire was 93%.

TABLE 1 Sample characteristics.

City	County	Frequency	Proportion (%)
Weinan	Dali	112	24.1
	Fuping	121	26.0
Baoji	Qishan	115	24.7
	Fengxiang	117	25.2
Total		465	100

3.2 Questionnaire design

To ensure the reliability and validity of the questionnaire, Questionnaire items should be developed in accordance with the following scientific processes, according to the research

TABLE 2 Measurement questionnaire.

Variable	Item	Observable item
Performance Expectancy	PE1	Using agricultural digital services saves agricultural production time
	PE2	Using agricultural digital services saves agricultural production time
	PE3	Can improve the family income
Effort Expectancy	EE1	Agricultural digital platform is simple and convenient to operate
	EE2	The interaction with the platform is clear
Social Influence	SI1	Agricultural technology extension practitioners recommend the use of agricultural digitization services
	SI2	Friends and family recommend digital agriculture services
	SI3	Large farmers recommend the use of agricultural digital services
Facility Condition	FC1	The service quality of agricultural digital platform is stable
	FC2	It is fast to use agricultural digital platform
	FC3	Internet coverage is excellent in my area
Perceived Cost	PC1	I feel the terminal price is high
	PC2	I feel the monthly fee is high
	PC3	I feel the price of communication traffic is high
	PC4	I feel the price of subscription information service is too high
Data Quality	DQ1	Agricultural digital platform service has authenticity
	DQ2	Agricultural digital platform service has accuracy
	DQ3	Agricultural digital platform service has timeliness
	DQ4	Agricultural digital platform service is easy to understand
Adoption Intention	AI1	I plan to use agricultural digital services in the future
	AI2	I intend to recommend relatives and friends to use agricultural digital services
	AI3	I am willing to use agricultural digital services frequently
Use Behhavioral	UB1	I have used agricultural digital services to start my business
	UB2	I help family and friends use agricultural digitization services

recommendations of Churchill (1979): (a) Variable items should be organized according to the relevant literature. (b) Measurement items should be back-translated. In this paper, the internationally accepted Likert 7-level scoring method is used to measure the latent variables such as performance expectation, effort expectation, social influence, facility condition, perceived cost, data quality, and adoption intention. The variable assignments are increasing in turn. Among them, completely disagree with "1", neither agree nor disagree with "4," and completely agree with "7." Based on the classic scale, the questionnaire items of this survey are further revised according to the characteristics of farmers and the "Shaanxi Agricultural Digital Platform." The measurement of performance expectation, effort expectation, social impact and facility conditions comes from the scale of Venkatesh et al. (2012), the measurement of perceived cost comes from the scale of Liu et al. (2001), the measurement of data quality comes from the scale of Wang and Strong (1996), and the measurement of adoption intention and use behavior comes from the scale of Venkatesh et al. (2003). The questionnaire covers all the contents required by this study. The questions involve eight latent variables (performance expectation, effort expectation, social influence, facility condition, perceived cost, data quality, adoption intention and use behavior). The latent variables and the observable variables included and their sources are shown in Table 2.

3.3 Technical analysis

The variables studied in this paper are many latent variables that are difficult to measure directly, such as performance expectation, effort expectation, social influence, facility condition and so on. Therefore, structural equation model is used to carry out empirical analysis. In this paper, SmartPLS is used to analyze the data (Joo and Sang, 2013). Compared with

 10.3389/fenvs.2023.1180072

TABLE 3 Reliability and validity.

Variables	Items	Loadings	Cronbach's α	CR	AVE
Adoption Intention	AI1	0.817	0.763	0.863	0.678
	AI2	0.821			
	AI3	0.833			
Data Quality	DQ1	0.882	0.905	0.934	0.779
	DQ2	0.916			
	DQ3	0.886			
	DQ4	0.845			
Effort Expectancy	EE1	0.956	0.9	0.952	0.909
	EE2	0.95			
Facility Condition	FC1	0.838	0.812	0.888	0.725
	FC2	0.858			
	FC3	0.858			
Perceived Cost	PC1	0.897	0.883	0.919	0.739
	PC2	0.891			
	PC3	0.81			
	PC4	0.838			
Performance Expectancy	PE1	0.888	0.819	0.893	0.737
	PE2	0.903			
	PE3	0.779			
Social Influence	SI1	0.842	0.842	0.893	0.677
	SI2	0.849			
	SI3	0.775			
	SI4	0.823			
Use Behhavioral	UB1	0.949	0.895	0.95	0.905
	UB2	0.954			

Note: CR, composite reliability; AVE, average variance extracted; VIF, variance inflation factors.

AMOS, the software has the following advantages: it can solve the problem of difficult or unrecognized model identification caused by too many measurement indicators, non-positive definite matrices, and coefficients greater than 1; in terms of fitting, it can solve the problem of insufficient model goodness of fit caused by too complex model. In addition, the software can solve the problem of parameter estimation bias caused by serious non-normal distribution of data.

3.4 Common method bias

The Haman single factor test method was used to detect the common method bias of the survey data, and all the measurement items of the questionnaire were analyzed by principal component analysis. The maximum variance interpretation rate of the first principal component without rotation was 32.433%, which was lower than 50%, indicating that the common method bias had no serious impact on this study.

3.5 Reliability and validity

Reliability analysis mainly refers to the internal quality of the measurement model. This paper first analyzes the reliability of the eight main variables, and uses the combined reliability (CR), the average variance extraction value (AVE) and the Cronbach α coefficient as the reliability and validity test indicators. Table 3 shows that the combined reliability (CR) of the eight main variables is above 0.8, and the Cronbac' α coefficient is greater than 0.7, so the survey data has good reliability. It is generally believed that the scale has good structural validity when the combined reliability (CR) is greater than 0.7 and the average

TABLE 4 Discriminant validity—Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio.

Variables	1	2	3	4	5	6	7	8
1. Adoption Intention	**0.824**	0.540	0.321	0.794	0.429	0.730	0.720	0.680
2. Data Quality	0.451**	**0.883**	0.352	0.574	0.275	0.430	0.502	0.586
3. Effort Expectancy	0.268**	0.313**	**0.953**	0.455	0.424	0.293	0.318	0.514
4. Facility Condition	0.623**	0.499**	0.387**	**0.851**	0.526	0.611	0.645	0.765
5. Perceived Cost	0.365**	0.246**	0.373**	0.453**	**0.86**	0.437	0.404	0.434
6. Performance Expectancy	0.578**	0.370**	0.251**	0.500**	0.379**	**0.859**	0.830	0.437
7. Social Influence	0.583**	0.442**	0.281**	0.540**	0.362**	0.693**	**0.823**	0.452
8. Use Behhavioral	0.564**	0.524**	0.462**	0.661**	0.388**	0.375**	0.398**	**0.951**

Note: **Correlation is significant at the 0.01 level (2-tailed), Bold diagonal entries are square root of AVEs, Heterotrait-Montrait ratios (HTMT) (Underlined) are below 0.85.

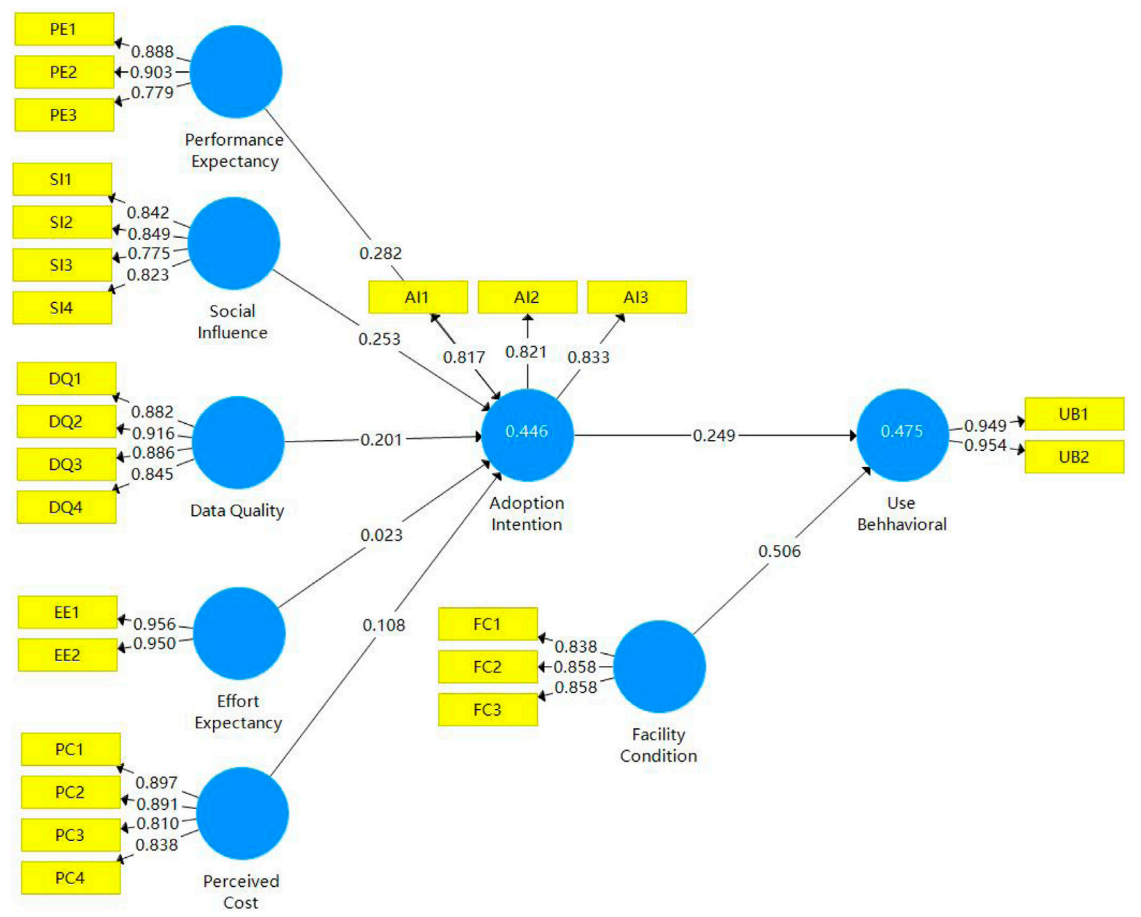


FIGURE 2
Path diagram of modified model.

variance extraction (AVE) is greater than 0.5. This scale is designed on the basis of previous scales and research results. In the process of design, it is revised by combining the opinions of experts and farmers, so it can be concluded that the content validity of this scale is good. The results of the Fornell-Larcker Criterion (Table 4) show that the AVE square roots of the eight latent variables in this study are greater than the correlation coefficients between the variable and other variables, indicating that the measurement model has good discriminant validity. Heterotrait-Montrait ratios (HTMT) (Underlined) are below 0.85.

TABLE 5 Results of hypothesis testing.

Hypothesis	Effect	Path	Path coefficient	Lower (2.5%)	Upper (97.5%)	t-statistics	*p*-value	Decision
Direct relationships								
H1	Direct	PE -> AI	0.28	0.136	0.417	3.944	0.000***	Accept
H2	Direct	SI -> AI	0.251	0.104	0.402	3.375	0.001***	Accept
H3	Direct	EE -> AI	0.023	−0.083	0.131	0.408	0.683	Refuse
H4	Direct	FC -> UB	0.507	0.401	0.607	9.696	0.000***	Accept
H5	Direct	AI -> UB	0.249	0.086	0.383	3.249	0.001***	Accept
H6	Direct	DQ -> AI	0.203	0.064	0.351	2.721	0.007**	Accept
H7	Direct	PC -> AI	0.113	0.006	0.221	1.954	0.051	Refuse
SRMR composite model = 0.047								
R^2_{AI} = 0.437; Q^2_{AI} = 0.285								
R^2_{UB} = 0.471; Q^2_{UB} = 0.424								

Note: Significant level: $p < 0.10$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4 Results

Figure 2 and Table 5 show the standardized path coefficient and significance of the farmers' agricultural digitization services use model. The results show that the standardized path coefficients of performance expectation and social influence on adoption intention are 0.28 and 0.251, respectively, and are significant at the confidence levels of 1%. Therefore, performance expectation and social influence have a positive correlation with farmers' adoption intention agricultural digitalization, so Hypothesis 1 and Hypothesis 3 are established. The influence of effort expectation on adoption intention is not significant, so Hypothesis 2 is not true. Among the increased latent variables, there is no correlation between perceived cost and adoption intention, so Hypothesis 4 is not established; Data quality has a positive correlation with farmers' adoption intention agricultural digitization, and is significant at the 1% confidence level, so Hypothesis 5 is established.

Through the use of agricultural digital platform, it can help farmers to obtain more accurate and timely information, help farmers to carry out planting management, improve planting quality, and then improve income level. Due to the social characteristics of rural areas, farmers are vulnerable to the influence of surrounding farmers in the use of agricultural digitization; the higher the quality of agricultural digitization, the less time and energy farmers spend on data screening. The authenticity, effectiveness, accuracy and timeliness of digitization will help farmers' agricultural production. Therefore, the higher the quality of data, the more willing farmers are to use agricultural digitization. The current Shaanxi agricultural digital platform is easy to use by farmers and easy to apply to agricultural production practice due to its friendly and simple operation interface. Empirical research shows that perceived cost has no effect on farmers' adoption intention, and there is no correlation between them. This conclusion is puzzling. One possible explanation is that agricultural digitization is still in the trial stage of promotion, and most of them are free for farmers to use, so this variable has no effect on adoption intention.

Secondly, there is a positive correlation between adoption intention and facility conditions on agricultural digital use behavior at the 1% confidence level. Hypothesis 6 and Hypothesis 7 are supported, and the original hypothesis is established. Among them, the adoption intention agricultural digitization has the most significant impact on farmers' digital use behavior, and positive adoption intention has a strong positive effect on the use behavior. The service quality, network coverage and speed of agricultural digitization have a positive impact on the use behavior of farmers' agricultural digitization. This result is consistent with most empirical research results. Farmers feel that the facility condition of use conditions will encourage them to use agricultural digitization.

The above research shows that the three variables of farmers' performance expectation, social impact and data quality of agricultural digitization are the pre-factors that affect the adoption intention. Further, these three variables will affect the use behavior through the adoption intention. In addition, the key variable facility conditions in the extended technology acceptance model have a direct positive impact on farmers' use behavior.

5 Discussion

5.1 Theoretical implications

First, further enhance the usefulness of agricultural digitization in rural areas. The research shows that performance expectation has a positive correlation with adoption intention, and the effect is the most significant. Therefore, in the process of developing and optimizing agricultural digital platforms, governments, mobile operators and relevant agricultural departments should consider digital service projects that can bring tangible benefits to farmers (Dong et al., 2022b).

Second, further improve the quality of agricultural digitization, ensure that the digitization is objective, accurate, timely, easy to understand and comprehensive, improve the supply capacity and analysis and utilization capacity of agricultural digitization such as climate, fertility and epidemic situation, and more effectively assist decision-making and production management (Dong et al., 2022a).

Third, further improve the use environment of agricultural digitization, focus on improving the operability and effectiveness of agricultural digitization solutions, and efficiently improve the efficiency of assisting farmers in solving wheat production and operation. Fourth, increase publicity and focus on word-of-mouth publicity. It can carry out publicity for small and medium-sized farmers, increase publicity frequency, delay publicity time, expand publicity channels, enrich delivery forms and other methods to carry out multi-directional and three-dimensional publicity, and improve farmers' awareness of agricultural digitization.

5.2 Managerial implications

Information gap is a key factor hindering the implementation of rural revitalization strategy and digital China strategy, so it is necessary to promote the transformation of information industry to traditional agriculture (Sukma and Leelasantitham, 2022c). Make information technology become an important driving force to improve the modernization of rural governance system and governance capacity, and exert the diffusion effect of information technology innovation, the spillover effect of information and knowledge, and the universal benefit effect released by digital technology, so as to promote the transformation of agricultural digitalization, the implementation of rural service digitalization and the play of farmers' digital power. However, on the one hand, modern information technology has promoted the rapid development of digital economy and information society (Sukma and Leelasantitham, 2022b), on the other hand, it has intensified the gap between urban and rural areas to a certain extent. Moreover, the low level of input in information resources, the fragmentation of rural information infrastructure, the fragility of villagers' information consumption ability, and the weak state of villagers' ability to obtain information have further widened the information gap in digital rural construction (Sukma and Leelasantitham, 2022a). The expansion of the information gap has compressed the opportunity of rural access to information resources, aggravated the crisis of "digital survival" of villagers, and then led to many practical symptoms of digital rural construction such as the project lag of digital agricultural production, regional differences in the development of rural e-commerce, the solidification of digital service application, and the gap between generations of digital culture consumption. There is no doubt that the situation of rural information infrastructure and farmers' information ability determine the horizontal expansion and vertical deepening of rural digitalization. The existence and expansion of information gap will accelerate the further expansion of the gap between tiers, regions and urban and rural areas, and further develop into information differentiation, which in turn accelerates the polarization of the rich and the poor and the social differentiation.

6 Conclusion

This paper takes Shaanxi agricultural digitization platform as the research object, based on the mature classical extended technology acceptance model in the field of information technology, starting from the cognitive psychological level of farmers, taking into account the characteristics of agricultural digitization, including two variables of perceived cost and data quality, and expanding the external variables of the extended technology acceptance model, in order to reveal the key influencing factors of the adoption intention and use behavior of agricultural digitization, and the transmission path of these key factors. Taking the exemplary Shaanxi agricultural digital platform as the research object, a field survey was conducted in Weinan City and Baoji City of Shaanxi Province. The situation of wheat growers in the two cities was obtained through household survey, and SmartPLS was used for analysis. The empirical results show that farmers ' agricultural digital use behavior is mainly affected by two key factors: adoption intention and facility conditions, among which adoption intention has a more significant impact on use behavior. Performance expectancy, social influence and data quality are important antecedents of behavioral behaviors.

7 Limitations and future research directions

There is still room for further discussion in this study, which is mainly reflected in the following aspects: first, the use of cross-sectional data in this study cannot reflect the dynamic role of agricultural digitization and farmers' agricultural digital service use behavior; second, there may be differences in resource endowment characteristics and technology use behavior in different regions. Due to the limitation of sample size, this study failed to distinguish and further explore.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

Conceptualization, HD and BW; methodology, HD; software, BW; validation, BW; formal analysis, BW; investigation, HD; resources, HD; data curation, HD; writing—original draft preparation, HD; writing—review and editing, HD; visualization, HD; supervision, BW; project administration, BW; funding acquisition, BW. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by Research project of Land Engineering Construction Group (DJNY-YB-2023-36, DJNY-YB-2023-37), Study on land ecological quality evaluation and spatio-temporal evolution in Shaanxi section of the Yellow River Basin based on '3S' technology (DJNY2022-28) and Construction of Shaanxi soil mass quality detection and evaluation sharing platform (2021PT-053).

Conflict of interest

Author BW and HD were employed by Shaanxi Provincial Land Engineering Construction Group Co.

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Abbasi, R., Martinez, P., and Ahmad, R. (2022). The digitization of agricultural industry – A systematic literature review on agriculture 4.0. *Smart Agric. Technol.* 2, 100042. doi:10.1016/j.atech.2022.100042

Abdullah, F., and Ward, R. (2016). Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors. *Comput. Hum. Behav.* 56, 238–256. doi:10.1016/j.chb.2015.11.036

Anderson, C. L., and Agarwal, R. (2010). Practicing safe computing: A multimethod empirical examination of home computer user security behavioral intentions. *MIS Q.* 34, 613–643. doi:10.2307/25750694

Angst, C. M., and Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Q.* 33, 339. doi:10.2307/20650295

Balezentis, T., Zickiene, A., Volkov, A., Streimikiene, D., Morkunas, M., Dabkiene, V., et al. (2023). Measures for the viable agri-food supply chains: A multi-criteria approach. *J. Bus. Res.* 155, 113417. doi:10.1016/j.jbusres.2022.113417

Bock, G.-W., Zmud, R. W., Kim, Y.-G., and Lee, J.-N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Q.* 29, 87–111. doi:10.2307/25148669

Brown, S. A., Dennis, A. R., and Venkatesh, V. (2014). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *J. Manag. Inf. Syst.* 27, 9–54. doi:10.2753/MIS0742-1222270201

Carmela Annosi, M., Brunetta, F., Capo, F., and Heideveld, L. (2020). Digitalization in the agri-food industry: The relationship between technology and sustainable development. *Manag. Decis.* 58, 1737–1757. doi:10.1108/MD-09-2019-1328

Dai, X., Chen, Y., Zhang, C., He, Y., and Li, J. (2023). Technological revolution in the field: Green development of Chinese agriculture driven by digital information technology (DIT). *Agriculture* 13, 199. doi:10.3390/agriculture13010199

Deng, L., Turner, D. E., Gehling, R., and Prince, B. (2010). User experience, satisfaction, and continual usage intention of IT. *Eur. J. Inf. Syst.* 19, 60–75. doi:10.1057/ejis.2009.50

Dong, H., Wang, B., Han, J., Luo, L., Wang, H., Sun, Z., et al. (2022a). Understanding farmers' eco-friendly fertilization technology adoption behavior using an integrated S-O-R model: The case of soil testing and formulated fertilization technology in shaanxi, China. . Frontiers in Environmental Science 10. Available at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.991255 (Accessed November 5, 2022).

Dong, H., Wang, H., and Han, J. (2022b). Understanding ecological agricultural technology adoption in China using an integrated technology acceptance model—theory of planned behavior model. *Front. Environ. Sci.* 10, 927668. doi:10.3389/fenvs.2022.927668

Faid, A., Sadik, M., and Sabir, E. (2022). An agile ai and IoT-augmented smart farming: A cost-effective cognitive weather station. *Agriculture* 12, 35. doi:10.3390/agriculture12010035

Fielke, S., Taylor, B., and Jakku, E. (2020). Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agric. Syst.* 180, 102763. doi:10.1016/j.agsy.2019.102763

Gao, D., Li, G., and Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247, 123395. doi:10.1016/j.energy.2022.123395

Halevy, N., Kreps, T. A., and De Dreu, C. K. W. (2019). Psychological situations illuminate the meaning of human behavior: Recent advances and application to social influence processes. *Soc. Personality Psychol. Compass* 13, e12437. doi:10.1111/spc3.12437

Jayne, T. S., Snapp, S., Place, F., and Sitko, N. (2019). Sustainable agricultural intensification in an era of rural transformation in Africa. *Glob. Food Secur.* 20, 105–113. doi:10.1016/j.gfs.2019.01.008

Jiang, Q., Li, J., Si, H., and Su, Y. (2022). The impact of the digital economy on agricultural green development: Evidence from China. *Agriculture* 12, 1107. doi:10.3390/agriculture12081107

Joo, J., and Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. *Comput. Hum. Behav.* 29, 2512–2518. doi:10.1016/j.chb.2013.06.002

Kamal, S. A., Shafiq, M., and Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technol. Soc.* 60, 101212. doi:10.1016/j.techsoc.2019.101212

Lai, T. L. (2004). Service quality and perceived value's impact on satisfaction, intention and usage of short message service (SMS). *Inf. Syst. Front.* 6, 353–368. doi:10.1023/B:ISFI.0000046377.32617.3d

Lioutas, E. D., Charatsari, C., and De Rosa, M. (2021). Digitalization of agriculture: A way to solve the food problem or a trolley dilemma? *Technol. Soc.* 67, 101744. doi:10.1016/j.techsoc.2021.101744

Liu, C., Arnett, K. P., Capella, L. M., and Taylor, R. D. (2001). Key dimensions of web design quality as related to consumer response. *J. Comput. Inf. Syst.* 42, 70–82. doi:10.1080/08874417.2001.11647041

Liu, W., Wei, S., Wang, S., Lim, M. K., and Wang, Y. (2022a). Problem identification model of agricultural precision management based on smart supply chains: An exploratory study from China. *J. Clean. Prod.* 352, 131622. doi:10.1016/j.jclepro.2022.131622

Liu, W., Zhou, W., and Lu, L. (2022b). An innovative digitization evaluation scheme for spatio-temporal coordination relationship between multiple knowledge driven rural economic development and agricultural ecological environment—coupling coordination model analysis based on guangxi. *J. Innovation Knowl.* 7, 100208. doi:10.1016/j.jik.2022.100208

Lutfi, A., Saad, M., Almaiah, M. A., Alsaad, A., Al-Khasawneh, A., Alrawad, M., et al. (2022). Actual use of mobile learning technologies during social distancing circumstances: Case study of king faisal university students. *Sustainability* 14, 7323. doi:10.3390/su14127323

Oliveira, T., Thomas, M., Baptista, G., and Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Comput. Hum. Behav.* 61, 404–414. doi:10.1016/j.chb.2016.03.030

Qin, T., Wang, L., Zhou, Y., Guo, L., Jiang, G., and Zhang, L. (2022). Digital technology-and-services-driven sustainable transformation of agriculture: Cases of China and the EU. *Agriculture* 12, 297. doi:10.3390/agriculture12020297

Rahi, S., Othman Mansour, M. M., Alghizzawi, M., and Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *J. Res. Interact. Mark.* 13, 411–435. doi:10.1108/JRIM-02-2018-0032

Remondino, M., and Zanin, A. (2022). Logistics and agri-food: Digitization to increase competitive advantage and sustainability. Literature review and the case of Italy. *Sustainability* 14, 787. doi:10.3390/su14020787

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., et al. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *J. Rural Stud.* 68, 112–122. doi:10.1016/j.jrurstud.2019.01.023

Silva, S., Nuzum, A.-K., and Schaltegger, S. (2019). Stakeholder expectations on sustainability performance measurement and assessment. A systematic literature review. *J. Clean. Prod.* 217, 204–215. doi:10.1016/j.jclepro.2019.01.203

Steinke, J., Etten, J., Müller, A., Ortiz-Crespo, B., Gevel, J., Silvestri, S., et al. (2020). Tapping the full potential of the digital revolution for agricultural extension: An emerging innovation agenda. International Journal of Agricultural Sustainability. Available at: https://www.tandfonline.com/doi/abs/10.1080/14735903.2020.1738754 (Accessed March 2, 2023).

Sukma, N., and Leelasantitham, A. (2022a). A community sustainability ecosystem modeling for water supply business in Thailand. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.940955

Sukma, N., and Leelasantitham, A. (2022b). From conceptual model to conceptual framework: A sustainable business framework for community water supply businesses. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1013153

Sukma, N., and Leelasantitham, A. (2022c). The influence and continuance intention of the E-government system: A case study of community water supply business. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.918981

Tang, Y., and Chen, M. (2022). The impact of agricultural digitization on the high-quality development of agriculture: An empirical test based on provincial panel data. *Land* 11, 2152. doi:10.3390/land11122152

Tseng, M.-L., Chang, C.-H., Lin, C.-W. R., Wu, K.-J., Chen, Q., Xia, L., et al. (2020). Future trends and guidance for the triple bottom line and sustainability: A data driven bibliometric analysis. *Environ. Sci. Pollut. Res.* 27, 33543–33567. doi:10.1007/s11356-020-09284-0

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Q.* 27, 425. doi:10.2307/30036540

Venkatesh, V., Thong, J. Y. L., and Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* 36, 157. doi:10.2307/41410412

Verma, P., and Sinha, N. (2018). Integrating perceived economic wellbeing to technology acceptance model: The case of mobile based agricultural extension service. *Technol. Forecast. Soc. Change* 126, 207–216. doi:10.1016/j.techfore.2017.08.013

Wang, R. Y., and Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *J. Manag. Inf. Syst.* 12, 5–33. doi:10.1080/07421222.1996.11518099

Zhang, Y., Wang, L., and Duan, Y. (2016). Agricultural information dissemination using ICTs: A review and analysis of information dissemination models in China. *Inf. Process. Agric.* 3, 17–29. doi:10.1016/j.inpa.2015.11.002

Zscheischler, J., Brunsch, R., Rogga, S., and Scholz, R. W. (2022). Perceived risks and vulnerabilities of employing digitalization and digital data in agriculture – socially robust orientations from a transdisciplinary process. *J. Clean. Prod.* 358, 132034. doi:10.1016/j.jclepro.2022.132034

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 06 July 2023
DOI 10.3389/fenvs.2023.1213961

Check for updates

OPEN ACCESS

EDITED BY
Vikas Kumar,
Birmingham City University,
United Kingdom

REVIEWED BY
Elkhan Richard Sadik-Zada,
Ruhr University Bochum, Germany
Mihaela Simionescu,
University of Bucharest, Romania

*CORRESPONDENCE
Anqi Wang,
angelwang1991@hnu.edu.cn

RECEIVED 28 April 2023
ACCEPTED 23 June 2023
PUBLISHED 06 July 2023

CITATION
Wang A and Ren J (2023), The impact of the digital economy on green total factor productivity in Belt and Road countries: the mediating role of energy transition.
Front. Environ. Sci. 11:1213961.
doi: 10.3389/fenvs.2023.1213961

The impact of the digital economy on green total factor productivity in Belt and Road countries: the mediating role of energy transition

Anqi Wang[1]* and Junyu Ren[2]

[1]College of Finance and Statistics, Hunan University, Changsha, China, [2]Hunan Provincial Tax Service, State Taxation Administration, Changsha, China

Introduction: The prospective Belt and Road (B&R) Initiative by China must be thoroughly examined by the participating nations in all respects. It is now essential to investigate whether the digital economy of the B&R countries can support green total factor productivity (GTFP). This study examines the connection between green total factor productivity (GTFP) and the digital economy in B&R countries with the aim of providing China with practical recommendations for advancing the initiative.

Methods: This study explores 40 B&R countries from 2006 to 2021, calculates the GTFP using the unexpected super-efficient SBM model and the Global Malmquist-Luenberger index method, and constructs the digital economy index using the principal component analysis method. OLS, FMOLS methods, and spatial panel regressions are used to examine the digital economy-GTFP nexus.

Results and Discussion: In the selected 40 B&R countries, there is a non-linear relationship between the digital economy and GTFP, and the overall effect of the digital economy on GTFP is negative, implying that the growth of the digital economy will cause a decline in GTFP. Energy transition has mediation effects that can mitigate the negative impact of digital economic growth on GTFP. The spatial spillover effects of the digital economy on the GTFP of neighboring countries are evident. There is also heterogeneity; the digital economy will reduce GTFP in high- and middle-income countries, but the negative effects are not evident in low-income countries. This paper adds to the discussion of the digital economy and green development by drawing different conclusions from previous studies using a variety of regression models, providing a fresh foundation for policy-making.

KEYWORDS

digital economy, green total factor productivity, energy transition, B&R, spatial regression

1 Introduction

In recent years, green and sustainable development has become a topic of intense discussion around the world. On the one hand, green and sustainable development is conducive to mitigating Earth crises such as climate change, species extinction, and environmental pollution. On the other hand, a green economy and sustainable development will also help countries around the world get out of the shadow of COVID-19 and restore their economic vitality. Total factor productivity reflects the allocation of resources, the technical level of generating means, the change of production objects, the level of production organization and management, the enthusiasm of workers for production and business activities, and the degree of influence of the economic system and various social factors on production activities. When studying the economy, the World Bank, the OECD, and other international institutions often look at the change in total factor productivity as an important ingredient in examining the quality of economic growth. Since ignorance toward environmental factors leads to biased measurement results and easily misleading policy choices, the term green total factor productivity (GTFP, hereafter) has emerged. GTFP incorporates energy consumption and pollution output in the total factor productivity framework, which is consistent with the idea of high-quality green development. The GTFP, which seeks to reconcile economic growth with environmental conservation, is widely used to measure green development and is considered one of the most important indicators related to the level of green production (Wang et al., 2020; Qiu et al., 2021a; Li et al., 2021; Ma et al., 2022; Hao et al., 2023).

At the same time, with the rapid development and progress of communication technology and Internet technology, the digital economy and digital trade have become important factors in changing the global information flow, industrial structure, trade mode, and trade pattern. The digital economy refers to a number of economic activities that use data as the primary production element, information networks as the primary carrier, and digital technology application as the driving force to improve the economy's and society's level of digitalization, networking, and intelligence (G20, 2016; Zhang et al., 2022a). It includes both the development of digital industries and the penetration of digital technology into other industries, or even the digitization of other industries. As the core industry of the digital economy, digital industries are classified differently around the world. For example, in China, digital industries cover four categories: digital product manufacturing, applications of digital technology, industries influenced by digital factors, and digital product services (Shi, 2022). In addition to the digital industry, the digital economy also includes the digitalization of traditional industries, digital government affairs, and other important content.

There appears to be a consensus that the digital economy has a favorable economic impact. At the macro level, existing research has found that ICT can boost output and generate economic spillover effects (Kim et al., 2021). Digital technology can help improve production efficiency and accelerate economic growth. The digital economy can promote the transition from traditional energy to renewable energy, improve the quality of exports, and have a positive and lasting impact on subsequent regional productivity (Tranos et al., 2020; Shahbaz et al., 2022; Yabo and Jie, 2022). At the meso level, Pan et al. (2022) pointed out that the digital economy is the driving force of provincial TFP innovation and development, and Hao et al. (2023) found that the digital economy can improve the green TFP of China's manufacturing industry (Pan et al., 2022; Hao et al., 2023). At the micro level, numerous studies on enterprises have found that digital transformation is conducive to improving the productivity and performance of enterprises and reducing the risk of stock price crashes (He and Liu, 2019; Li and Wang, 2021; Dong et al., 2022).

On the other hand, the contribution of the digital economy to green, sustainable development is not necessarily linearly beneficial. An inverted "U"-shaped non-linear relationship between CO_2 emissions and the digital economy was discovered by Li et al. (2021) using panel data for 190 countries from 2005 to 2016. This finding suggests that the digital economy encouraged CO_2 emissions in the early stages of its development, supporting the environmental Kuznets curve (EKC) hypothesis (Li et al., 2021). The influence of the growth of the digital economy on green total factor energy efficiency (GTFEE) dramatically inverts from negative to positive as the digital economy expands, according to Zhao et al. (2022). They accomplished this by studying panel data from 281 Chinese cities at the prefecture level between 2003 and 2018 (Zhao et al., 2022a). The ICT and Internet industries greatly increase electricity consumption in both OECD nations and China. The utilization of massive global data centers and mobile data traffic may cause manufacturing-related electronic waste (Sadorsky, 2012; Dr et al., 2015; Salahuddin and Alam, 2016; Ren et al., 2021).

In recent years, China has made great strides in the field of the digital economy. By October 2022, China had signed memoranda of understanding on "Digital Silk Road" cooperation with 17 countries and established bilateral cooperation mechanisms on "Silk Road e-commerce" with 23 countries, deepening cooperation on "Digital Silk Road". At the same time, China's determination to actively respond to environmental changes and safeguard global ecological security is also reflected in the Belt and Road Initiative. Making new progress between China and countries along the Belt and Road in the field of digital economic cooperation and jointly promoting green, ecological, and sustainable development has become an issue that China and countries along the Belt and Road need to discuss together. However, research on the digital economy-GTFP nexus in B&R countries is just beginning.

In summary, although the discussion on the relationship between GTFP and DE has become the focus of many scholars, there are few existing studies on the "Green Belt and Road" and the "Digital Silk Road". In other words, few studies have examined the impact of digital economy development in countries along the Belt and Road on GTFP. From this perspective, this paper measures the development level of GTFP and the digital economy in countries along the Belt and Road; explores the relationship between the digital economy and GTFP; and analyzes its mediation mechanism, spatial spillover effect, and heterogeneity among different countries.

The marginal contributions of this paper are as follows. First, this study enriches the research on the impact and transmission mechanisms of the digital economy on green development at the national level of the Belt and Road Initiative. The digital economy and GTFP of 40 Belt and Road countries from 2006 to 2021 are measured for the first time. Secondly, the empirical results of this paper find that for countries along the Belt and Road, the digital economy will inhibit the growth of GTFP, which is different from the conclusions of many past studies. This paper analyzes and discusses the reasons for this result, which also makes this study different from the previous ones. Thirdly, in this paper, the quadratic of DE is added to the regression, while the nonlinear relationship between the digital economy and GTFP is considered, respectively, which also enriches the research conclusions. Finally, in the past, for examining the heterogeneity of sample countries, the World Bank's division of national income levels in the current year was usually used; however, the income levels of sample countries changed dynamically in inter-temporal data. This paper adopts the World Bank's classification criteria for the income level of countries in each year from 2006 to 2021, which makes the heterogeneity analysis of this paper more reliable.

The remaining part of the study is organized as follows. We briefly provide a structured literature review and present the theoretical hypotheses in Section 2. Section 3 details the methodology, variables, and data. We also conduct unexpected output super-efficiency SBM model and global Malmquist-Luenberger indexes to calculate the GTFP and measure digital economy levels using the principal component analysis (PCA) method from 2006 to 2021 for the 40 B&R countries in Section 3. After a series of tests on panel data, such as the slope heterogeneity test, cross-sectional correlation test, panel unit root test, and cointegration test, Section 4 shows the OLS and FMOLS regression results. Spatial regression, heterogeneity checks, and robustness checks are then presented. Finally, Section 5 contains conclusions, suggestions, and outlooks.

2 Literature review and research hypotheses

2.1 The digital economy-GTFP nexus

Identifying the influencing factors of green development is considered the primary factor in improving the efficiency of green development, and numerous scholars have analyzed the influencing factors of green development efficiency from different perspectives and dimensions. Since GTFP is developed on the basis of TFP, theories related to TFP can be transplanted into GTFP.

Emerging technologies, such as big data, artificial intelligence, and the Internet of Things, are driving changes in the mode of economic operation, guiding economic entities to adopt more advanced technologies and modern applications, and forming a different scope, scale, and level of production. Under the current technological and economic paradigm of the digital economy, digital and information technologies have rapidly realized industrialization and marketization and accelerated their penetration into the whole range of economic activities, changing the original mode of production, organization, and management (Du and Zhang, 2021). Therefore, through technological innovation in the ICT sector, the digital economy spreads technology to different production sectors, optimizes production allocation efficiency, and finally, realizes the improvement of macro TFP. Specifically, the mechanism of the digital economy to improve productivity includes the following two aspects.

On the one hand, the digital economy leads to the transformation of production factors and production functions. The popularization of the Internet can improve the real *per capita* GDP and change the industrial structure (Liu and Chen, 2017). When "data" production factors are added to the production process, production efficiency can be greatly improved through the channel effect of data development and application and data dissemination and sharing (Li and Wang, 2021). On the other hand, the characteristic that the value of "data" increases with the increase in the amount of data can generate the increasing return to scale effect, which expands the production possibility curve and greatly improves output efficiency (Shi et al., 2019; Ding, 2020).

On the other hand, the digital economy promotes technological efficiency and progress. It has been found that the digital economy has greatly contributed to social productivity through high-tech innovations and applications (Nambisan, 2017). The association between the digital economy index and provincial TFP in China was demonstrated by Pan et al. (2022), demonstrating the role of the digital economy as an innovation engine for the broad and sustained development of TFP (Pan et al., 2022). Zhang et al. (2022) found that the digital economy can effectively promote technological progress and efficiency improvement and promote green total factor productivity growth under the coupling effect (Zhang et al., 2022a). The application of ICT can also improve the digitalization of enterprises and governments, thereby increasing productivity and governance efficiency. According to Sadik-Zada et al. (2022), the adoption of electronic government in the delivery of public sector services has been the central factor that has contributed to the reduction of almost all corruption in developing and transition economies. E-government presents one of the greatest opportunities for socio-economic development and offers solutions for improving the efficiency and effectiveness of public administration (Sadik-Zada et al., 2022).

However, considering the environmental constraints, the impact of the digital economy on GTFP is more complex and difficult to judge. It is difficult to judge whether the digital economy promotes or inhibits GTFP. Modern information technology promotes the innovation of urban development modes, which produce technological effects, allocation effects, and structural effects through innovation drives and then reduces urban environmental pollution through the above three effects. However, the ICT industry itself is a high energy consumption industry (Shi et al., 2018). In the early stages of the digital economy, limited resources are devoted to the development of infrastructure, leading to few opportunities for industrial structure optimization. Through increased expenditure on digital devices and infrastructure, as well as the digitization of existing commercial enterprises, the digital economy increases pollution emissions and energy consumption (Wang, 2022). The degree of penetration of the digital economy in different industries was obviously unbalanced. According to Guo and Liang (2021), the siphon effect of talent and capital brought on by digital industrialization hampered technical advancement (Guo and Liang, 2021). According to Zhou et al. (2021), based on the panel data of Chinese cities from 2011 to 2019, the digital economy significantly increased the GTFP of central cities, but the "siphon effect" hindered the green total factor productivity improvement of peripheral cities (Zhou et al., 2021). Xu and Liu. (2023) found that the digital economy and the green economy in central and western China have not yet had a positive interaction (Xu and Liu, 2023). There is a vertical deepening process from the Internet economy to the digital economy, and the dimensions of the digital economy "enabling" economic transformation and green development are more extensive and the mechanism of action is more complex (Guo and Liang, 2021).

While technology embedding in economic transformation based on digital technology development takes a lot of time, with the transformation of the digital economy and industrial structure, future development of the digital economy can improve GTFP through innovative technology, better capacity management, increased worker productivity, resource management, more

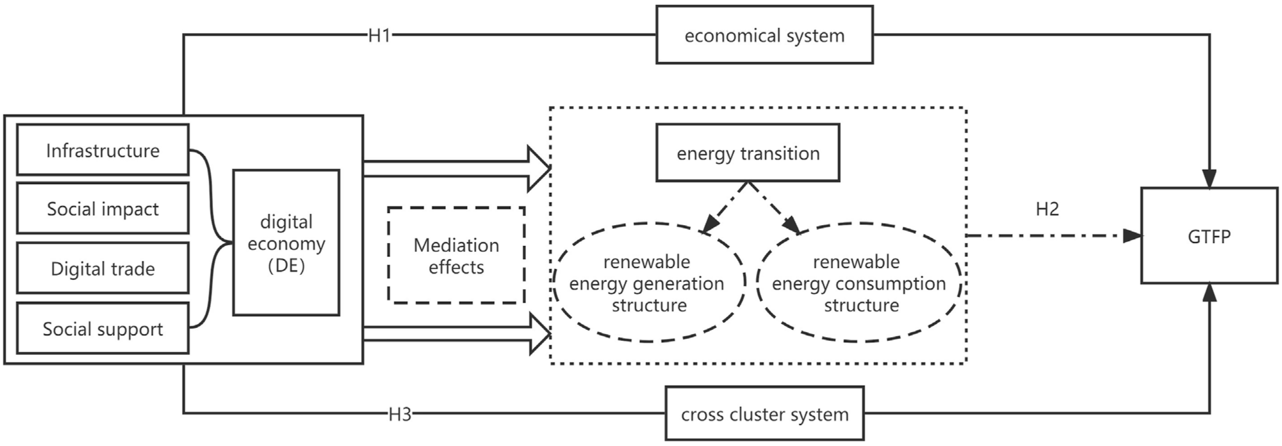


FIGURE 1
The conceptual framework of the digital economy on GTFP.

rational environmental regulations, higher energy efficiency, reduced energy consumption, and lower pollution (Lange et al., 2020; Huang and Lei, 2021). Therefore, the promotion effect of the digital economy on GTFP may have a time-lag effect.

On the basis of these elements, we propose the following theory.

Hypothesis 1: The digital economy has a nonlinear impact on GTFP. At the same time, the promotion effect of the digital economy on GTFP has a time lag.

2.2 Mediating role of energy transition in the digital economy on GTFP

Factors that are considered for GTFP include energy input and output, meaning that efficiency of energy usage is crucial for GFTP. Pao andd Fu. (2013) revealed the positive relationship between clean energy and green growth, thereby explaining the importance of promoting clean energy applications (Pao and Fu, 2013). Taskin et al. (2020) also described the positive effect of renewable resources on sustainable development, which is consistent with Pao and Fu. (2013) (Taskin et al., 2020).

Considering that the process of digital industrialization can affect the energy structure, the role of energy transformation in studies of the digital economy's impact on GTFP cannot be ignored. The digital economy encourages the digital transformation of established sectors and the development of new business models, particularly those with low energy consumption and emissions. The digital economy can also have a positive impact on energy transformation by enhancing government governance, improving the efficiency of traditional energy use, and promoting the generation and consumption of renewable energy (Shahbaz et al., 2022). Fan et al. (2022) demonstrated that the development of new digital infrastructure has a positive effect on China's energy restructuring (Fan et al., 2022). Wang et al. (2023) found that RETI (renewable energy technological innovation) significantly improves GTFP in China (Wang et al., 2023). According to some data, the digital economy may improve energy efficiency, lower CO2 emissions, and alter the composition of energy consumption (Rodríguez Casal et al., 2005).

It can be seen that the digital economy may affect GTFP through energy transition; however, few studies have discussed the mediating role of energy transition in the past.

On the basis of these factors, we put forth the following theory.

Hypothesis 2: Energy transition plays a mediating role in the digital economy–GTFP nexus.

As the aforementioned study demonstrates, the digital economy can contribute to energy transition, and we consider two aspects of energy transition: the structure of the use of renewable energy and the structure of the production of renewable energy.

2.3 The spillover effects of the digital economy on GTFP

The development of the digital economy not only accelerates the spread of information and reduces the cost of information flow but also creates new resources and promotes knowledge sharing. The digital economy can break the traditional time and space constraints, making closer ties between regions and countries, thus improving labor efficiency, productivity, and management locally, and even crossing borders, presenting spatial spillover effects from digitization to GFTP. Furthermore, according to the theory of technology diffusion and the new economic geography, geographical proximity may be an important factor influencing the effect of the digital economy (Zhao et al., 2022a; Shahbaz et al., 2022).

At the same time, the Internet may exhibit different effects on socio-economic and green development in regions with different levels of economic development and different locational conditions. Countries differ greatly in terms of available resources and capabilities for designing e-government strategies and measures. A country's e-government development plans may not necessarily

TABLE 1 Valuation index system of GTFP.

	Perspective	Sub-Perspective	Specific Indicators
Green Total Factor Productivity (GTFP)	Inputs	Capital Factor	Fixed Capital Stock
		Labor factor Unit	employees at the end of the year
		Energy factor	Primary energy consumption
	Output	Expected output	GDP
		Unexpected output	Total CO_2 emissions

TABLE 2 Comprehensive index system of the digital economy.

Primary indexes	Secondary indexes	Units	Data sources	Indicator Attribute
Infrastructure	Fixed broadband subscriptions	per 100 people	ITUI TU ITU	+
	Fixed telephone subscriptions	per 100 people		+
	Telecommunication Infrastructure Index		UN	+
Social impact	Individuals using the Internet	% of population	ITU	+
	Individuals using a cellphone	% of population	ITU	+
	E-Participation Index		UN	+
	Medium and high-tech manufacturing value added	% of manufacturing value added	World bank	+
Digital trade	ICT goods exports	% of total goods Exports	World bank	+
	ICT goods imports	% of total goods Imports	World bank	+
Social support	Per capita value added of service (constant 2015 US$)	$US/person	World bank	+

benefit from government spending or economic growth due to internal political, social, and bureaucratic issues (Niftiyev, 2022b). Due to historical, cultural, and religious reasons in countries along the Belt and Road, there may also be spatial heterogeneity in the impact of the digital economy on GTFP in these countries. Niftiyev (2022) analyzed three countries in the South Caucasus (Armenia, Azerbaijan, and Georgia), which are also Belt and Road Initiative (BRI) countries, and found that the three countries have different growth speeds in the ICT sector and digitalization levels, resulting in differences in manufacturing labor productivity. This has also led to differences in China's foreign economic interests in these countries (Niftiyev, 2022a). However, this point is typically ignored by academics.

We propose Hypothesis 3 according to the above study.

Hypothesis 3: The spatial spillover effect of digital economy on GTFP is statistically significant.

In general, our research focuses on three mechanisms. (Figure 1).

3 Econometric model and data

3.1 Econometric methods

The major dependent variable in this study is green total factor productivity (GTFP), whereas the key independent variable is the digital economy (DE), with the aim of examining the link between these two variables. This study introduces a series of control variables to control for the impact of macroeconomic factors. Due to the fact that panel data is selected for empirical analysis, we construct a multivariate framework as Eq. 1:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 DE_{i,t} + \sum\nolimits_3^7 \alpha_k CON_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{1}$$

where subscripts i represent countries and t represent years; The explanatory variable *GTFP* is green total factor productivity, *DE* is the digital economy indicator, and *CON* stands for a vector that contains the control variables; μ_i denotes individual fixed effects of countries i that do not vary over time; γ_t refers to time fixed effects; ε denotes random disturbance terms; and α_0 is an intercept term, α_1 and α_k are the coefficients for *DE* and *CON*, respectively.

Since many studies have shown that there may be a non-linear relationship between the digital economy and green development, in order to verify Hypothesis 1, we run the regression in two ways.

First, a quadratic term for the level of development of the digital economy DE^2 is added to the previous linear model and, thus, can be transformed into a regression model, given as Eq. 2.

$$GTFP_{i,t} = \alpha_0 + \alpha_1 DE_{i,t} + \alpha_2 DE_{i,t}^2 + \sum\nolimits_3^7 \alpha_k CON_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{2}$$

In addition, according to previous studies, digital technology needs time to spread, which means the digital economy may have a time lag; therefore, the lag period of DE is added to Eq. 2.

TABLE 3 Descriptive Statistics.

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
GTFP	628	1.118	0.483	0.312	6.093
DE	679	0.351	0.191	0.000	1.000
lnFDI	662	24.68	0.996	0.000	25.27
lnService	673	3.975	0.200	3.074	4.545
lnUrban	680	4.070	0.364	2.901	4.605
lnIC	680	4.612	0.288	3.737	5.223
lnRGDP	680	8.940	1.081	6.163	11.20

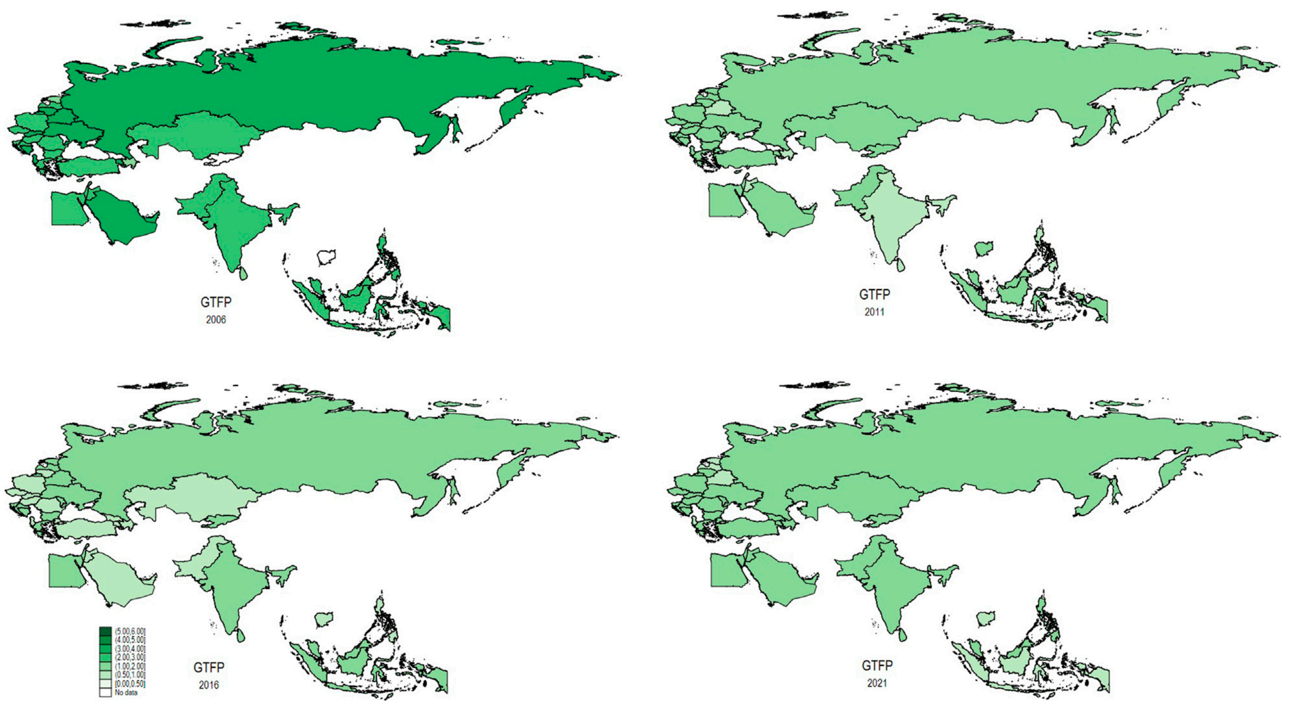


FIGURE 2
the GTFP of B&R countries in the years 2006, 2011, 2016, and 2021.

In the previous discussion of the transmission mechanism, we discussed how the digital economy may affect GTFP through energy transition. The indirect effect of the independent variable on the dependent variable through the intermediate variable is called the mediating effect (Mackinnon et al., 2000). To test whether the above factors can play the role of mediating variables, this paper adopts a standardized intermediary effect model to carry out further empirical investigation. Specifically, to verify Hypothesis 2, the indirect influence of the explanatory variable (X) on the explained variable (Y) through the intermediate variable (M), the following Eqs 3–5 are used:

$$Y = \alpha X + \varepsilon_1 \tag{3}$$

$$M = \beta X + \varepsilon_2 \tag{4}$$

$$Y = \alpha' X + \gamma M + \varepsilon_3 \tag{5}$$

This paper regards GTFP as the explanatory variable Y. Renewable energy generation (REG) and renewable energy consumption (REC) are regarded as intermediary variables M to be tested, and the DE is regarded as an explanatory variable X to construct the intermediary effect model.

Moreover, spatial panel econometric models are usually used in empirical studies of regions because they can take into account the inherent properties of the regions themselves and their spatial linkages. To verify Hypothesis 3, the underlying panel regression is extended to a spatial panel Durbin model (Eq. 6).

$$\begin{aligned} GTFP_{i,t} = {} & \alpha_0 + \rho WGTFP_{i,t} + \phi_1 WDE_{i,t} + \alpha_1 DE_{i,t} + \phi_2 WDE_{i,t}^2 \\ & + \alpha_2 DE_{i,t}^2 + \phi_3 WCON_{i,t} + \alpha_3 CON_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where: ρ represents the spatial autoregressive coefficient; W is the spatial weight matrix; ϕ_1, ϕ_2, and ϕ_3 are the elasticity coefficients of the primary and secondary terms of the digital economic development level and the spatial interaction terms of the control variables.

In model estimation, the variables are standardized from 0 to 1 to avoid the effect of different magnitudes on the results. In order to accurately estimate the interrelationship between the digital economy and green development, it is necessary to select the most appropriate model among different types of spatial panel econometric models for parameter estimation, i.e., combining LM, Robust LM, Wald, and other statistics with the Hausman test for judgment and selection (Jiang, 2016).

Where, if $\phi_{1,2,3} = 0$, the spatial Durbin model can be reduced to a spatial lag model (7); if $\phi_{1,2,3} + \rho\alpha_{1,2,3} = 0$, the spatial Durbin model can be reduced to a spatial error model (8).

$$GTFP_{i,t} = \gamma WGTFP_{i,t} + \alpha_0 + \alpha_1 DE_{i,t} + \alpha_2 DE_{i,t}^2 + \alpha_3 CON_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{7}$$

$$GTFP_{i,t} = \lambda WGTFP_{i,t} + \alpha_0 + \alpha_1 DE_{i,t} + \alpha_2 DE_{i,t}^2 + \alpha_3 CON_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{8}$$

Where: γ denotes the degree of influence of the GTFP of neighboring countries in the previous period on the GTFP of the region; λ denotes the spatial dependence effect of the GTFP of countries.

3.2 Variable measures and data sources

3.2.1 Unexpected output super-efficiency SBM model and global Malmquist-Luenberger index

As a non-parametric method, Data Envelopment Analysis (DEA) is superior in computing GTFP involving multiple input-output factors. While the past DEA method is not suitable for cases where there are multiple outputs, such as unexpected outputs, Tone (2002) constructed the SBM model for unexpected outputs (Tone, 2002). It can increase expected output while reducing unexpected output (Guo et al., 2022). Considering that outputs are difficult to predict, we expect to have less waste regardless of inputs. Therefore, the most efficient production method in the context of achieving green development must be the green production method, i.e., producing more expected outputs with fewer inputs as well as fewer unexpected outputs.

Compared with the general radial DEA model, the super-SBM model takes relaxation into account. Since Tone (2002) did not give the formula for the super-efficiency SBM model with unexpected output, this paper refers to Cheng (2014) and uses the super-efficiency SBM model with unexpected output to evaluate DMU (x_0, y_0, z_0) (Cheng, 2014).

Assumed to be present are n decision-making units (DMUs), each of which has three components: inputs, anticipated results, and unexpected results (production emissions such as wastewater, carbon dioxide, and soot), represented by three vectors (X, Y, Z).

The DMU (x_0, y_0, z_0) is evaluated using the super-efficiency SBM model with unexpected outputs, as shown in Eq. 9.

$$\begin{aligned}
\rho = min & \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^x}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}} + \sum_{t=1}^{s_2}\frac{s_l^z}{z_{l0}}\right)} \\
s.t.\ \ & x_{i0} \geq \sum_{j=1}^{n}\lambda_j x_j + s_i^x, \forall i \\
& y_{k0} \leq \sum_{j=1}^{n}\lambda_j y_j - s_k^y, \forall k \\
& z_{k0} \geq \sum_{j=1}^{n}\lambda_j z_j - s_l^z, \forall l; \\
& 1 - \frac{1}{s_1 + s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}} + \sum_{l=1}^{s_2}\frac{s_l^z}{z_{l0}}\right) > 0; \\
& s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall i, j, k, l;
\end{aligned} \tag{9}$$

$s^x \in R^m, s^z \in R^{s^2}$ denote the excess of inputs and unexpected outputs, $S^y \in R^{sl}$ then represents the shortage of expected outputs. ρ denotes the efficiency value of the decision unit and m, s_1, and s_2 represent the number of variables for inputs, expected outputs, and unexpected outputs, respectively.

To measure the dynamic green efficiency in B&R countries, we first follow Paster and Lovell (2005), who constructed a production technology set formed by all period data of all DMUs as a common production frontier, then calculate the Global-Malmquist productivity index (GM index, hereafter), the same frontier used by the global reference Malmquist, to derive the single Malmquist index (Pastor and Lovell, 2005).

Since the GTFP measure includes unexpected output, this paper also uses the Global Malmquist-Luenberger Index (GMLI) model to measure the dynamic change of GTFP, referring to the GMLI model proposed by Oh (Oh, 2010), with the following Eq 10.

$$\begin{aligned}
GML^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) &= \frac{1 + D^G\left(x^t, y^t, b^t\right)}{1 + D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \\
&= \frac{1 + D^t\left(x^t, y^t, b^t\right)}{1 + D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \times \left[\frac{\frac{\left(1+D^G\left(x^t,y^t,b^t\right)\right)}{\left(1+D^t\left(x^t,y^t,b^t\right)\right)}}{\frac{\left(1+D^G\left(x^{t+1},y^{t+1},b^{t+1}\right)\right)}{\left(1+D^{t+1}\left(x^{t+1},y^{t+1},b^{t+1}\right)\right)}}\right] \\
&= \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right] = EC^{t,t+1} \times BPC^{t,t+1}
\end{aligned} \tag{10}$$

The technical efficiency change index (EC) is the efficiency change indicator. Best practice gap change (BPC) measures technical change between the two time periods. Hence, $BPC^{t,\ t+1}$ measures how closely a contemporaneous technology frontier shifts toward the global technology frontier in the direction of more desirable outputs and less undesirable outputs. $BPC^{t,\ t+1} > (<)$ 1 corresponds to technical progress (regress) (Oh, 2010).

Eqs 11, 12 introduce the specific composition of EC and BPC:

$$EC_c = \frac{E_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_c^t\left(x^t, y^t\right)} \tag{11}$$

$$BPC_c = \frac{E_C^G\left(x^{t+1}, y^{t+1}\right) / E_C^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_C^G\left(x^t, y^t\right) / E_C\left(x^t, y^t\right)} \tag{12}$$

Based on green development and model data requirements, we followed Meng and Zhao (2022), Zhao et al. (2022), Xie et al. (2021), who constructed a system of input and output indicators that are needed to measure GTFP (Table 1) (Xie et al., 2021; Zhao et al., 2022c; Meng and Zhao, 2022).

This paper refers to Zhang et al. (2019) and uses the perpetual inventory method to estimate the capital stock of the sample countries, in which the depreciation rate is taken as 6% (Zhang et al., 2019). The labor input is obtained by directly subtracting the total number of unemployed from the total labor force, and the units are human beings; the unemployment is obtained from IFS (International Financial Statistics). Primary energy consumption, total CO2 emissions, and GDP are obtained from WDI (World Development Indicators).

3.2.2 Digital economy indicators

There is relatively little relevant literature on specifically measuring the level of digital economy development, so this paper follows Shahbaz et al. (2022) and Zhao et al. (2022) to construct a digital economy index based on four sub-indicators representing infrastructure, social impact, digital trade, and social support using principal component analysis (PCA), denoted as DE, and standardizing the DE from 0 to 1 (Zhao et al., 2022b; Shahbaz et al., 2022). The specific variables and data sources are shown in Table 2.

3.2.3 Control variables

We select five control variables that may influence green efficiency.

(1) Openness (FDI). According to the technology spillover theory, foreign direct investment (FDI) can bring more advanced production technology and a more scientific management system to the host country. Additionally, FDI promotes the technological progress of the host country through technology spillover and has a positive impact on the ecological environment. Therefore, we control FDI as the earlier studies do (Antweiler et al., 2001; Qiu et al., 2021b; Du and Ma, 2022).
(2) Industry Structure (Service). Industrial structure can reflect a country's economic structure and development pattern. According to the followers of structuralism, the evolution of industrial structure is actually the process of transferring input factors from low-productivity sectors to high-productivity sectors, thus realizing a "structural dividend". Therefore, changes in industrial structure affect GTFP, and the industry structure in this study is expressed by service industry value added to GDP (Jiang et al., 2022).
(3) Urbanization (Urban). Chinnery and Syrquin (1975) proposed a "development model" of urbanization and industrialization, and it argues that the development of urbanization is initially driven by industrialization and that its role in urbanization diminishes in the later stages of industrialization (Chenery and Syrquin, 1975). Industrialization brings more frequent economic activities to cities, and the influx of large numbers of people in cities undoubtedly provides a more sufficient impetus for urban economic growth. Economies of scale bring many benefits, such as lower transaction costs. However, they are usually accompanied by higher levels of industrial pollution. Therefore, the development of urbanization is assumed to have an impact on GTFP. Following Liu et al. (2022), we choose urbanization as a control variable (Liu et al., 2022).
(4) Industrial Concentration (IC). The number of secondary industries is selected to calculate the location entropy, which measures the level of industrial agglomeration in Belt and Road countries (Zhang et al., 2022c).
(5) GDP *per capita* (RGDP). The level of economic development reflects the comprehensive development status of a country. The more developed the economy is, the better the endowment conditions are, which can not only provide better capital conditions for industrial upgrading and transformation but also attract resources and talent, therefore providing better foundations for green development. Following Mikayilov et al. (2018), the GDP *per capita* of each country is selected as the measurement index of economic development level (Mikayilov et al., 2018).

The data on GDP *per capita*, FDI, value added of the service industry, and urbanization level are obtained from the World Bank Development Database (WDI), and industrial concentration is calculated according to the World Bank Development Database (WDI). Missing data are supplemented by interpolation and regression methods, as applied frequently in previous studies (Zhao et al., 2022a; Ma and Zhu, 2022).

In order to avoid the problems caused by the distributive characteristics of the data series, all the selected control variables are converted into logarithmic form in this study.

Table 3 shows the results of the descriptive statistics for the variables.

Between 2006 and 2021, the minimum value of GTFP of the B&R sample countries is 0.312 and the maximum value is 6.093; the higher the GTFP, the "greener" the B&R countries.

We show the dynamic changes of GTFP and DE in the years 2006, 2011, 2016, and 2021 from B&R countries in Figure 2 and Figure 3, in which the darker colors indicate a higher level of GTFP (DE).

Overall, the average GTFP of the 40 sample countries along the Belt and Road shows a W-shaped characteristic of falling and rising, then falling and rising again, with countries such as Azerbaijan, Brunei, and Kyrgyzstan declining slightly from 2006 to 2021, while GTFP in European countries such as Albania, Armenia, Belarus, and Moldova shows a strong downward trend (Figure 2).

The maximum value of the digital economy is 1 (Singapore in 2021) and the minimum value is 0 (Cambodia in 2012). The highest urbanization rate in the sample countries is 100% (Singapore), and the lowest urbanization rate in the sample period is 18.196% (Sri Lanka). The highest share of the service sector in GDP is 94.15% (Lebanon, 2021), and the lowest is 21.632% (Azerbaijan, 2007). Industrial concentration (IC), on the other hand, lies between 0.419 (Georgia, 2006) and 1.856 (Czechia, 2005). The highest value of GDP *per capita* among the sample countries is $72794.003 (Singapore), and the lowest is only $539.747 (Cambodia), which proves that there is a large gap between countries involved in the Belt and Road initiative.

4 Empirical methodology and results

4.1 Pre-estimation diagnostics

Table 4 demonstrates the correlation coefficients between the variables, showing that variables are low correlated, thus having a lower probability of multicollinearity.

10.3389/fenvs.2023.1213961

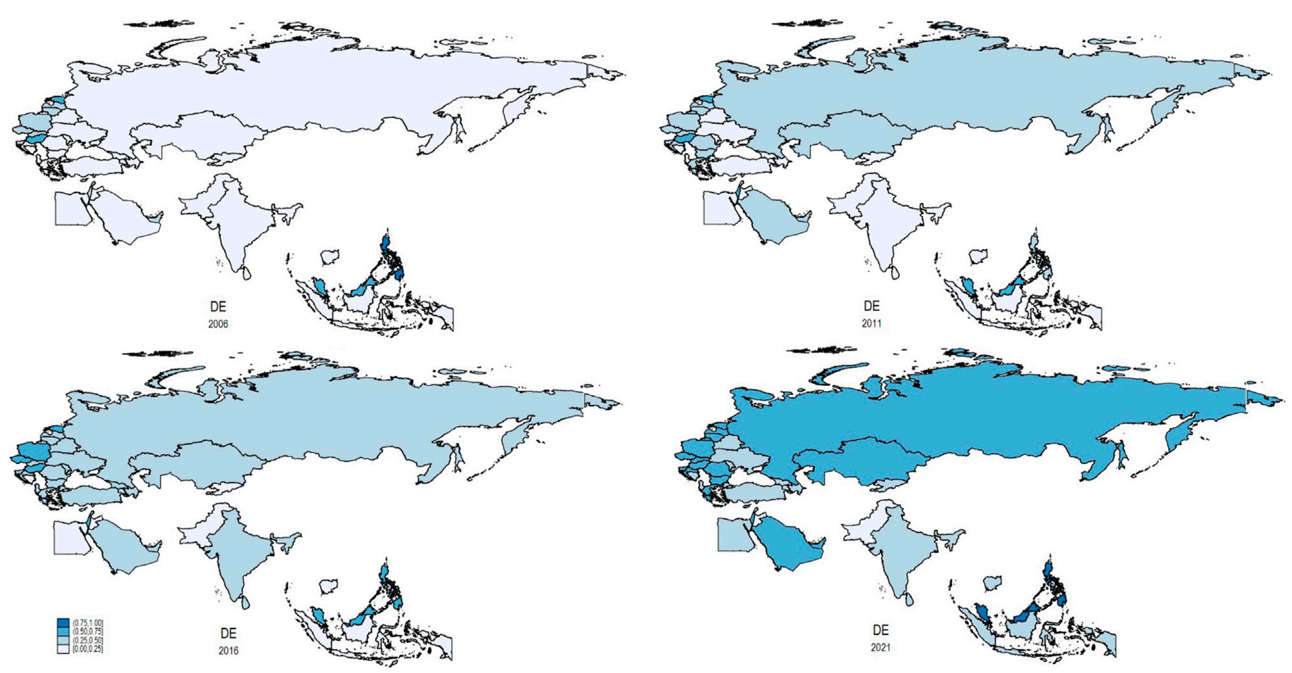


FIGURE 3
the DE of B&R countries in the years 2006, 2011, 2016, and 2021.

TABLE 4 Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) GTFP	1.000						
(2) DE	−0.113	1.000					
(3) lnFdi	0.010	−0.161	1.000				
(4) lnService	−0.003	0.397	−0.057	1.000			
(5) lnUrban	0.006	0.478	−0.070	0.322	1.000		
(6) lnIC	0.110	0.081	0.081	0.098	0.050	1.000	
(7) lnRGDP	−0.094	0.608	−0.101	0.353	0.698	0.170	1.000

4.2 Heterogeneity and cross-sectional dependence

While the data have been analyzed using descriptive statistics, there is a need for a slope heterogeneity analysis. The research factors in panel data analysis may be impacted by a variety of information, including social, economic, or technological information. Therefore, before starting the estimation procedure, slope heterogeneity and cross-sectional correlation tests should be used. The results for slope heterogeneity are shown in Table 5. The slope coefficient test's statistical value is significant at the 1% level, rejecting the null hypothesis of homogeneity. The findings indicate that the variables are heterogeneous, necessitating a cross-sectional dependence test.

When analyzing the relationship between all variables in panel data models, cross-sectional correlation is a key issue that needs to be considered; ignorance of cross-section dependence may cause substantial estimation bias and size distortions (Pesaran, 2007). Thus, before assessing the stationary nature of the variables, this analysis first examines the presence of any potential cross-sectional dependence in the panel.

TABLE 5 Slope heterogeneity test.

Homogenous/Heterogeneous slope coefficient testing	
Test	Statistic
$\tilde{\Delta}$	4.596***
$\tilde{\Delta}^{Ajusted}$	7.094***

Note: Significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

TABLE 6 Cross-sectional dependence tests.

Cross-sectional dependence testing	
Pesaran test	63.460***
Friedman test	64.154**
Frees test	4.249***

Note: Significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

The Pesaran test, the Friedman test, and the Frees test are applied, and the results are presented in Table 6. As shown in the table, the statistics for the Pesaran test and Frees test significantly reject the null hypothesis at the 1% significance level, and the statistics for the Friedman test significantly reject the null

TABLE 7 Panel unit-root tests.

variable	Level		1st difference		Level of integration
	Intercept	Intercept and trend	Intercept	Intercept and trend	
Pesaran CADF test					
GTFP	−5.424***	−3.070***	−9.186***	−3.534***	I (0)
DE	−2.053**	−2.496*	−2.602***	−2.741***	I (0)
DE^2	−2.059**	−1.744**	−5.912***	−2.117**	I (0)
lnFDI	−3.883***	−3.179***	−9.264***	−8.243***	I (0)
lnService	−2.575***	0.925	−5.881***	−2.672***	I (1)
lnUrban	−1.584	−2.219	−2.273***	−2.582**	I (1)
lnIC	−2.064**	−2.877***	−3.142***	−3.197***	I (0)
lnRGDP	−1.294	1.946	−2.499*	−2.672***	I (1)

Notes: Null hypothesis is that variables are not stationary. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8 Cointegration test.

Westerlund ECM panel cointegration tests			
Statistic	value	Z-value	*p*-value
G_t	−2.108	−4.103	0.000***
G_a	−19.361	−14.646	0.000***
P_t	−7.703	−1.625	0.052*
P_a	−12.085	−11.571	0.000***

Note: Significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

hypothesis at the 5% significance level, which provides strong evidence for the cross-sectional dependence among B&R countries. Therefore, in further analysis using this panel sample, we use estimation techniques that allow for cross-sectional dependence.

4.3 Unit root analysis and cointegration tests

To prevent erroneous regression, panel unit root tests must be carried out prior to parameter estimation in the panel data model. The first-generation conventional panel unit root tests, including the Levin-Lin Chu (LLC), Im, Pesaran, Shin (IPS), augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests, are not appropriate due to the presence of cross-sectional dependency in the panel data (Dou et al., 2021). As a result, the Pesaran cross-sectionally augmented IPS (CIPS) test and the cross-sectionally ADF (CADF) test, two second-generation panel unit root tests that take into account cross-sectional dependence, are more applicable in this investigation (Pesaran et al., 2007). The stationarity and level of integration of the variables are therefore examined in this study using the CADF test. Table 7 displays the results of the stationarity test.

It can be seen from Table 7 that not all variables I (0) are stationary, but the null hypothesis of unit root is significantly rejected in all first-order differences. Thus, our choice of variables is order-one stationary, providing the conditions for us to perform the cointegration test. The Westerlund ECM Cointegration Test is employed in the study to achieve this. The test results in Table 8 show the rejection of the null hypothesis. The significant *p*-values indicate the presence of long-term associations between variables indicating DE, and the control variables are associated with GTFP in B&R countries, illustrating long-term equilibrium relationships among the selected variables. Therefore, the following estimate of the DE-GTFP nexus is reliable and valid.

4.4 Benchmark estimates

After the discussion of data stationarity and cointegration, this paper conducts an empirical analysis of the DE-GTFP nexus by estimating Eq. 1. Table 9 shows the baseline regression results. For the OLS method, the Hausman test results suggest that the fixed effect model should be used. If the OLS estimation is still used when there are unit roots and cointegration relationships among the variables, although the OLS super-consistent estimator will be obtained, the asymptotic distribution of the OLS estimator is non-standard and is affected by noise parameters, which cause the commonly used test procedures to fail. In order to avoid possible endogeneity problems among variables, Phillips and Hansen (1990) suggested using non-parametric methods to modify OLS estimators and proposed the fully modified least squares method (FMOLS) for time series (Hansen and Phillips, 1990). On this basis, Pedroni (2001) proposed FMOLS estimation for panel data, including within-dimension FMOLS estimation and between-dimension panel estimation (Pedroni, 2001). The two methods are also compared, and it is found that the inter-group panel FMOLS has better small-sample properties and flexible condition setting than the intra-group FMOLS, so we use the

TABLE 9 Benchmark estimates.

	OLS		FMOLS		PCSE	
	(1)	(2)	(3)	(4)	(5)	(6)
DE	−0.423**	−0.425*	−0.339***	−1.602***	−0.425***	−1.017***
	(-1.97)	(-1.90)	(-4.112)	(-5.903)	(-5.17)	(-7.56)
DE^2				1.567***		0.782***
				(5.135)		(5.53)
lnFDI		−0.002	0.012	0.001	−0.002	−0.001
		(-0.23)	(1.307)	(1.064)	(-1.28)	(-0.51)
lnService		0.101	0.164***	0.171***	0.101*	0.100
		(0.54)	(3.082)	(3.682)	(1.67)	(1.57)
lnUrban		−0.237	0.185***	0.211***	−0.237	−0.045
		(-0.46)	(4.92)	(6.503)	(-0.51)	(-0.10)
lnIC		−0.050	0.017**	0.018***	−0.050	0.024
		(-0.34)	(4.809)	(5.771)	(-1.04)	(0.45)
lnRGDP		−0.167**	−0.052***	−0.034***	−0.167***	−0.170***
		(-2.31)	(-3.550)	(-2.741)	(-4.25)	(-4.12)
Constant	3.09***	5.227	-	-	5.227***	4.201**
	(20.16)	(1.18)	-	-	(2.81)	(2.15)
N	628	628	587	587	605	605
R^2	0.763	0.756	0.216	0.251	0.756	0.757

t statistics in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

inter-group panel FMOLS for estimation. In order to correct the cross-sectional dependence problem, we also adopt the PCSE estimation method. Regressions in columns (1), (3), and (5) show the estimated coefficients of the digital economy (i.e., DE) based on the OLS, FMOLS, and PCSE methods are consistently negative, indicating a monotonically decreasing relationship between the digital economy and green total factor productivity (GTFP).

The findings also support the validity and reliability of the theoretical derivation, which is supported by our theoretical expectation and Hypothesis 1, given in Section 3. The estimated coefficients for DE differ because two cross sections are dropped from the FMOLS estimation because of the missing data. Specifically, in columns (1), (2), (3), and (5), a 0.1 decrease in DE will cause GTFP to decline by approximately 0.04. Columns (4) and (6) present the estimation results for the nonlinear model of Eq. 2 and show that the coefficient of the quadratic term of DE is significantly positive, which proves that DE has a U-shaped relationship with GTFP, which is in line with the Kuznets curve. By calculating the marginal effects in column (6), it can be concluded that the turning point nearly occurs at DE equal to 0.6. The development of the digital economy has all the time inhibited the improvement of GTFP in B&R countries. While the level of the digital economy is below 0.6, as DE increases, the negative effect of DE on GTFP is increasing. With the development of the digital economy, when it reaches a certain level, for example, 0.6, the inhibition effect of the digital economy on GTFP will start to diminish. This conclusion is also in line with the existing literature on the study of the Internet, digital economy, and economic efficiency (Guo and Liang, 2021). In the meantime, over the sample period of the sample countries, although the

TABLE 10 digital economy lagging behind 1, 2, and 3 period.

	(1)	(2)	(3)
L1.DE	−0.506***		
	(-6.12)		
L2.DE		−0.142*	
		(-1.76)	
L3.DE			0.189**
			(2.31)
Controls	Y	Y	Y
N	604	570	534
R^2	0.750	0.159	0.226

t statistics in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

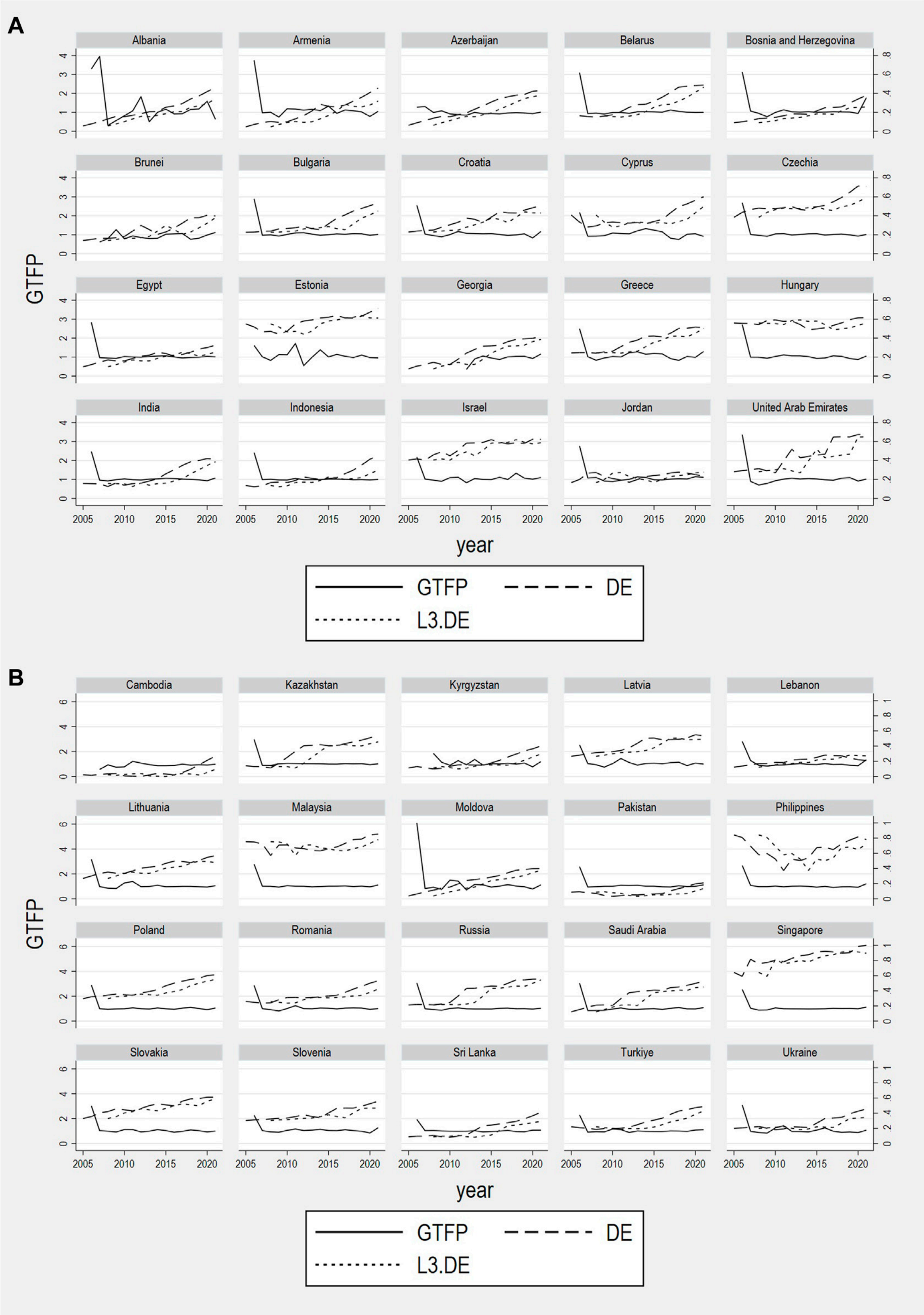


FIGURE 4
GTFP, DE, lagged DE for 3 years in B&R countries **(A, B)**.

coefficient of the quadratic term of DE is significantly positive, the total contribution of the digital economy to GTFP is consistently negative. Our findings are also in line with Zhao et al. (2022), who proved that the coefficient for the effect of digital economy development on green total factor energy efficiency (GTFEE) is significantly negative (Zhao et al., 2022a). There are two plausible

TABLE 11 Mediating Effect Test.

	(1) REC	(2) REG	(3) GTFP	(4) GTFP
DE	0.136***	20.29***	−0.404***	−0.408***
	(2.79)	(3.31)	(-5.32)	(-5.31)
REC			0.157***	
			(2.80)	
REG				0.001***
				(2.77)
Controls	Y	Y	Y	Y
Constant	−4.503***	−536.8***	5.869***	5.833***
	(-9.91)	(-10.15)	(2.78)	(2.79)
N	654	654	605	605
R^2	0.952	0.937	0.756	0.756

t statistics in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

explanations for these findings. First, massive investment in the construction of digital infrastructure such as network sites and data centers, as well as matching digital technologies, drives investment in ICT equipment manufacturing, chips, steel, optical fiber, and other industries, thus increasing energy consumption. Agricultural and land surveys have been carried out with the help of the Beidou navigation system, while projects such as digital connectivity, digital railways, ports, roads, energy, and water resources have been rapidly developed, driving power consumption up.

As for the control variables in column (4), the estimated coefficients of industry structure (i.e., lnService), Urbanization level (i.e., lnUrban), industry concentration (i.e., lnIC), and GDP *per capita* (i.e., lnRGDP) are all significant, and their signs mostly coincide with those 38 B&R countries' actual conditions (as two cross-sections are dropped). Specifically, the GDP *per capita* has a negative impact on the growth rate of GTFP in all the columns of Table 9. The results may be explained in the following ways: rapid economic expansion is typically accompanied by high energy consumption, which has a positive impact on the rise in household CO_2 emissions. These results are consistent with previous studies (Nasir et al., 2019; Pham et al., 2020; Shahbaz et al., 2020; Nasir et al., 2021). Large CO2 emissions lower the GTFP of the country. As rural residents rely heavily on coal consumption (Dou et al., 2021), the urbanization process contributes to the centralized utilization of energy, which can effectively improve energy utilization efficiency and, thus, improve GTFP. Since the energy consumption per unit output value of industry exceeds that of the service industry, and the scale effect brought by industrial concentration can improve the utilization efficiency of energy, capital, and labor, the increase in the proportion of tertiary industries (i.e., lnService) and the increase in the concentration of secondary industries (i.e., lnIC) can both lead to the improvement of GTFP.

In the early days of the digital economy, investment in digital infrastructure required the consumption of limited local resources. Moreover, the optimization of the production and organization modes of the secondary industry is often ignored in the early stages of the development of the digital economy. In addition, the "enabling" of the digital-based economy requires a certain amount of time for technological precipitation and penetration so as to play the role of the digital economy in optimizing the industrial structure and production mode. These factors may together lead to the reverse effect of the early development of the digital economy on GTFP. On the other hand, due to the "digital" nature of the digital economy, it is usually reflected in the improvement of the efficiency and output value of the tertiary industry, especially in the aspects of platform economy, digital currency, digital finance, *etc.* Although high efficiency in these areas contributes to economic development, it has a limited effect on energy conservation and emission reduction. In order to further explore the lagged effect brought by DE and confirm the research conclusions, we conducted regression with lagged terms. We find that the three-order lag term of DE has a significantly positive effect on GTFP, and the result is listed in column (3) of Table 10. This suggests that there is a significant lagged effect from DE on GTFP, supporting Wei and Hou (2022), who also reached the same conclusion (Wei and Hou, 2022). Figure 4 shows the intuitive trend. It has been shown that the improvement of GTFP depends on the level of environmental regulations and the optimal allocation of resources among secondary and tertiary industries, and the penetration of "digital" in these aspects usually requires a longer "enabling" process (Zhang et al., 2022c).

4.3 Mediating effect test

Muhammad Shahbaz et al. (2022) found that the digital economy positively affects energy transition; therefore, we explore the mediating effect of energy transition on the digital economy–green efficiency relationship. Following Shahbaz et al. (2022), the renewable energy consumption structure and the renewable energy generation structure are used as proxies for energy transition in this article, including data from the EIA for renewable energy consumption (REC) and renewable energy generation (REG) (Shahbaz et al., 2022). Table 6 presents the mediating effects results.

Columns (1) and (2) of Table 11 present that the digital economy can significantly raise REC and REG, meaning that the digital economy promotes energy transition in the sample countries. While columns (3) and (4) show that energy transitions can significantly contribute to the growth of GTFP, the results mean that B&R sample countries have been undergoing energy transitions with the help of the digital economy, and the decline of GTFP brought on by the digital economy may be partially offset by the intermediary effect and become a nonlinear relationship. Table 11 verifies Hypothesis 2.

According to Muhammad Shahbaz et al. (2022), countries or regions with more mature renewable energy transition, the digital economy will contribute more obvious effects on that transition. Developed countries are more experienced in improving the application scope of renewable energy through digital technology. However, most B&R countries are less developed, which means that they are less skilled at energy transition and are not technologically advanced. Moreover, they use fewer renewable energies, therefore having a limited ability to raise GTFP. When the digital economy plays a highly vital role in improving industrial production efficiency and raising the economy, those less experienced B&R countries then have additional carbon emissions, which have a negative total effect on GTFP.

TABLE 12 The test of spatial correction of GTFP and DE.

year	GTFP		DE	
	Moran's I	Z-Value	Moran's I	Z-Value
2006	−0.036	−0.191	0.069**	2.535
2007	−0.043	−0.372	0.095***	3.195
2008	−0.014	0.399	0.078***	2.721
2009	−0.067	−0.952	0.087***	2.961
2010	0.003	0.872	0.089***	3.036
2011	0.178***	5.460	0.053**	2.099
2012	−0.071	−1.130	0.039*	1.726
2013	0.033	1.618	0.040*	1.774
2014	−0.031	−0.045	0.038*	1.731
2015	−0.098*	−1.846	0.040*	1.776
2016	−0.004	0.674	0.042*	1.839
2017	0.013	1.071	0.035	1.643
2018	−0.061	−0.843	0.038*	1.719
2019	−0.105*	−1.908	0.055**	2.126
2020	0.055**	2.118	0.063**	2.338
2021	0.019	1.496	0.065**	2.386

4.4 Spatial spillover effect

Moran's I test is used to analyze the spatial distribution of GTFP. The global Moran's I index is calculated by Eq 10.

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\left[\sum_{i=1}^{n}(y_i - \bar{y})^2\right]} \tag{13}$$

Where y_i denotes the value of the indicator for country i, n is the total number of countries in the sample, and W_{ij} is the weight matrix. Moran's I is within the range of [-1, 1], and a value larger than zero implies a positive geographical correlation, while a value less than zero indicates a negative spatial correlation, and a value equal to 0 indicates no spatial correlation. In this paper, we use the matrix of inverse bilateral distance between countries (Wang, 2013).

The values of Moran's I are shown in Table 12.

It can be seen that Moran's index of GTFP of countries along the Belt and Road is significant in 2011, 2015, 2019, and 2020, which proves that there is not always spatial correlation in the GTFP of countries along the Belt and Road; however, there is a significant spatial correlation between the variables of the digital economy from 2006 to 2021. Therefore, this paper discusses the spatial spillover effect of the DE-GTFP nexus.

The LM, Robust LM, Wald, and Hausman tests suggest that the SDM model should be used. In column (3) of Table 13, the SDM model estimation results prove that the coefficient of DE is significantly negative and the coefficient of DE2 is significantly positive. In addition, within the range of sample values, the total effect of the digital economy on GTFP is negative, which is consistent with our benchmark regression results. Urbanization is significantly positive, while GDP *per capita* is significantly negative, which is also consistent with our benchmark regression.

The direct and indirect effects are shown in Table 14. The regression results prove that DE has both a significant direct effect

TABLE 13 Regression results of spatial panel model.

	(1)	(2)	(3)
	SAR	SEM	SDM
Main			
DE	−0.981***	−0.980***	−0.963**
	(-2.89)	(-2.88)	(-2.55)
DE^2	0.949***	0.947***	0.963**
	(2.67)	(2.66)	(2.39)
lnFDI	−0.00195	−0.00191	−0.00211
	(-0.23)	(-0.22)	(-0.24)
lnUrban	1.391***	1.391***	1.955***
	(2.66)	(2.66)	(3.30)
lnService	0.156	0.156	0.0538
	(0.92)	(0.92)	(0.30)
lnIC	0.0239	0.0234	−0.000915
	(0.17)	(0.16)	(-0.01)
lnRGDP	−0.237***	−0.237***	−0.211***
	(-3.78)	(-3.78)	(-3.18)
N	512	512	512
R^2	0.006	0.006	0.027
Log lik	111.9	111.9	116.7

t statistics in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 14 Direct effects and indirect effects.

Variable	Direct effects	Indirect effects	Total effects
DE	−0.962** (−2.48)	4.803** (2.12)	3.841* (1.73)
DE2	0.952** (2.30)	−4.101** (−2.00)	−3.157 (−1.57)
lnFDI	−0.001 (−0.15)	0.030 (0.87)	0.028 (0.80)
lnUrban	1.920*** (3.25)	7.258** (2.25)	9.179*** (2.80)
lnService	0.057 (0.34)	−1.113 (−0.83)	−1.055 (−0.77)
lnIC	0.008 (0.06)	−2.098** (−2.09)	−2.090** (−2.03)
lnRGDP	−0.212*** (−3.06)	0.186 (0.53)	−0.026 (−0.08)
R^2	0.110		

t statistics in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 15 Spatial heterogeneity measurement results.

Region	EU	ASEAN	ASIA
DE	−0.662***	0.212	−0.287**
	(-3.25)	(1.56)	(-2.23)
Controls	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y
N	306	94	205
R^2	0.714	0.942	0.891

t statistics in parentheses.
**p* < 0.1, ***p* < 0.05, ****p* < 0.01.

and a significant indirect effect. That is, the development of DE will cause the decline of domestic GTFP and the rise of GTFP in neighboring countries through spillover effects. This inconsistent result may be because it takes time for digital technology to spread. On the other hand, the majority of infrastructure investment is borne by the home country, so other countries can enjoy the benefits of digital progress without having to bear a large cost. As the foundation of the digital economy, the advancement of Internet technology has increased the flow of information, cut the cost of information transmission, and considerably reduced the spatiotemporal distance between regions. The increased usage of Internet technology has boosted management efficiency, broadened the market, and improved the structure of energy use. Therefore, the development of the digital economy promotes the improvement of GTFP in neighboring countries by improving the quality of innovation and upgrading the industrial structure.

The same phenomenon has been captured in previous studies (Su et al., 2021; Zhao et al., 2022a).

4.5 Analysis of heterogeneity

As can be seen in Table 15, the contribution of the digital economy to GTFP is significantly negative in European countries and ASEAN (Association of Southeast Asian Nations) countries, while the effect is positive but not significant in Asian countries other than ASEAN countries (mainly Central, South, and West Asian countries).

For high- and middle-income countries, DE progress brings a decline in GTFP, while in low-income countries, the coefficient of DE is not significant (see Table 16). At the same time, we can see that for middle-income countries, the negative impact of the digital economy on GTFP is greater than that of high-income countries, which is consistent with our previous analysis of industrial stages and household consumption in different countries.

The classification of countries can be found in Appendix Tables A1; Table B1. This paper uses the World Bank's annual classification of national income levels to classify the income levels of countries along the Belt and Road. The national income classification changes dynamically from year to year.

4.6 Robustness tests

Table 17 presents the robustness tests. Since there are numerous ways to measure the digital economy, this paper replaces the digital economy index with the Online service index in the UN e-government report. The Online service index is based on an overall synthesis of service delivery, technology, institutional frameworks supporting e-government development, content delivery, and e-participation. Online service indexes can also reflect the development of the digital economy (Zhang et al., 2022b). The regression results prove that the model and conclusions of this paper are robust.

Meanwhile, in order to exclude the influence of COVID-19, this paper also conducts a regression on the data from 2006 to 2019, and the regression results show that our conclusions still hold.

In addition, this paper uses the dynamic least squares (DOLS) method to test the robustness of the benchmark empirical models. Columns (5)–(6) in Table 15 show the results. The DOLS regression coefficients have the same direction and have similar values with FMOLS, which also proves that our benchmark regression model is reliable.

TABLE 16 Heterogeneity test for different income levels.

Country classification	Low-income	Middle-income	High-income
DE	−6.305	−1.240***	−0.860***
	(-1.66)	(-3.55)	(-4.45)
Country FE	Y	Y	Y
Year FE	Y	Y	Y
N	16	373	239
R^2	0.077	0.050	0.060

t statistics in parentheses.
**p* < 0.1, ***p* < 0.05, ****p* < 0.01.

TABLE 17 Robustness Tests.

Variables	Changing the Explanatory Variable		Excluding COVID-19 Period		DOLS method	
	(1)	(2)	(3)	(4)	(5)	(6)
Online	−0.161***	−0.204**				
	(-4.09)	(-5.14)				
DE			−0.374***	−0.463***	−0.266**	−1.299***
			(-5.10)	(-5.74)	(-2.043)	(-3.361)
DE^2						1.182***
						(2.837)
Controls	N	Y	N	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	628	605	548	528	605	605
R^2	0.763	0.756	0.773	0.766	0.044	0.056

tstatistics in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Conclusion and policy implications

For politicians and academics, the digital economy and green total factor productivity are becoming more and more appealing. Though numerous studies have examined the factors that influence GTFP, estimates of the effects of the digital economy on GTFP are scarce, especially for B&R countries. This study looks into the relationship between green total factor productivity and the digital economy in this environment. The following critical conclusions are highlighted.

First, the digital economy has a significant negative impact on green total factor productivity, which is reflected in a U-shaped relationship. The positive effect of the digital economy on GTFP has a time lag.

Second, as an intermediary variable, energy transition can effectively weaken the negative effect of digital economy development on GTFP.

Third, the impact of the digital economy on GTFP has a spatial spillover effect.

Finally, there is heterogeneity in the DE-GTFP nexus among B&R countries. Among these middle-income countries, DE growth has the largest negative impact on GTFP.

Based on the above findings, several critical policy implications are highlighted as follows.

First, the negative effect of DE on GTFP is an essential issue for countries along the Beltand Road in the context of optimizing government governance, increasing environmental regulations, applying digital technologies to reduce carbon and pollution emissions, and promoting economic development to improve GTFP and to avoid the path dependence of "polluting first, then treating".

Second, in view of the fact that energy transformation can weaken the negative impact of digital economy development on GTFP, Belt and Road countries should actively promote energy transformation, increase investment in renewable energy, and increase the proportion of generation and consumption of renewable energy.

Third, due to the existence of a spatial spillover effect, strengthening international cooperation and enhancing communication among Belt and Road countries can help share the cost of digital infrastructure construction, bridge the "digital divide", and jointly promote each other's green economic development.

Finally, considering that different levels of digital economy development have different impacts on GTFP, countries along the Belt and Road should take the initiative to learn from the experience of developed countries and formulate measures to manage the possible negative impacts of the digital economy.

Countries along the Belt and Road have different geographical locations, resource endowments, and stages of social development, and their ICT infrastructure construction is also different. For China, improving the construction of the Belt and Road requires a deeper understanding of these countries, and when evaluating investment projects, it is necessary to consider both the level of digital economy development and the level of GTFP in these countries. At the same time, China should promote the development of big data platforms and international cooperation on environmental protection technologies; share its experience in addressing climate change, global ocean governance, and biodiversity conservation; and effectively promote the Green Belt and Road Initiative.

Limitations of the study: (1) The data from 40 sample countries was only from 2006 to 2021, and detailed information was difficult to obtain due to a lack of data availability. Data for several Belt and Road countries cannot be obtained; while the geographical location of these countries is very important, they connect the sample countries. Due to the lack of data, the analysis of spatial measurement and the spatial spillover effect is not accurate enough, as is the analysis of spatial heterogeneity. (2) This study lacked the ability to investigate whether the digital economy and GTFP have a dynamic relationship (Hao et al., 2023); moreover, there may be other mechanisms of the digital economy on GTFP that can play a mediation role, such as industrial structure transformation, FDI, and fintech, that were not revealed here. (3) Different countries play different roles in the BRI, and the exact relationship between the BRI and the sample of 40 countries participating in this China-initiated and led economic project deserves further in-depth discussion, some kind of methodological control for the project is worth adding. The above aspects represent the current study's limitations and should be considered in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, AW; methodology, AW; software, AW; resources, JR; writing-original draft preparation, AW; writing—review and editing, AW and JR; supervision, JR; validation, AW; project administration, JR All authors have read and agreed to the published version of the manuscript. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1213961/full#supplementary-material

References

Antweiler, W., Copeland, B. R., and Taylor, M. S. (2001). Is free trade good for the environment? *Am. Econ. Rev.* 91, 877–908. doi:10.1257/aer.91.4.877

Chenery, H. B., and Syrquin, M. (1975). *Patterns of development, 1950-1970*. Africa: African Economic History.

Cheng, G. (2014). *Data envelopment analysis method and MaxDEA software*. Beijing, China: Intellectual Property Press.

Ding, Z.-F. (2020). Research on the mechanism of digital economy driving high quality economic development: A theoretical analysis framework. *Mod. Econ. Res.* 1, 85–92. doi:10.13891/j.cnki.mer.2020.01.011

Dong, B., Xu, H., and Wang, J. (2022). Enterprise digital strategic commitment and stock price crash risk. *J. Account. Res.* 09, 112–126.

Dou, Y., Zhao, J., Dong, X., and Dong, K. (2021). Quantifying the impacts of energy inequality on carbon emissions in China: A household-level analysis. *Energy Econ.* 102, 105502. doi:10.1016/j.eneco.2021.105502

Dr, K. D. K. K., Lennerfors, T. T., Fors, P., and Van Rooijen, J. (2015). ICT and environmental sustainability in a changing society. *Inf. Technol. People* 28, 758–774. doi:10.1108/itp-09-2014-0219

Du, C.-Z., and Zhang, Y. (2021). On the mechanism of the impact of digital economic development on the growth of enterprise productivity. *Secur. Mark. Her.* 02, 41–51.

Du, L., and Ma, Y. (2022). *Efficiency measurement and driving factors of green development for countries along the "Belt and road"*. China: Journal of Sichuan University, 173–183.

Fan, L., Zhang, Y., Jin, M., Ma, Q., and Zhao, J. (2022). Does new digital infrastructure promote the transformation of the energy structure? The perspective of China's energy industry chain. *Energies* 15, 8784. doi:10.3390/en15238784

G20 (2016). G20 digital economy development and cooperation initiative [Online]. Available at: http://www.g20chn.org/hywj/dncgwj/201609/t20160920_3474.html. [Accessed September 22 2016].

Guo, J., and Liang, S. (2021). The impact mechanism of the digital economy on China's total factor productivity:an up-lifting effect or a restraining effect? *South China J. Econ.* 2021, 9–27. doi:10.19592/j.cnki.scje.390281

Guo, J., Zhang, K., and Liu, K. (2022). Exploring the mechanism of the impact of green finance and digital economy on China's green total factor productivity. *Int. J. Environ. Res. Public Health* 19, 16303. doi:10.3390/ijerph192316303

Hansen, B. E., and Phillips, P. C. B. (1990). Statistical inference in instrumental variable regression with I(I) processes. *Rev. Econ. Stud.* 57, 99–125.

Hao, X., Wang, X., Wu, H., and Hao, Y. (2023). Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity? *Sustain. Dev.* 31, 360–378. doi:10.1002/sd.2397

He, F., and Liu, H. (2019). The Performance Improvement Effect of Digital transformation Enterprises from the Digital Economy Perspective. *Reform*. 4, 137–148.

Huang, L., and Lei, Z. (2021). How environmental regulation affect corporate green investment: Evidence from China. *J. Clean. Prod.* 279, 123560. doi:10.1016/j.jclepro.2020.123560

Jiang, L., Chen, Y., and Huang, J. (2022). Impact of fiscal expenditure efficiency on green total factor productivity:based on panel data of 284 Chinese cities. *Econ. Geogr.* 42, 28–36. doi:10.15957/j.cnki.jjdl.2022.11.004

Jiang, L., Chen, Y., and Huang, X. (2016). Selective activation of CB2 receptor improves efferocytosis in cultured macrophages. *J. Statistics Inf.* 31, 10–18. doi:10.1016/j.lfs.2016.07.013

Kim, K., Bounfour, A., Nonnis, A., and Zaygen, A. (2021). Measuring ICT externalities and their contribution to productivity: A bilateral trade based approach. *Telecommun. Policy* 45, 102085. doi:10.1016/j.telpol.2020.102085

Lange, S., Pohl, J., and Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecol. Econ.* 176, 106760. doi:10.1016/j.ecolecon.2020.106760

Li, X., Liu, J., and Ni, P. (2021). The impact of the digital economy on CO2 emissions: A theoretical and empirical analysis. *Sustainability* 13, 7267. doi:10.3390/su13137267

Li, Z.-G., and Wang, J. (2021). Digital economy development, data factor allocation and manufacturing productivity improvement. *Economist* 10, 41–50. doi:10.16158/j.cnki.51-1312/f.2021.10.005

Liu, J., and Chen, W. (2017). An empirical study on the relationship between internet development level and economic growth in China. *Econ. Geogr.*, 37.08, 108–113+154. doi:10.15957/j.cnki.jjdl.2017.08.014

Liu, L., Ding, T., and Wang, H. (2022). Digital economy, technological innovation and green high-quality development of industry: A study case of China. *Sustainability* 14, 11078. doi:10.3390/su141711078

Ma, D., Zhu, Q., Business, J. O., and Woodside, A. G. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* 145, 801–813. doi:10.1016/j.jbusres.2022.03.041

Ma, D., and Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* 145, 801–813. doi:10.1016/j.jbusres.2022.03.041

Mackinnon, D. P., Krull, J. L., and Lockwood, C. M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prev. Sci.* 1 (4), 173–181.

Meng, F., and Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environ. Sci. Pollut. Res.* 29, 79497–79515. doi:10.1007/s11356-022-21434-0

Mikayilov, J. I., Galeotti, M., and Hasanov, F. J. (2018). The impact of economic growth on CO2 emissions in Azerbaijan. *J. Clean. Prod.* 197, 1558–1572. doi:10.1016/j.jclepro.2018.06.269

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneursh. theory Pract.* 41, 1029–1055. doi:10.1111/etap.12254

Nasir, M. A., Canh, N. P., and Lan Le, T. N. (2021). Environmental degradation and role of financialisation, economic development, industrialisation and trade liberalisation. *J. Environ. Manag.* 277, 111471. doi:10.1016/j.jenvman.2020.111471

Nasir, M. A., Huynh, T., and Tram, H. (2019). Role of financial development, economic growth and foreign direct investment in driving climate change: A case of emerging ASEAN. *J. Environ. Manag.* 242, 131–141. doi:10.1016/j.jenvman.2019.03.112

Niftiyev, I. (2022a). China's interests in the industrialization of the South Caucasus: Comparative analysis of labor productivity in the manufacturing sector. *Ekon. i Sotsialnye Peremeny* 15, 205–222. doi:10.15838/esc.2022.2.80.13

Niftiyev, I. (2022). "The role of public spending and the quality of public services in E-government development," in Materials II International Conference "Digital Economy: Modern Challenges and Real Opportunities, Baki, 28-29 April 2022, 2022b, 450–454.

Oh, D. H. (2010). A global Malmquist-Luenberger productivity index. *J. Prod. Analysis* 34, 183–197. doi:10.1007/s11123-010-0178-y

Pan, W., Xie, T., Wang, Z., and Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *J. Bus. Res.* 139, 303–311. doi:10.1016/j.jbusres.2021.09.061

Pao, H. T., and Fu, H. C. (2013). The causal relationship between energy resources and economic growth in Brazil. *Energy Policy* 61, 793–801. doi:10.1016/j.enpol.2013.06.113

Pastor, J. T., and Lovell, C. A. K. (2005). A global Malmquist productivity index. *Econ. Lett.* 88, 266–271. doi:10.1016/j.econlet.2005.02.013

Pedroni, P. (2001). "Fully modified OLS for heterogeneous cointegrated panels," in *Nonstationary panels, panel cointegration, and dynamic panels*. Editors B. H. BALTAGI, T. B. FOMBY, and R. CARTER HILL (Bingley, United Kingdom: Emerald Group Publishing Limited).

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross section dependence. *J. Appl. Econ.* 22, 265–312. doi:10.1002/jae.951

Pesaran, M. H., Smit, L. V., and Yamagata, T. (2007). Panel unit root tests in the presence of a multifactor error structure. *Camb. Work. Pap. Econ.* 175, 94–115. doi:10.1016/j.jeconom.2013.02.001

Pham, N. M., Huynh, T. L. D., and Nasir, M. A. (2020). Environmental consequences of population, affluence and technological progress for European countries: A malthusian view. *J. Environ. Manag.* 260, 110143. doi:10.1016/j.jenvman.2020.110143

Qiu, S. L., Wang, Z. L., and Geng, S. S. (2021b). How do environmental regulation and foreign investment behavior affect green productivity growth in the industrial sector? An empirical test based on Chinese provincial panel data. *J. Environ. Manag.* 287, 112282. doi:10.1016/j.jenvman.2021.112282

Qiu, S., Wang, Z., and Liu, S. (2021a). The policy outcomes of low-carbon city construction on urban green development: Evidence from a quasi-natural experiment conducted in China. *Sustain. Cities Soc.* 66, 102699. doi:10.1016/j.scs.2020.102699

Ren, S., Hao, Y., Xu, L., Wu, H., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

RodríGUEZ Casal, C., Van Wunnik, C., Delgado Sancho, L., Claude Burgelman, J., and Desruelle, P. (2005). How will ICTs affect our environment in 2020? *foresight* 7, 77–87. doi:10.1108/14636680510581330

Sadik-Zada, E. R., Gatto, A., and Niftiyev, I. (2022). E-government and petty corruption in public sector service delivery. *Technol. Analysis Strategic Manag.* 2022, 1–17. doi:10.1080/09537325.2022.2067037

Sadorsky, P. (2012). Information communication technology and electricity consumption in emerging economies. *Energy Policy* 48, 130–136. doi:10.1016/j.enpol.2012.04.064

Salahuddin, M., and Alam, K. (2016). Information and communication technology, electricity consumption and economic growth in OECD countries: A panel data analysis. *Int. J. Electr. Power and Energy Syst.* 76, 185–193. doi:10.1016/j.ijepes.2015.11.005

Shahbaz, M., Nasir, M. A., Hille, E., and Mahalik, M. K. (2020). UK's net-zero carbon emissions target: Investigating the potential role of economic growth, financial development, and R&D expenditures based on historical data (1870–2017). *Technol. Forecast. Soc. Change* 161, 120255. doi:10.1016/j.techfore.2020.120255

Shahbaz, M., Wang, J., Dong, K., and Zhao, J. (2022). The impact of digital economy on energy transition across the globe: The mediating role of government governance. *Renew. Sustain. Energy Rev.* 166, 112620. doi:10.1016/j.rser.2022.112620

Shi, D., Ding, H., Wei, P., and Liu, J. (2018). *Can smart city construction reduce environmental pollution*. China: China Industrial Econom-ics, 117–135.

Shi, D. (2022). Evolution of industrial development trend under digital economy. *China Ind. Econ.* 11, 26–42. doi:10.19581/j.cnki.ciejournal.2022.11.001

Shi, L., Wang, S., and Wang, J. (2019). Economic analysis from stock to flow: On the construction of theoretical framework of flow economics. *Acad. Mon.* 01, 50–28. doi:10.19862/j.cnki.xsyk.2019.01.005

Su, J., Su, K., and Wang, S. (2021). Does the digital economy promote industrial structural upgrading?—a test of mediating effects based on heterogeneous technological innovation. *Sustainability* 13, 10105. doi:10.3390/su131810105

Taskin, D., Vardar, G., and Okan, B. (2020). Does renewable energy promote green economic growth in OECD countries? *Sustain. Account. Manag. Policy J.* 11, 771–798. doi:10.1108/sampj-04-2019-0192

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Operational Res.* 143, 32–41. doi:10.1016/s0377-2217(01)00324-1

Tranos, E., Kitsos, T., and Ortega-ArgiléS, R. (2020). Digital economy in the UK: Regional productivity effects of early adoption. *Reg. Stud.* 55, 1924–1938. doi:10.1080/00343404.2020.1826420

Wang, H., Cui, H., and Zhao, Q. (2020). Effect of green technology innovation on green total factor productivity in China: Evidence from spatial Durbin model analysis. *J. Clean. Prod.* 288, 125624. doi:10.1016/j.jclepro.2020.125624

Wang, J. C. (2022). Understanding the energy consumption of information and communications equipment: A case study of schools in taiwan. *Energy* 249, 123701. doi:10.1016/j.energy.2022.123701

Wang, J., Dong, X., and Dong, K. (2023). Does renewable energy technological innovation matter for green total factor productivity? Empirical evidence from Chinese provinces. *Sustain. Energy Technol. Assessments* 55, 102966. doi:10.1016/j.seta.2022.102966

Wang, S., Liu, M. Y., and Wang, F. (2013). Anti-amnesic effect of pseudoginsenoside-F11 in two mouse models of Alzheimer's disease. *J. Quantitative Econ.* 30, 57–67. doi:10.1016/j.pbb.2013.03.010

Wei, L., and Hou, Y. (2022). Research on the impact of China's digital economy on urban green development. *J. Quantitative Technol. Econ.* 39, 60–79. doi:10.13653/j.cnki.jqte.2022.08.005

Xie, F., Zhang, B., and Wang, N. 2021. Non-linear relationship between energy consumption transition and green total factor productivity: A perspective on different technology paths. *Sustain. Prod. Consum.,* 28, 91–104.doi:10.1016/j.spc.2021.03.036

Xu, J., and Liu, Z. (2023). Research on the measurement and synergistic interaction effect of China's provincial digital economy and green economy. *Ecol. Econ.* 39, 57–62.

Yabo, L., and Jie, C. (2022). Research on the export quality effect of digital economy. *World Econ. Stud.* 17, 32–134. doi:10.13516/j.cnki.wes.2022.03.006

Zhang, J., Lyu, Y., Li, Y., and Geng, Y. (2022a). Digital economy: An innovation driving factor for low-carbon development. *Environ. Impact Assess. Rev.* 96, 106821. doi:10.1016/j.eiar.2022.106821

Zhang, J. Z., Zhao, W. Q., Cheng, B. D., Li, A. X., Wang, Y. Z., Yang, N., et al. (2022b). The impact of digital economy on the economic growth and the development strategies in the post-COVID-19 era: Evidence from countries along the "Belt and road. *Front. Public Health* 10, 856142. doi:10.3389/fpubh.2022.856142

Zhang, Q., Yan, F., Li, K., and Ai, H. (2019). Impact of market misallocations on green TFP: Evidence from countries along the Belt and road. *Environ. Sci. Pollut. Res.* 26, 35034–35048. doi:10.1007/s11356-019-06601-0

Zhang, Y., Wang, M., and Cui, L. (2022c). Impact of the digital economy on green total factor productivity in Chinese cities. *Econ. Geogr.* 42, 33–42. doi:10.15957/j.cnki.jjdl.2022.09.004

Zhao, S. A., Zhang, Y. C., Iftikhar, H., Ullah, A., Mao, J., and Wang, T. T. (2022b). Dynamic influence of digital and technological advancement on sustainable economic growth in Belt and road initiative (BRI) countries. *Sustainability* 14, 15782. doi:10.3390/su142315782

Zhao, S., Peng, D., Wen, H., and Wu, Y. (2022a). Nonlinear and spatial spillover effects of the digital economy on green total factor energy efficiency: Evidence from 281 cities in China. *Environ. Sci. Pollut. Res.* 2022, 1–21. doi:10.1007/s11356-022-22694-6

Zhao, X., Nakonieczny, J., Jabeen, F., Shahzad, U., and Jia, W. (2022c). Does green innovation induce green total factor productivity? Novel findings from Chinese city level data. *Technol. Forecast. Soc. Change* 185, 122021. doi:10.1016/j.techfore.2022.122021

Zhou, X., Liu, Y., Peng, L., et al. (2021). Progress of esophageal stricture prevention after endoscopic submucosal dissection by regenerative medicine and tissue engineering. *Shanghai J. Econ.* 17, 51–60. doi:10.1016/j.reth.2021.01.003

Appendix

TABLE A1 List of countries by income levels (Classified by the World Bank).

Groups	Countries
Low-income	Cambodia (2006–2014), India (2006), Kyrgyzstan (2006–2012), Pakistan (2006, 2007)
Middle-income	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Cambodia (2015–2021), Croatia (2006, 2007, 2016), Egypt, Georgia, Hungary (2006, 2012, 2013), India (2007–2021), Indonesia Jordan, Kazakhstan, Kyrgyzstan (2013–2021), Latvia (2006–2008, 2010,2011), Lebanon, Lithuania (2006–2011), Malaysia, Moldova, Pakistan (2008–2021), Philippines, Poland (2006–2008), Romania (2006–2018, 2020), Russia (2006–2011, 2015–2021), Slovakia (2006), Sri Lanka, Türkiye, Ukraine
High-income	Brunei, Croatia (2008–2015, 2017–2021), Cyprus, Czechia, Estonia, Greece, Hungary (2007–2011, 2014–2021), Israel, Latvia (2009, 2012–2021), Lithuania (2012–2021), Poland (2009–2021), Romania (2019,2021), Russia (2012–2014), Saudi Arabia, Singapore, Slovakia (2007–2021), Slovenia, United Arab Emirates

TABLE B1 List of countries by region.

Groups	Countries
ASEAN	Brunei, Cambodia, Indonesia, Malaysia, Philippines, Singapore
ASIA (Except ASEAN)	Cyprus, Egypt, India, Israel, Jordan, Kazakhstan, Kyrgyzstan, Lebanon, Pakistan, Saudi Arabia, Sri Lanka, Türkiye, United Arab Emirates
EU	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Estonia, Georgia, Greece, Hungary, Latvia, Lithuania, Moldova, Poland, Romania, Russia, Slovakia, Slovenia, Ukraine

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 10 July 2023
DOI 10.3389/fenvs.2023.1215866

OPEN ACCESS

EDITED BY
Grigorios L. Kyriakopoulos,
National Technical University of Athens, Greece

REVIEWED BY
Ahmad Ibrahim Aljumah,
Al Ain University, United Arab Emirates
Ioannis Sebos,
National Technical University of Athens, Greece

*CORRESPONDENCE
Jinzhe Yan,
yanjz@gachon.ac.kr

RECEIVED 02 May 2023
ACCEPTED 28 June 2023
PUBLISHED 10 July 2023

CITATION
Wang L and Yan J (2023), Effect of digital transformation on innovation performance in China: corporate social responsibility as a moderator.
Front. Environ. Sci. 11:1215866.
doi: 10.3389/fenvs.2023.1215866

Effect of digital transformation on innovation performance in China: corporate social responsibility as a moderator

Lei Wang[1] and Jinzhe Yan[2]*

[1]Changzhou Vocational Institute of Engineering, Changzhou, China, [2]College of Business, Gachon University, Seongnam, Republic of Korea

Introduction: In the digital economy, digital transformation (DT) is a deliberate decision to improve organizational procedures, alter production processes, introduce precision marketing, and more, ultimately impacting how well businesses innovate. This is why the current article investigates the effect of DT and the firm's innovation performance and the boundary condition of corporate social responsibility (CRS).

Method: This study proposed a conceptual research model for the effect of DT on innovation performance and discussed the boundary condition of CRS. We collected China's listed A-share firms' data to examine the proposed hypotheses statistically. After Hausman test, the current study adopted fixed-effect regression, examined the heterogeneity issues resulting from different industry classifications, and robustness test for the correctness of the results.

Results and Implications: The following main conclusions are drawn: 1) DT can significantly enhance product innovation performance; 2) DT can significantly improve process innovation performance; 3) There is a time lag effect on the innovation performance (both product and process innovation performance) of the previous period on the innovation performance of the current period; 4) CSR positively moderates the role of DT on innovation performance; and 5) The impact of DT is heterogeneous across industries and patent. This study not only enriched the literature on DT and innovation performance but also provided the guidelines to promote digital transformation at the firm level.

KEYWORDS

CSR, digital transformation (DT), product innovation performance, process innovation performance, innovation performance

1 Introduction

Digital transformation (DT) is causing a wave of change in countries and industries worldwide. Digital technology is commonly used to transform corporate development and promote high-quality corporate development, especially concerning sustainability goals.

The literature on enterprise digitalization focuses on essential digitalization theory, digital capabilities, DT, the impact of digitalization on enterprise performance, and the underlying mechanisms of action. DT and digitalization are fundamentally different. Hess et al. (2016) hold that digitalization converts information from an analog to a digital format, whereas DT is the digital change that technology brings. Kim et al. (2011) believe that the digitization (capability) level reflects the ability of information-based technical facilities, human resources, and comprehensive management. DT is the use of recent digital technologies (e.g., social media, mobile technology, analytics, or embedded devices) by corporations to realize important business enhancements, improve client expertise, optimize operations, or create new business models (Fitzgerald et al., 2014). Within an enterprise, DT is outlined as an associate structure amendment toward big data analytics, cloud computing, social media platforms, and so on (Kane, 2017).

The current literature on DT focuses on three areas: 1) Business transformation, 2) technology as a driver of DT, and 3) institutional and social impact. Business transformation is the foundation of DT; it focuses on the effect of DT on business systems, where digital technology affects not only the transformation of merchandise, business processes, or sales but conjointly the whole business model (Hess et al., 2016). Research on business transformation covers two main areas: business combination and structure modification. Existing studies on business portfolios focus on strategy, and experimentation and implementation of digital technologies alone are insufficient to achieve transformation because a digital strategy must also be developed (Sebastian et al., 2017). The DT process must combine a company's multiple practices with all its strategies, including digital, business, and information technology (IT) business strategies (A. Bharadwaj et al., 2013; Matt et al., 2015). The DT process for organizational change can be analyzed through the lens of resource theory. Liu et al. (2011) developed the resource matching theory by combining the resource base theory and strategic matching perspective. New technologies are the driving force behind DT, which profoundly affects the existing structures. IT investments are critical for business performance (Gerth and Peppard, 2016). Sebastian et al. (2017) consider how social technologies, mobile technologies, cloud computing, and IT are new digital technologies. White (2012) proposes four ideal digital technologies: mobile, big data, cloud computing, and search-based applications. In addition to new technologies and business models, DT depends on how society innovates and becomes more open, collaborative, and global (Bogers et al., 2018). Hinings et al. (2018) believe that the era of DT demands new theories that successively lead to institutional modification. Zhang et al. (2022) tested the relationship between digital transformation and corporate sustainability. Li and Fei (2023) suggested that DT is positively associated with a firm's performance and network embeddedness plays a mediation role.

The idea of social responsibility was first introduced in the early 1950s. Bowen (1953) presents specific concepts concerning corporate social responsibility (CSR)—that business people's choices and actions affect their stakeholders, employees, and customers, which in turn directly impacts the life standard in society as a whole. In the 1960s, mainstream academic thinkers argued that social, economic, and political changes pressured business people to reexamine their social roles and responsibilities. In the 1970s, social movements and new legislation influenced the understanding of CSR. In the 1980s, the international community became progressively conscious of environmental protection and property development and, indirectly, of company behavior. In the 1990s, major international events influenced the international community's view on social responsibility and sustainable development. In celebration of the year 2000, the global organization called General Assembly was established, giving businesses a wider variety of responsibilities concerning human and labor rights, the environment, anti-corruption, and property development. In the 2010s, the Paris Agreement and the adoption of the "Property Development Goals" in 2015 ushered in a new accord. During this period, the literature on CSR focused on the impact on the performance of specific sectors, organizations, and industries that can be linked to the SDGs and generate shared values. Porter and Kramer (2011) claim that traditional, limited corporate methods, which frequently overlook the broad elements that affect their long-term success, are partly to blame for the need to produce shared value Based on the literature on greenhouse gas reduction (Sebos et al., 2020), carbon (Sebos, 2022), and air pollution (Progiou et al., 2023), we supposed that Greenhouse gas reduction is the outcome of digital transformation, a bridge linking digital transformation and CSR(Wu et al., 2023).

In academia, there are two main themes regarding CSR. One is that CSR has four dimensions: economic responsibility, obligation, moral responsibility, and philanthropic responsibility (Carroll, 1991). In addition, Elkington and Rowlands (1999) hold that CSR should include economic, social, and environmental responsibility; this is from a stakeholder perspective. Clarkson (1995) believes that all stakeholders (e.g., shareholders, employees, and consumers) must be involved in the business development process, meaning that companies are accountable to all stakeholders. The existing literature on the drivers and behavioral outcomes of CSR presents different research findings. Academics investigate the factors that drive CSR behavior from institutional, organizational, and individual levels. Campbell (2007) claims that CSR comes from the pressure of mandatory policies set by government departments and related organizations. Competition and learning among companies, the corporate mission, organizational culture and identity, the governance structure, business strategy, or trade orientation promote CSR (Khan et al., 2013; Schultz et al., 2013; Abhinav et al., 2017). Companies respond to increased malpractice risk by strategically increasing their investment in employee-related CSR (e.g., work and life wellbeing, health and safety policies, etc.; Flammer and Luo, 2017). For CSR to serve the interests of shareholders, important resources must be invested early on, as the benefits of CSR activities can only be collected once the CSR threshold has been met (Nollet et al., 2016). Cho and Tsang (2020) emphasize the importance of considering a company's product strategy when evaluating CSR investments.

Drucker (1993) believes that innovation is a recombination of entrepreneurs' production factors and conditions. Schumpeter (1982) proposes that innovation includes product innovation (manufacturing of new products or transformation of old products), technological innovation (adoption of new production processes), organizational or institutional innovation (adoption of new organizational forms), market innovation (exploration of new markets), and resource allocation innovation (search for new supply markets). Rochford and Rudelius (1997) consider that innovation performance (IP) is the degree of innovation of improved and new products resulting from a firm's innovation activities. IP involves the entire process of generating a new concept, developing a new product from the new concept, and introducing the product to the market (Ernst, 2001). Sosik et al. (2012) consider the value of corporate innovation brought by corporate add-on products and pioneering product innovation as corporate IP. IP is also considered the result of the output and the improvement of production efficiency after the firm has invested certain resources in the innovation system, including product innovation performance (PDIP) and process innovation performance (PCIP; Guler and Nerkar, 2012).

Studies on the factors influencing IP have primarily been conducted from macro and micro perspectives. From a macro standpoint, Ahuja and Katila (2004) highlight that one effective factor for enhancing a firm's IP is a good regional environment, as the regional setting has an important impact on the firm's IP. Lindič et al. (2011) evaluate the factors that influence IP and conclude that government assistance could help SMEs improve their IP. From a micro perspective, Butlin and Carnegie (2001) delineate the antecedents of IP, namely, an ambitious business agenda, clear goals, rules-based forms, intimacy with customers, leadership, structure culture, infrastructure, and certain skills. In addition, Felin and Hesterly (2007) find that IP was associated with the knowledge and behavior of the people who manage this knowledge. Rouse and Daellenbach (2002) acknowledge that data, strategy, technology, structure, and culture are the main determinants of IP.

Prior research verified the DT effect on enterprise performance (Li and Fei, 2023; Ren et al., 2023), Corporate Social Performance (Meng et al., 2022), corporate sustainability (Zhang et al., 2022). However, few researchers investigated the effect on innovation performance. Chen and Kim (2023) verified the relationship between DT and innovation quantity and pointed out the mediation mechanism of knowledge flows and innovation awareness. Li et al. (2023) analyzed the influence of DT on innovation performance by adopting a fixed effect model with a total number of patents. This study presumed that DT could improve business capabilities, production, and management and help enterprises cross the "digital divide," enabling them to operate efficiently and highlight their core competitiveness. White (2012) believes that economic integration could be achieved through digital processes and collaboration tools. Bouncken and Barwinski (2021) argue that DT should be incorporated into existing business views as this process involves technological amendments. Companies should not only rely on DT to enhance innovation capabilities but also take the initiative to assume greater social responsibility. Therefore, this study proposes that DT positively affects a firm's IP and that CSR moderates the relationship between DT and IP.

This study provides the following potential contributions. Firstly, unlike DT literature, this study classified the innovation performance into product and process innovation performance, which enriched the literature on DT and innovation performance. Secondly, we introduced the CRS as a moderation variable. Finally, this study also investigated the multiplicative effect of DT and IP considering the heterogeneity of industry and ownership, using panel threshold regression, which is meaningful in constructing and improving the innovation theory of Chinese-listed companies.

2 Literature review and hypotheses development

According to Guler and Nerkar (2012), IP is the increase in productivity (including PDIP and PCIP) exhibited after the input of resource elements into the firm's innovation system. We elaborate on both PDIP and PCIP below.

2.1 DT and PCIP

Scholars agree that to realize economic gains from process innovation, a mix of explicit and tacit new knowledge is necessary (Un and Asakawa, 2015). Un and Asakawa (2015) confirm that data should be rigorously embedded in a firm's structure and technological systems to develop process innovation. Companies must acquire and assimilate internal and external information, reorganize existing and recently nonheritable information, and apply the remodeled information to their operations (Jansen et al., 2005). Theory of knowledge scholars expect firms to be able to assimilate external information (Zahra and George, 2002). A seamless flow of production-related details is generated through digitization, such as system access to external information, technology systems for enterprise resources coming up, offer chain management, or client relationship management. Data are generated to make production process issues visible in the manufacturing process and thereby improve the transparency of process operations and performance (Hendricks et al., 2007). PCIP can be positioned as a firm's resource endowment (Sorescu et al., 2003). According to enterprise resource theory, in dynamic economic conditions, applying digital technologies in DT will improve the exploitation of resources, which would then enhance the ability of corporations to introduce and gain a proprietary competitive advantage (Henfridsson et al., 2018). According to process reengineering theory, companies improve their business performance by introducing digital information technology, which works backward within the organization and the workflow to help develop new products, organizational processes, and services (Scuotto et al., 2017). It simplifies corporate communication and organizational structure (Moeuf et al., 2020). A commitment to digitalization facilitates communication between companies and access to new kinds of information and related resources, which is believed to enhance firm IP (Parida et al., 2012). Liang and Li (2022) divided the innovation performance into PCIP and PDIP and verified DT promotes both PCIP and PDIP. Based on the analysis above, we propose the following:

H1: DT positively affects PCIP.

2.2 DT and PDIP

Companies actively exploit the Internet, big data, artificial intelligence (AI), and alternative digital technology to innovate manufacturing processes and comprehensively improve product design, manufacturing practices, and management (Kang et al., 2016). In the digital economy, digitizing merchandise and services has become a serious means for corporations to achieve a competitive advantage. Companies that believe in digital products and services tend to maintain a good position in a competitive market (Frank et al., 2019). Regarding product–service innovation, companies provide advanced services, such as research and development (R&D), centered around a collaborative research process with customers to improve products and services to meet continuous customer needs through close interaction (Baines and Lightfoot, 2014). Kohtamäki et al. (2013) emphasize the tempering result of network capability (network management capability, network integration capability, and network learning capability) on product innovation. Strong information-learning capabilities allow firms to accumulate new skills and resources and integrate knowledge into internal capabilities to supply innovative merchandise, develop new product markets, cut R&D prices, and improve IP (Lew et al., 2013). According to stakeholder theory, for a company to achieve its product and service innovation goals, it must balance the conflicting interests of its contractual stakeholders as a whole, including management, general employees, shareholders, suppliers, regulators, and consumers. The government, as a regulator, requires companies to comply with environmental, policy, and regulatory requirements, which puts pressure on companies to innovate (Berchicci and King, 2007). Requests from customer provide information about their expectations for new merchandise and processes (Laforet, 2008). Suppliers and departments that are directly affected by the innovation can serve as co-creators or producers of the innovation (Yeniyurt et al., 2014). Liang and Li (2022) divided the innovation performance intwo PCIP and PDIP and verified DT promote both PCIP and PDIP Considering the studies discussed above, we propose the following:

H2: DT has a significant positive impact on PDIP.

2.3 Heterogeneity in the role of DT on IP

This study examines the differential impact of DT on IP from two perspectives: the nature of the firm's equity and the type of industry.

Brynjolfsson (1993) finds that IT investment within the service sector had a considerably higher result on firm performance than that within the manufacturingsector. Tippins and Sohi (2003) believe that IT capabilities indirectly affect the performance of manufacturing companies. The ability to integrate the enterprise may generate important improvements in business performance with the IT chain (Rai et al., 2006). Parsons et al. (1990) believe that IT has an important contribution to the development of the banking industry. Franks (2012) consider that the emergence of mobile payment services has not significantly impacted financial markets and that the ease of payment has not led to an increase in the number of market investors. Previous studies indicated that the manufacturing industry typically uses digital technology to create digital production lines and digital factories to improve the efficiency of enterprise production and operation, and non-manufacturing enterprises strengthen their capabilities in areas such as predictive analytics and merchandising management through digital infrastructure, digital processes, and digital marketing.

According to the equity nature of enterprises in China, enterprises are categorized as state-owned enterprises (SOEs) or non-state-owned enterprises (NON-SOEs, including private enterprises, foreign-funded enterprises, and mixed enterprises). In China's socialist market economy environment, the system is favorable to the development of SOEs (Zheng and Scase, 2013). SOEs are more likely to receive financial support through loan guarantees or government policies (Cui and Jiang, 2012). By contrast, NON-SOEs have limited access to financial aid and lack an intermediary for DT. In the process of digitalization, a big gap exists in the resources obtained by SOEs and NON-SOEs, and the resource difference determines the speed and level of their digitalization. In a socialist market economy, SOEs, which typically have more resources, have higher levels of digitization, whereas NON-SOEs may have lower levels. Accordingly, we propose the following:

H3: The impact of DT on IP is heterogeneous across industries and state ownership.

2.4 Moderating effect of CSR

According to the synergy effect, the interaction or cooperation of two things gives rise to a whole that is greater than the simple sum of its parts. Digitalization alone cannot successfully provide companies with a competitive advantage. Still, it can be useful in resource integration for purposes of CSR and sharing of business practices and specific resources, which gradually would help in forming an irreplaceable overall system and improving the IP of companies. Forcadell et al. (2020) note that corporate sustainability and digitalization are increasingly important to businesses, society, and policymakers worldwide. The combination of corporate sustainability and digitalization can enhance each other's strengths, thereby producing better results. According to the theory of corporate resources, companies can increase their digital innovation investment and PCIP by continuously absorbing new knowledge regarding social responsibility, creating a corporate culture that actively fulfills social responsibility, and fostering an atmosphere and mechanism for continuous innovation (Carrasco-Monteagudo and Buendía-Martínez, 2013). According to stakeholder theory, the relationship between a company and its stakeholders can be better maintained through CSR, leading to a wide and deep social relationship network (Lončar et al., 2019). Access to information, skills, and resources that are necessary for digital activities can reduce innovation costs and facilitate DT (La Rosa et al., 2018). Based on the discussion above, we propose the following:

H4: CSR positively moderates the relationship between DT and PCIP.

By engaging in socially responsible practices, companies could attract social and governmental capital and reduce the financing constraint of DT and maintain an honest image and establish products and production processes that satisfy market demand (Katmon et al., 2019). According to stakeholder theory, higher levels of investor social responsibility indicate that firms value communication with stakeholders and reduce the cost of

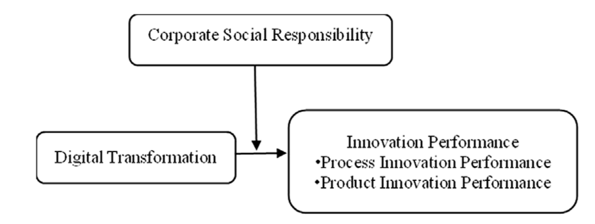


FIGURE 1
Research model.

developing innovative merchandise (Eccles et al., 2012). Management's practices of social responsibility toward internal stakeholders will considerably affect funding constraints. By contrast, social responsibility toward external stakeholders will alleviate the pressure of funding constraints and allow the allocation of additional funds to digital product transformation (Jianfei and Yun, 2019). Moreover, shareholders' fulfillment of social responsibility enhances the company name. This creates an honest company image, and the higher the company's reputation, the lower the cost of equity capital the company faces, and thus, the more it invests in digitalization (Lin-Hi and Blumberg, 2018). By increasing the recognition and social involvement of the company's employees, the firm would be able to attract the best employees and improve its level of digitalization, thereby enhancing its PDIP. Managers ought to specialize in coaching and recruiting staff with various business skills and a sense of responsibility (Groysberg and Lee, 2009). Strong learning capabilities and responsible practices help corporations accumulate new skills and resources and integrate them into internal capabilities to provide an innovative product, develop new product markets, cut back on R&D costs, and improve IP (Lew et al., 2013). How businesses operate is influenced by environmental, social, and economic trends, and DT will affect the business models (Chandola, 2015). DT considerably contributes to reducing waste emissions and enhancing environmental protection, leading individuals to unravel existing issues and address them in environmentally friendly ways (Feroz et al., 2021). Based on the analysis above, we propose the following:

H5: CSR positively moderates the relationship between DT and PDIP.

The research model is presented in Figure 1 below.

3 Research design

3.1 Data sources and samples

We selected Chinese A-share listed enterprises from 2010 to 2019 and obtained their data from the China Stock Market and Accounting Research (CSMAR) database. The data for the DT variables came from the annual reports of enterprises from 2010 to 2019, collected through CNINF and examined using Python for keyword text analysis. The data for the CSR variable were obtained from the China Hexun database on professional measurements of listed companies. Subsequently, enterprises belonging to the ST, ST*, and finance sectors were excluded. Finally, to mitigate the influence of outliers on the regression results, this study winsorized all continuous variables at the 1% and 99% levels. Panel data for 950 sample companies were included in the analysis.

3.1.1 Variable selection and measurement

3.1.1.1 Explained variables

Innovation Performance (IP). According to the previous analysis, IP promotes technological innovation, including PCIP and PDIP. PCIP concerns the application of new or improved corporate manufacturing business processes, whereas PDIP involves developing and producing new products. Following Jimenez-Jimenez and Sanz-Valle (2008), we measured PCIP in terms of annual innovation investment as a percentage of operating revenue and PDIP in terms of the number of patent applications (including invention, utility model, and design patents). To highlight the innovation of invention patents, weightings of 30% for invention patents, 20% for utility model patents, and 10% for design patents were assigned, and the resulting values were then summed up.

3.1.1.2 Explanatory variables

Digital Transformation (DT). Following Chun et al. (2021a), we compiled the annual reports of A-share listed companies on the Shanghai and Shenzhen exchanges through a Python tool to search, match, and count the word frequency of feature words from the data, sum up the word frequencies of key technology directions, and construct an index system for DT. For robustness testing, drawing on Huaijin et al. (2020), the degree of annual change in the digital economy as a percentage of total intangible assets (DT_R) was used as a proxy variable to validate DT on PCIP. To validate DT on PDIP, we used the sum of the number of uses of DT (AI technologies, blockchain technologies, cloud computing technologies, big data technologies, digital technology applications) of listed companies from the CSMAR database (DT_RN) as a proxy variable.

3.1.1.3 Moderating variable

Based on stakeholder theory and drawing on the research of Zuanyong and Dian (2021), we adopted the professional CSR measurement index system of China Hexun for listed companies to measure CSR fulfillment comprehensively.

3.1.1.4 Control variables

Based on Zhu and Jin (2023) and Zuo et al. (2021), this study set business growth, enterprise scale, gearing ratio, cash flows from operating activities, scales cost ration, return on total assets, board, Corporate equity concentration, nature of shareholding, number of years in the market and industry as control variables.

Business growth (GRO). The purpose of company growth analysis is to observe the event of a company's business capability exceeding an explicit amount. Therefore, the growth magnitude relation is a vital indicator of the company's development rate.

Enterprise scale (SIZE). The growth of innovation activity tends to rise gradually with the firm's size (Acemoglu and Linn, 2004). The size of an enterprise reflects its capability in product production or mounted assets for production and operation. We used the

Napierian logarithm of total assets to measure this variable (Vij and Farooq, 2016).

Gearing ratio (GER). This indicator reflects the proportion of creditors' assets in the enterprise's total assets; it indicates the peril of using creditors' credit facilities as well as the enterprise's ability to boost debt.

Cash flows from operating activities (CFA). This indicator captures the cash flow generated from all the enterprise transactions and events other than investing and financing activities. We measured CFA by taking the Napierian logarithm of a company's internet income from operations.

Sales cost ratio (SCR). The cost of goods sold ratio reflects a company's cost of goods sold per unit of sales revenue and corresponds to the gross margin. An abnormally high cost of goods sold ratio indicates that a company is selling incorrectly or is in an unfavorable competitive position in the market. SCR = (Total profit/Total costs and expenses) × 100%.

Return on total assets (RTA). This indicator represents the listed company's ability to use capital to generate profit, which may mirror aggressiveness, development ability, and comprehensive management ability.

Board size (BOS). Most studies indicate that the size of the board of directors has a vital impact on the company's decision-making, access to external resources for development, the building of a decent company image, and effective management. We used the number of directors to capture this variable.

Corporate equity concentration (CEC). The concentration of equity is a quantitative indicator of whether the equity is concentrated or dispersed among shareholders. We measured this variable by taking the logarithm of the shareholding of the largest shareholder.

Nature of shareholding (NOS). The nature of equity denotes a company's control through its shareholdings in a given company. The value is 1 if the enterprise is an SOE and 0 otherwise.

Number of years in the market (TIME). The number of years in the market is the period from the time of listing to the current time, which we measured by subtracting the present time from the listing time and taking the natural logarithm.

Industry (IND). The dummy variable for the industry is set as 1 for manufacturing and 0 for non-manufacturing.

3.2 Model specification

3.2.1 Benchmark model

To verify the hypotheses, we employed the economic models described below.

$$IP_{it} = \alpha + \beta_1 DT_{it} + \sum Control_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

In Eq. 1, subscripts i and t stand for the i^{th} firm and the year, respectively. IP denotes the firm's IP; DT denotes the firm's level of DT; *Control* indicates the control variables, including business growth (GRO), enterprise scale (SIZE), gearing ratio (GER), cash flows from operating activities (CFA), sales cost ratio (SCR), return on total assets (RTA), board size (BOS), corporate equity concentration (CEC), nature of shareholding (NOS), number of years in the market (TIME), and industry (IND). μ_i denotes the industry fixed effect, and ε is the random error term.

3.2.2 Moderation model

To investigate the moderating role of CSR, we added the CSR and the interaction term of DT and CSR to the benchmark model.

$$IP_{it} = \alpha + \beta_1 DT_{it} + \beta_2 CSR_{it} + \sum Control_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$IP_{it} = \alpha + \beta_1 DT_{it} + \beta_2 CSR_{it} + \beta_3 DT_{it} * CSR_{it} + \sum Control_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

In Eqs 2, 3, subscripts i and t stand for the i^{th} firm and the year, respectively. IP denotes the firm's IP; DT denotes the firm's level of DT, and CSR means corporate social responsibility. *Control* indicates the control variables, including business growth (GRO), enterprise scale (SIZE), gearing ratio (GER), cash flows from operating activities (CFA), sales cost ratio (SCR), return on total assets (RTA), board size (BOS), corporate equity concentration (CEC), nature of shareholding (NOS), number of years in the market (TIME), and industry (IND). μ_i denotes the industry fixed effect, and ε is the random error term. DT*CSR in Eq. 3 means the interaction term of DT and CSR.

4 Empirical results and analysis

4.1 Study 1: Empirical study of DT on PCIP

4.1.1 Descriptive statistics

The descriptive statistics analysis shows that the dependent variable PCIP has a maximum value of 0.244, a minimum value of 0, a mean value of 0.044, and a standard deviation of 0.042, indicating little difference in the PCIP of the sample of listed companies. The maximum value of the independent variable DT is 538; the minimum value is 1; the mean value is 66.118, and the standard deviation is 101.71, indicating a large gap in the degree of DT in the sample. From the robustness test, the maximum value of the proxy variable (DT_R) is 1; the minimum value is 0; the mean is 0.089, and the standard deviation is 0.182, indicating a wide variation in the percentage of the digital economy in the total intangible assets of listed companies. The maximum value of the moderating variable CSR is 76.015; the minimum value is −2.6; the mean is 25.928 and the standard deviation is 16.741, with some but no significant differences among samples (See Supplementary Table S1).

4.1.2 Correlation analysis and variance inflation factor

For an initial test of the role of DT on PCIP, Pearson correlation analysis was conducted on the key variables, and the results are shown in Supplementary Table S2. The dependent variable PCIP shows a positive relationship with the independent variable DT and the robustness test proxy variable (DT_R) and a negative relationship with the moderating variable CSR. To examine further the issue of multicollinearity among the main variables, the variance inflation factor (VIF) was tested for all explanatory and control variables, and we found that the maximum VIF value is

TABLE 1 OLS Regression vs. Fixed Effects Regression.

Variable	PCIP (OLS)	PCIP (FE)
DT	.000	.000
	(26.05)**	(11.60)**
GRO	−.010	−.012
	(7.19)**	(14.59)**
SIZE	−.006	.008
	(7.56)**	(7.12)**
GER	−.012	−.011
	(5.05)**	(4.42)**
CFA	−.019	−.007
	(5.27)**	(3.17)**
SCR	−.091	−.071
	(25.11)**	(20.03)**
RTA	−.004	−.005
	(3.64)**	(8.98)**
BOS	.000	.001
	(0.66)	(5.02)**
CEC	−.000	−.000
	(10.64)**	(4.14)**
TIME	−.034	
	(15.01)**	
o.TIME		.000
_cons	0.213	0.022
	(29.98)**	(2.01)*
R2	0.36	0.13
N	9,500	9,500

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

1.95 and the mean value is 1.36, suggesting no covariance problem in the model.

4.1.3 Regression analysis

To test the role of DT on PCIP, a mixed ordinary least squares (OLS) regression approach and panel data regression were used for empirical testing. Before conducting the panel data regressions, we administered a Hausman test to determine whether to use a fixed or random effects model. As Prob > chi2 = 0.0000, the difference between the fixed and random effects was significant, favoring the fixed effects model. Table 1 combines the OLS and panel data regression results.

Table 3 shows that DT significantly positively affects PCIP in both the OLS and fixed effects regressions, thus verifying H1. However, in terms of the degree of explanation, the OLS regression (t = 26.05) surpassed the fixed effects regression (t = 11.6), indicating that a fixed effects model fixes some factors, thus giving a slight reduction in explanatory power. Nevertheless, both results are significant at the 5% level and do not reach the 1% level of significance, indicating that the degree of DT of Chinese listed companies needs further improvement.

4.1.4 Endogeneity analysis

DT can significantly improve PCIP, and PCIP has a continuity feature; that is, the PCIP in the previous period may impact the PCIP in the current period. In addition, owing to the many factors that affect PCIP, the problem of omitted variables is inevitable when constructing the empirical model, which causes endogeneity issues. To deal with the aforementioned two endogeneity issues, we used the system generalized method of moments (SYS-GMM) to empirically test the relationship between prior- and current-period PCIP and then compare the results of the OLS, fixed effects, and SYS-GMM regressions. Table 2 displays the test results.

In Table 4, the SYS-GMM results show that the PCIP lagged by one period has a significant positive effect on the current period and passes the 1% statistical significance level test. AR (1) = 0.000 < 0.05 and AR (2) = 0.891 > 0.1, which indicates a first-order autocorrelation and no second-order autocorrelation for the random disturbance term. The Hansen test value = 0.115 > 0.1 indicates that the model does not have an over-identification problem and that the overall model is well estimated. After controlling for endogeneity, DT still has a significant positive effect on PCIP; hence, H1 is further supported. The analysis above reveals that PCIP has a certain lag and long-term nature, which suggests that the benefits of PCIP are uncertain and that PCIP transmission requires some time.

4.1.5 Heterogeneity analysis

Are there differences in the performance of DT on PCIP across industries and by the nature of equity? Drawing on Lau et al. (2016), we divided the study sample into four subsamples: Manufacturing (MAF), non-manufacturing (NON-MAF), state-owned enterprises (SOE), and non-state-owned enterprises (NON-SOE), and used a panel fixed effects approach for group testing and likelihood uncorrelated estimation. We found significantly different random disturbance terms, allowing for coefficient comparisons. Table 3 shows the test results.

As shown in Table 3, the DT of both SOEs and NON-SOEs significantly positively affect PCIP. Furthermore, a comparison of the regression coefficients and t-values shows that the DT of NON-SOEs is more likely to promote PCIP than that of SOEs; hence, H3 is verified. Similarly, manufacturing firms show a significant positive effect on PCIP compared with non-manufacturing listed firms, and the comparison of regression coefficients and t-values shows that manufacturing firms are better able to promote PCIP than non-manufacturing firms, with a 5% statistical significance, thus verifying H3.

4.1.6 Moderation analysis

To drawing on Hansen (1999), we conducted Bootstrap sampling by iterating the estimation process 1,000 times to determine whether a threshold exists. Table 4 shows the results, from which the following conclusions can be drawn. The F-statistic is significant at the 5% level for both the one- and two-threshold models; that is, the p-value is less than 0.05, suggesting that there are

TABLE 2 Comparison of OLS, FE, and SYS-GMM.

Variable	PCIP (OLS)	PCIP (FE)	PCIP (SYS-GMM)
L.PCIP			.7251237
			(24.04)***
DT	.000	.000	.000
	(26.05)**	(11.60)**	(2.71)***
GRO	−.010	−.012	−.013
	(7.19)**	(14.59)**	(−9.72)***
SIZE	−.006	.008	−.003
	(7.56)**	(7.12)**	(−0.83)
GER	−.012	−.011	.017
	(5.05)**	(4.42)**	(1.14)
CFA	−.019	−.007	−.027
	(5.27)**	(3.17)**	(−2.12)**
SCR	−.091	−.071	−.037
	(25.11)**	(20.03)**	(−2.47)**
RTA	−.004	−.005	.000
	(3.64)**	(8.98)**	(0.21)
BOS	.000	.001	−.001
	(0.66)	(5.02)**	(−0.94)
CEC	−.000	−.000	.000
	(10.64)**	(4.14)**	(1.7)
TIME	−.034		−.012
	(15.01)**		(−0.97)
o.TIME		.000	
_cons	.213	.022	.08
	(29.98)**	(2.01)*	(2.58)***
R2	0.36	0.13	
Wald chi2 (19)			13094.59
N	9,500	9,500	8500
AR (1)			.000
AR (2)			.891
Hansen test			.115

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

two thresholds in the model. Table 4 presents the results of the specific threshold estimates, which are −0.18 and 6.09. That is, the moderating variables are treated in three segments in conjunction with the number-for-transformation, namely, the first segment: CSR ≤ −0.18; second segment: −0.18 < CSR ≤ 6.09; and third segment: CSR > 6.09.

Figure 2 plots the existence of the two threshold estimates of CSR; it specifically shows the likelihood ratio function at a 95% confidence interval for the two thresholds of −0.18 and 6.09.

TABLE 3 Heterogeneity test results.

Variable	SOE	NON-SOE	MAF	NON-MAF
	PCIP (1)	PCIP (2)	PCIP (3)	PCIP (4)
DT	0.000	0.000	0.000	0.000
	(6.13)**	(9.38)**	(8.59)**	(6.48)**
GRO	−0.006	−0.014	−0.011	−0.015
	(4.77)**	(13.70)**	(13.58)**	(6.35)**
SIZE	0.020	0.002	0.010	0.007
	(12.70)**	(1.14)	(9.09)**	(2.28)*
GER	−0.018	−0.004	−0.008	−0.032
	(4.62)**	(1.19)	(3.12)**	(4.30)**
CFA	0.000	−0.008	−0.001	−0.026
	(0.06)	(3.21)**	(0.55)	(4.54)**
SCR	−0.056	−0.075	−0.050	−0.136
	(9.76)**	(16.81)**	(13.78)**	(13.50)**
RTA	−0.005	−0.005	−0.005	−0.005
	(4.10)**	(8.28)**	(8.66)**	(3.23)**
BOS	0.001	0.001	0.001	0.001
	(3.54)**	(3.00)**	(4.88)**	(2.25)*
CEC	−0.000	−0.000	−0.000	−0.000
	(3.88)**	(3.99)**	(3.72)**	(1.81)
o.TIME	0.000	0.000	0.000	0.000
_cons	−0.112	0.089	−0.018	0.087
	(7.11)**	(6.11)**	(1.63)	(2.88)**
R2	0.17	0.13	0.13	0.18
N	3,245	6,255	7,534	1,966

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

We further obtained the results of the panel threshold regressions along with the derived threshold values (see Table 5). Table 5 shows that the interaction between DT and CSR is split into three segments. In the first segment, the regression coefficient of DT•I (CSR ≤ −0.18) is 7.15e-05, and the t-value is 8.66, which is significant at the 1% level; that is, when CSR ≤ −0.18, the DT and CSR interaction has a significantly positive effect on PCIP. In the second segment, the regression coefficient of DT•I (−0.18 < CSR ≤ 6.09) is 0.000120, and the t-value is 12.83, which is significant at the 1% level; that is, when −0.18 < CSR ≤ 6.09, the effect of the interaction between DT and CSR on PCIP is also significantly positive. In the third segment, the regression coefficient of DT•I (CSR > 6.09) is 2.24e-05, and the t-value is 4.66, which is significant at the 1% level; that is, when CSR > 6.09, the effect of the interaction between DT and CSR on PCIP is still significantly positive. In addition, although the interaction of all three segments of CSR and DIT are significantly positive for both enterprise PCIP, the effects differ. From the magnitude of the regression coefficients and t-values, it can be judged that the

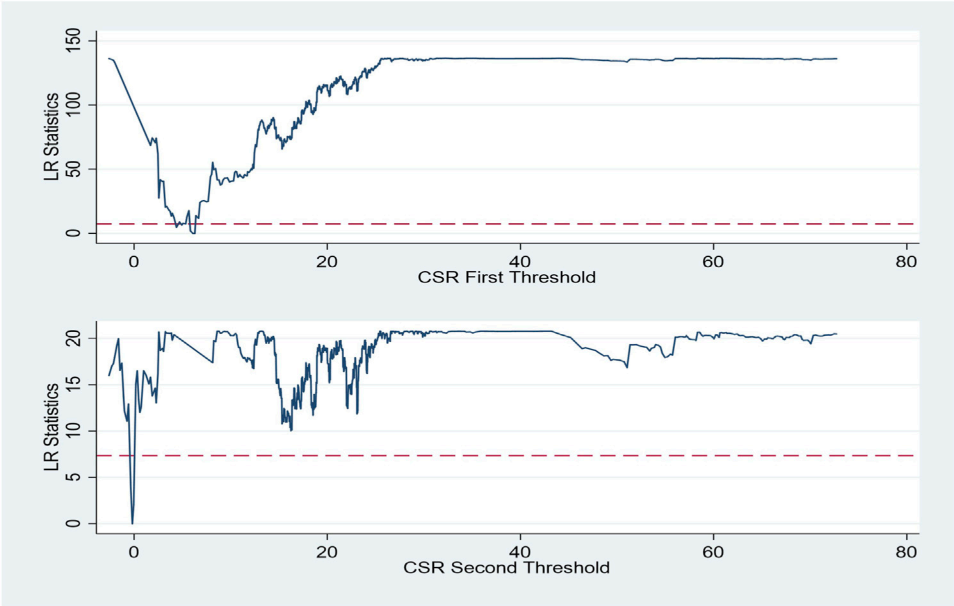


FIGURE 2
Threshold estimation chart.

TABLE 4 Threshold effect test.

	Threshold	Fstat	Prob	Crit10	Crit5	Crit1
CSR	one	148.53	0.0000	13.8914	15.6815	27.2027
	two	20.79	0.0400	15.4545	19.4730	25.6061

	Threshold value	95% confidence interval
CSR	−0.1800	(-0.4600, −0.0400)
	6.0900	(5.7500, 6.2900)

interaction effect of the first segment is smaller than that of the second segment, and the interaction effect of the second segment is larger than that of the third segment. These results signify a process of first strengthening and then weakening. In summary, the interaction between DT and CSR is significantly positive on PCIP, which verifies H4.

4.1.7 Robustness test

To examine the robustness of the study findings, we conducted robustness tests in two ways. The first was by replacing the explanatory variables. We replaced the independent variable DT with the proportion of the digital economy-related portion of the year-end intangible asset to total intangible assets (DT_R). The second was by adding a control variable (DUA), which indicates when one person is both a member of the board of directors and the general manager. After repeating the regression analysis discussed above, Table 6 shows that in the OLS and fixed effects regressions, the proportion of the digital economy-related component to the total intangible assets (DT_R) has a significant positive effect on PCIP. In the SYS-GMM model, the lagged one-period PCIP has a significant positive effect on the current period. Moreover, the proportion of the digital economy-related component to the total intangible assets ratio (DT_R) has a positive and significant effect on PCIP: AR (1) = 0.000 < 0.05; AR (2) = 0.348 > 0.1, which indicates the existence of first-order autocorrelation and no second-order autocorrelation for the random disturbance term. Furthermore, the Hansen test value equals 0.945 > 0.1, indicating that the model does not have an over-identification problem, and the previous findings still hold.

4.2 Study 2: Empirical study of DT on PDIP

4.2.1 Descriptive statistics

Supplementary Table S3 shows that the maximum value of the dependent variable PDIP is 1,294.5; the minimum value is 0; the mean value is 78.542, and the standard deviation is 178.7, indicating large differences in the PDIP of the sample of listed companies, and the fractional places in the maximum and mean

TABLE 5 Panel threshold regression estimation.

Variable	PCIP	t value
GRO	−0.000***	−12.51
SIZE	0.012***	11.00
GER	−0.015***	−6.60
CFA	−0.001	−0.66
SCR	−0.064***	−17.22
RTA	−0.005***	−9.19
BOS	0.001***	5.32
CEC	−6.04e-05	−1.51
o.TIME	0.000	
DT•I (CSR ≤ −0.18)	7.15e-05***	8.66
DT•I (−0.18<CSR≤6.09)	0.000120***	12.83
DT•I (CSR>6.09)	2.24e-05***	4.66
Constant	−0.029**	−2.57
Observations	9,490	
Number of stock	949	
R-squared	0.133	

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

TABLE 6 Robustness check results.

Variable	PCIP (OLS)	PCIP (FE)	PCIP (SYS-GMM)
L.PCIP			.621
			(9.95)***
DT_R	0.049	0.009	.075
	(14.64)**	(4.74)**	(2.25)**
GRO	−0.008	−0.012	−.007
	(6.13)**	(14.44)**	(−1.90)*
SIZE	−0.002	0.013	−.018
	(2.03)*	(12.23)**	(-0.90)
GER	−0.014	−0.010	.043
	(5.60)**	(4.23)**	(1.29)
CFA	−0.022	−0.008	−.045
	(5.97)**	(3.63)**	(-1.46)
SCR	−0.096	−0.072	−.046
	(24.87)**	(19.91)**	(-1.45)
RTA	−0.006	−0.005	−.016
	(5.66)**	(10.09)**	(−2.13)**
BOS	0.000	0.001	−.002
	(0.20)	(4.91)**	(-0.80)
CEC	−0.000	−0.000	0.000
	(13.51)**	(5.63)**	(0.65)
0b.DUA	0.000	0.000	
1.DUA	0.003	−0.000	−.015
	(3.52)**	(0.20)	(−1.19)
TIME	−0.044		−.068
	(18.50)**		(−1.29)
o.TIME		0.000	
_cons	0.195	−0.019	.297
	(26.04)**	(1.87)	(2.07)**
R2	0.31	0.12	
Wald chi2 (20)			6847.78
N	9,500	9,500	8550
AR (1)			0.000
AR (2)			0.348
Hansen test			0.945

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

values are due to winsorization. From the robustness test, the maximum value of the proxy variable DT_RN is 115.5; the minimum value is 0; the mean is 7.826, and the standard deviation is 18.982, which still indicate a large variation among samples. The presence of fractional places in the maximum and mean values are also due to winsorization. The descriptive statistics of the independent variable DT and the control variables have been described in the discussion of the empirical evidence of DT on PCIP and will not be repeated in this section.

4.2.2 Correlation analysis

To examine the impact of DT on PDIP, we conducted a Pearson correlation analysis on the variables, the results of which are shown in Supplementary Table S4. The dependent variable PDIP has a positive relationship with the independent variable DT, the robustness test proxy variable DT_RN, and the moderating variable CSR. We also conducted the variance expansion factor test and passed it.

4.2.3 Regression analysis

With reference to the previous study, we used negative binomial regression (NBR) and negative binomial panel regression for empirical testing. We initially conducted a Hausman test to determine whether to use negative binomial panel fixed effects regression (NBFR) or negative binomial panel random effects. As Prob > chi2 = 0.0000, the difference between fixed and random effects is significant, which favors the fixed effects model. The results of the two regressions are combined in Table 8.

Table 7 shows that in the NBR model, DT has a significant positive effect on PDIP with lnalpha = 0.261 and z = 17.39 ≠ 0; these results prove that the model is well structured. In the NBFR model, DT also significantly impacts PDIP, thus verifying H2. However, there is a difference in the degree of explanation, with z = 14.36 for DT in the NBR versus z = 13.66 for the NBFR.

TABLE 7 Comparison of regression results.

Variable	PDIP(NBR)	PDIP(NBFR)
DT	0.002	0.002
	(14.36)**	(13.66)**
GRO	0.069	−0.056
	(1.24)	(2.00)*
SIZE	1.482	0.815
	(50.39)**	(28.56)**
GER	0.214	−0.044
	(2.25)*	(0.58)
CFA	−0.571	−0.147
	(4.33)**	(2.15)*
SCR	0.115	−0.375
	(0.96)	(4.02)**
RTA	−0.148	−0.180
	(4.53)**	(8.53)**
BOS	−0.006	−0.000
	(1.00)	(0.04)
CEC	0.003	−0.007
	(2.78)**	(8.41)**
TIME	−0.615	−1.320
	(6.15)**	(10.82)**
_cons	−9.953	−5.219
	(38.69)**	(19.16)**
lnalpha	0.261	
	(17.39)**	
	9,490	9,490

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

TABLE 8 Heterogeneity test.

Variable	MAF	NON-MAF	SOE	NON-SOE
	PDIP (1)	PDIP (2)	PDIP (3)	PDIP (4)
DT	0.002	0.001	0.002	0.001
	(7.22)**	(10.87)**	(14.69)**	(7.07)**
GRO	0.022	−0.086	−0.036	−0.178
	(0.40)	(2.62)**	(1.26)	(2.48)*
SIZE	0.957	0.867	1.086	0.485
	(21.18)**	(21.85)**	(33.09)**	(7.68)**
GER	−0.827	0.358	0.046	−0.221
	(6.29)**	(3.96)**	(0.57)	(1.17)
CFA	−0.472	0.063	−0.024	−0.067
	(3.75)**	(0.78)	(0.33)	(0.42)
SCR	0.183	−0.706	−0.516	0.200
	(1.01)	(6.44)**	(5.03)**	(0.90)
RTA	−0.149	−0.187	−0.156	−0.194
	(2.88)**	(8.18)**	(7.10)**	(3.66)**
BOS	−0.003	−0.002	−0.002	0.002
	(0.55)	(0.36)	(0.53)	(0.19)
CEC	−0.015	−0.001	−0.003	−0.009
	(9.81)**	(0.79)	(2.59)**	(4.36)**
TIME	−0.103	−2.515	−1.528	−0.937
	(0.45)	(13.71)**	(11.28)**	(3.32)**
_cons	−7.846	−4.499	−7.489	−3.214
	(14.98)**	(12.00)**	(23.85)**	(5.51)**
	3,215	6,241	7,523	1,952

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

4.2.4 Heterogeneity analysis

To explore the impact of DT on PDIP under different equity natures and industries, we divided the study sample into four subsamples: manufacturing (MAF), non-manufacturing (NON-MAF), state-owned enterprises (SOE), and non-state-owned enterprises (NON-SOE), following the procedures explained above. Grouping tests and seemingly uncorrelated estimation were performed using negative binomial stationary regression, and random disturbance terms were found to be considerably completely different, permitting constant comparisons. Table 8 shows the test results.

As shown in Table 8, DT has a significant positive effect on PDIP for both SOEs and NON-SOEs, and from the comparison of regression coefficients and t-values, the DT of NON-SOEs is more effective than that of SOEs in promoting PDIP; hence, H3 is verified. In both MAF and NON-MAF classifications, DT has a significant positive effect on PDIP, which passes the statistical significance test of 5%. A comparison of the regression coefficients and t-values shows that the DT of MAF firms also promotes PDIP more than NON-MAF firms, thus verifying H3.

4.2.5 Moderation analysis

Following Hansen (1999), this study conducted Bootstrap sampling by iterating the estimation process 1,000 times to estimate three thresholds and two thresholds for CSR and determine whether a threshold impact exists. Table 9 shows the results, which lead to the following conclusions. The one-threshold F-statistic is significant at the 5% level; the two-threshold F-statistic is significant at the 10% level, and the three-threshold F-statistic is significant at the 1% level, which indicate that there are three thresholds in the model. Table 9 shows the results of the specific threshold estimates, which are 29.84, 30.94, and 43.97. The joint action of CSR and DIT is treated in four segments. For the first segment, CSR ≤ 29.84; for the second segment, 29.84 < CSR ≤ 30.94; for the third segment, 30.94 < CSR ≤ 43.97; and for the fourth segment, CSR > 43.97.

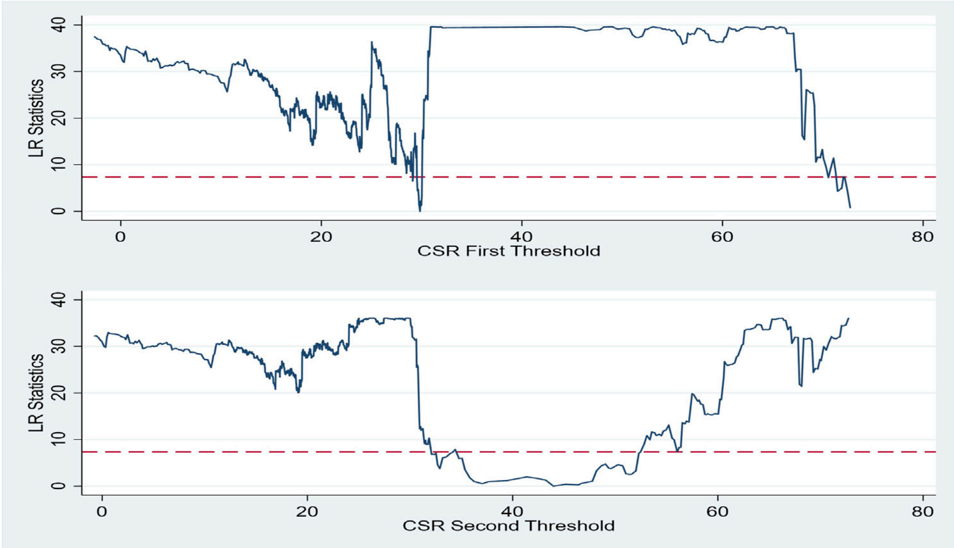


FIGURE 3
Threshold estimation chart.

TABLE 9 Threshold effect test and threshold estimation.

	Threshold	Fstat	Prob	Crit10	Crit5	Crit1
CSR	one	56.84	0.0000	18.3795	21.2294	22.2519
	two	36.89	0.0400	15.3627	23.1107	64.6335
	three	38.85	0.5500	18.3795	21.2294	22.2519
	Threshold value	95% confidence interval				
CSR	29.8400	(29.6200, 29.8800)				
	30.9400	(30.8400, 31.0300)				
	43.9700	(38.8150, 45.2000)				

Figure 3 plots the likelihood ratio function at 95% confidence intervals for the three thresholds of 29.84, 30.94, and 43.97 and illustrates the presence of the three threshold estimates of CSR.

For further analysis, this study used panel threshold regression (see Table 10). Table 10 reveals that the interaction between DT and CSR is actually divided into four segments. For the first segment, the regression coefficient of DT·I (CSR ≤ 29.84) is 0.107, and the t-value is 5.10, which is significant at the 1% level; that is, when CSR ≤ 29.84, the DT and CSR interaction has a significantly positive effect on PDIP. For the second segment, the regression coefficient of DT·I (29.84 < CSR ≤ 30.94) is 0.521, and the t-value is 10.08, which is significant at the 1% level; that is, when 29.84 < CSR ≤ 30.94, the effect of the interaction between DT and CSR on PDIP is also significantly positive. For the third segment, the regression coefficient of DT·I (30.94 <CSR ≤ 43.97) is 0.159, and the t-value is 3.34, which is significant at the 1% level; that is, when 30.94 < CSR ≤ 43.97, the effect of the interaction between DT and CSR on PDIP is still significantly positive. For the fourth segment, the regression coefficient of DT·I (CSR > 43.97) is −0.0840, and the t-value is −2.24, which is significant at the 5% level, meaning that the interaction of DT and CSR has a significantly negative effect on PDIP when CSR > 43.97. Although in all three segments, CSR interacts with DT and has a significantly positive impact on PDIP, the effects differ. From the magnitude of the regression coefficients and t-values, it can be judged that the interaction of DT and CSR on PDIP is a process that first has positive effects, then the positive effects increase, and then gradually decreases until it finally becomes negative. Although the interaction between DT and CSR shows a significantly negative effect on PDIP when CSR > 43.97, its regression coefficient is equal to −0.084, whereas the interaction coefficients of the first three segments of DT are 0.107, 0.521, and 0.159, and the positive and negative effects are still neutralized after a positive effect. Therefore, in general, CSR positively moderates the role of DT on the PDIP, thus verifying H5.

TABLE 10 Panel threshold regression results.

Variable	PDIP	t value
GRO	−12.15***	−3.59
SIZE	143.1***	28.10
GER	−29.17***	−2.85
CFA	−0.772	−0.09
SCR	−31.35*	−1.90
RTA	−3.787*	−1.65
BOS	−0.265	−0.53
CEC	0.562***	3.16
o.TIME	0.000	
DT•I(CSR≤29.84)	0.107***	5.10
DT•I (29.84<CSR≤30.94)	0.521***	10.08
DT•I (30.94<CSR≤43.97)	0.159***	3.34
DT•I(CSR>43.97)	−0.0840**	−2.24
Constant	−1,289***	−25.24
Observations	9,490	
Number of stock	949	
R-squared	0.158	

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

TABLE 11 Robustness tests.

Variable	PDIP(NBR)	PDIP(NBFR)
DT_RN	0.008	0.003
	(9.41)**	(6.58)**
GRO	0.067	−0.056
	(1.24)	(1.99)*
SIZE	1.496	0.878
	(50.06)**	(31.02)**
GER	0.298	−0.068
	(3.10)**	(0.90)
CFA	−0.572	−0.154
	(4.40)**	(2.25)*
SCR	0.069	−0.415
	(0.57)	(4.44)**
RTA	−0.153	−0.195
	(4.68)**	(9.13)**
BOS	−0.003	−0.001
	(0.57)	(0.26)
CEC	0.002	−0.009
	(1.97)*	(9.92)**
TIME	−0.623	−1.412
	(6.34)**	(11.59)**
0b.DUA	0.000	0.000
1.DUA	0.143	0.036
	(4.38)**	(1.55)
_cons	−10.027	−5.578
	(37.48)**	(20.19)**
lnalpha	0.268	
	(18.37)**	
	9,500	9,500

*Denotes $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

4.2.6 Robustness test

To examine the robustness of the findings, we conducted robustness tests by first replacing the independent variables. We replaced the independent variable DT with the sum of the number of times listed companies used the following: AI technology, blockchain technology, cloud computing technology, big data technology, and digital technology application, as indicated in the CSMAR database (DT_RN). Second, we added a control variable, DUA, which indicates when the same person holds the chairman and general manager positions. We then repeated the process described above and found that DT has a significant positive effect on PDIP in both NBR and NBFR; hence the previous findings still hold. The details are shown in Table 11.

5 General discussion

Based on resource theory, process reengineering theory, and stakeholder theory, this study investigated in depth the theoretical basis of DT, CSR, and IP. It analyzed the mechanism of DT's impact on PCIP and PDIP, considering the role of DT on IP and the mechanism of CSR's moderating effect on it. The inner logical relationships among DT, CSR, and IP were thus clarified. The impact mechanisms of DT, CSR, and IP were empirically tested using a combination of literature review and empirical testing using data from the CSMAR database and China Hexun data from 2010 to 2019. The following main conclusions are drawn: 1) DT can significantly enhance PCIP; 2) DT can significantly improve PDIP; 3) There is a time lag effect of the IP of the previous period on the IP of the current period; 4) CSR positively moderates the role of DT on IP; and 5) The impact of DT is heterogeneous across industries and ownership.

Li et al. (2023) measured the innovation performance using a total number of patents. This study not only measured the innovation performance at product and process level and used weight score (weightings of 30% for invention patents, 20% for utility model patents, and 10% for design patents). In line with Li et al. (2023), Chen and Kim (2023), our empirical finding suggested that the level of DT positively promotes innovation performance.

6 Theoretical and managerial implications

Regarding theoretical implications, by focusing on the impact of DT on IP, this study revealed the impact mechanisms, providing insight into the interaction and impact on IP. In addition, research on the dynamic effect of DT on IP is lacking, and this study filled this gap. This study also investigated the multiplicative effect of DT and IP considering the heterogeneity of industry and ownership, using panel threshold regression, which is meaningful in constructing and improving the innovation theory of Chinese-listed companies.

The results indicate that at the organizational level, the organizational structure should be re-optimized with the concept of digitalization to achieve a clear division of labor, clear functions, and authority and responsibility. First, the top management of the company should analyze the current industry in which it is located, including the characteristics of competitors and changes in the external environment, apply digital concepts, combine digital technology and the current business model of the company, and design an innovative ecology that is appropriate for the enterprise. Second, in the process of DT, enterprises should deploy and invest in the company's organizational structure, business processes, and communication information technology. Finally, a relevant evaluation team should be established to assess the implementation plan and PCIP activities.

At the technical level, the leading innovation role of DT should be highlighted. Enterprises perform innovation activities, increase their investment in R&D, improve the investment mechanism of enterprise technology innovation, keep abreast with the advances in technology, modify the previous production mode, and make the production activities greener to realize environmental protection and higher efficiency. Emphasis should be placed on combining the interests of industries, academia, and the research environment, through the relationships among upstream, midstream, and downstream innovation to achieve a comprehensive application of technology, establish an open innovation system, focus on the set up of research platforms, promote high-quality scientific talent, update the configuration of production factors, and enhance the value of data applications.

At the market level, the first challenge is implementing balanced management of the inputs and outputs of digital transformation and minimizing the risks associated with digital transformation. Implement a goal management-oriented strategy, which means dividing the digital transformation into several projects, implementing the evaluation of the capital budget and goal achievement for each project, and confirming whether the set goals are completed after the project, and if they are completed, then a new extension project can be started, and if they are not completed, analyze the reasons for not completing them, and if necessary, terminate them. In addition, to take advantage of the zero-distance role between digitalization and market information, companies and consumers should maintain efficient communication, in-depth understanding of consumer habits, rapid response to customer needs, provide customized products and services for consumers, establish consumer value identity and brand identity of the product, and improve consumer loyalty.

7 Limitations and further works

Firstly, regarding the dimensional division of IP, this study examined the impact of DT on two dimensions, namely, PCIP and PDIP. According to Melville et al. (2004), organizational IP is also a dimension of corporate IP. However, this dimension was not studied here because it cannot be measured by the data published in the annual reports of listed companies and the existing literature does not provide much basis for it. However, in future studies, this dimension may be included in the model to explore further the association between DT, CSR, and this dimension.

Secondly, when exploring the moderating role of CSR in the model, only the moderating effect of the overall CSR was verified in this study. CSR has multiple dimensions. For example, according to Jamali et al. (2008), CSR is divided into mandatory economic responsibility, legal responsibility, ethical responsibility, strategic responsibility, and philanthropic responsibility. According to stakeholder theory, CSR is also categorized into corporate accountability to shareholders, employees, suppliers, consumers, customers, the environment, and society. Subsequent research can expand on the hierarchy to examine further the positive, negative, or insignificant effects of the different dimensions of CSR to provide a reference for theoretical research and corporate management Moreover, we will explore the environmental impact of digital processes based on the current study

Thirdly, the research methodology needs to be innovative. This paper uses OLS regression, panel fixed-effects regression, and SYS-GMM regression to analyze the data separately, but they do not reflect the dynamic changes of DT. DT is a complex and systematic process, and innovation input, learning capability, and entrepreneurial output may also change at different stages of DT, which leads to differences in the mechanism of action between different variables. In addition, this paper only uses property rights and industry as classification criteria to develop heterogeneity analysis, which is well represented but cannot fully show the full picture of heterogeneity. Therefore, the subsequent study can further examine the impact of dynamic changes of digital transformation on other variables, expand industry data sources, and investigate the dynamic impact of DT on firms' IP through panel fixed-effects regression. The DID double difference method can also be incorporated into the study to explore the policy shock effects of DT on IP in different industries at different points in time.

Finally, stakeholder analysis is vital in assessing digital transformation's impact on innovation and corporate social responsibility's role, as it identifies key parties influencing the transformation and their power dynamics (Ioanna et al., 2022). We will extend current research by adding stakeholder analysis in further research.

8 Conclusion

In the digital economy, digital transformation is a deliberate decision to improve organizational procedures, alter production processes, introduce precision marketing, and more, ultimately impacting how well businesses innovate. Corporate social responsibility combines internal governance, environmental improvement, and social reputation. Companies that exhibit high levels of social responsibility are more likely to receive internal and external recognition and support and greater access to social resource allocation, thereby influencing the company's innovative development. This paper analyzes the impact of digital transformation on both process and product innovation performance and examines the heterogeneity issues resulting from different industry classifications and property rights. The study also explores endogeneity problems arising from the lag period of enterprise innovation performance in the current period. Finally, this study verifies the positive moderating effect of corporate social responsibility on process and product innovation performance in the context of digital transformation.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

WL: Formal analysis, writing—original draft preparation, and supervision. JY: Visualization and project administration. Both authors contributed to the conceptualization, methodology, validation, data curation, writing—review, and editing, and read and agreed to the published version of the manuscript. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1215866/full#supplementary-material

References

Abhinav, G., Forrest, B., and C, H. D. (2017). Red, blue, and purple firms: Organizational political ideology and corporate social responsibility. *Strategic Manag. J.* 38 (5), 1018–1040. doi:10.1002/smj.2550

Acemoglu, D., and Linn, J. (2004). Market size in innovation: Theory and evidence from the pharmaceutical industry. *Q. J. Econ.* 119 (3), 1049–1090. doi:10.1162/0033553041502144

Ahuja, G., and Katila, R. (2004). Where do resources come from? The role of idiosyncratic situations. *Strategic Manag. J.* 25 (8-9), 887–907. doi:10.1002/smj.401

Baines, T., and Lightfoot, H. W. (2014). Servitization of the manufacturing firm: Exploring the operations practices and technologies that deliver advanced services. *Int. J. Oper. Prod. Manag.* 34 (1), 2–35. doi:10.1108/ijopm-02-2012-0086

Berchicci, L., and King, A. (2007). 11 postcards from the edge: A review of the business and environment literature. *Acad. Manag. Ann.* 1 (1), 513–547. doi:10.5465/078559816

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., and Venkatraman, N. v. (2013). Digital business strategy: Toward a next generation of insights. *MIS Q.* 37 (2), 471–482. doi:10.25300/misq/2013/37:2.3

Bogers, M., Chesbrough, H., and Moedas, C. (2018). Open innovation: Research, practices, and policies. *Calif. Manag. Rev.* 60 (2), 5–16. doi:10.1177/0008125617745086

Bouncken, R., and Barwinski, R. (2021). Shared digital identity and rich knowledge ties in global 3D printing—a drizzle in the clouds? *Glob. Strategy J.* 11 (1), 81–108. doi:10.1002/gsj.1370

Bowen, H. R. (1953). in *Social responsibilities of the businessman* (Iowa City, IA: University of Iowa Press). 2013.

Brynjolfsson, E. (1993). The productivity paradox of information technology. *Commun. ACM* 36 (12), 66–77. doi:10.1145/163298.163309

Butlin, M., and Carnegie, R. (2001). "Developing innovation in a medium business: A practical approach," in *Innovation and imagination at work*, 107–131.

Campbell, J. L. (2007). Why would corporations behave in socially responsible ways? An institutional theory of corporate social responsibility. *Acad. Manag. Rev.* 32 (3), 946–967. doi:10.5465/amr.2007.25275684

Carrasco-Monteagudo, I., and Buendía-Martínez, I. (2013). Corporate social responsibility: A crossroad between changing values, innovation and internationalisation. *Eur. J. Int. Manag.* 7 (3), 295–314. doi:10.1504/ejim.2013.054327

Carroll, A. B. (1991). The pyramid of corporate social responsibility: Toward the moral management of organizational stakeholders. *Bus. Horizons* 34 (4), 39–48. doi:10.1016/0007-6813(91)90005-g

Chandola, V. (2015). *Digital transformation and sustainability: Study and analysis*. Cambridge: Havard University.

Chen, P., and Kim, S. (2023). The impact of digital transformation on innovation performance-The mediating role of innovation factors. *Heliyon* 9 (3), e13916. doi:10.1016/j.heliyon.2023.e13916

Cho, E., and Tsang, A. (2020). Corporate social responsibility, product strategy, and firm value. *Asia-Pacific J. Financial Stud.* 49 (2), 272–298. doi:10.1111/ajfs.12291

Chun, Y., Tusheng, X., Chunxiao, G., and Yu, S. (2021a). Digital transformation and division of labor: Specialization or vertical integration. *China's Ind. Econ.* (09), 137–155.

Clarkson, M. E. (1995). A stakeholder framework for analyzing and evaluating corporate social performance. *Acad. Manag. Rev.* 20 (1), 92–117. doi:10.2307/258888

Cui, L., and Jiang, F. (2012). State ownership effect on firms' fdi ownership decisions under institutional pressure: A study of Chinese outward-investing firms. *J. Int. Bus. Stud.* 43 (3), 264–284. doi:10.1057/jibs.2012.1

Drucker, P. F. (1993). The rise of the knowledge society. *Wilson Q.* 17 (2), 52–72.

Eccles, R. G., Ioannou, I., and Serafeim, G. (2012). *The impact of a corporate culture of sustainability on corporate behavior and performance*, 17950. Cambridge, MA, USA: National Bureau of Economic Research.

Elkington, J., and Rowlands, I. H. (1999). Cannibals with forks: The triple bottom line of 21st century business. *Altern. J.* 25 (4), 42.

Ernst, H. (2001). Patent applications and subsequent changes of performance: Evidence from time-series cross-section analyses on the firm level. *Res. Policy* 30 (1), 143–157. doi:10.1016/s0048-7333(99)00098-0

Felin, T., and Hesterly, W. S. (2007). The knowledge-based view, nested heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge. *Acad. Manag. Rev.* 32 (1), 195–218. doi:10.5465/amr.2007.23464020

Feroz, A. K., Zo, H., and Chiravuri, A. (2021). Digital transformation and environmental sustainability: A review and research agenda. *Sustainability* 13 (3), 1530. doi:10.3390/su13031530

Fitzgerald, M., Kruschwitz, N., Bonnet, D., and Welch, M. (2014). Embracing digital technology: A new strategic imperative. *MIT sloan Manag. Rev.* 55 (2), 1.

Flammer, C., and Luo, J. (2017). Corporate social responsibility as an employee governance tool: Evidence from a quasi-experiment. *Strategic Manag. J.* 38 (2), 163–183. doi:10.1002/smj.2492

Forcadell, F. J., Aracil, E., and Úbeda, F. (2020). The impact of corporate sustainability and digitalization on international banks' performance. *Glob. Policy* 11, 18–27. doi:10.1111/1758-5899.12761

Frank, A. G., Mendes, G. H., Ayala, N. F., and Ghezzi, A. (2019). Servitization and industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technol. Forecast. Soc. Change* 141, 341–351. doi:10.1016/j.techfore.2019.01.014

Franks, B. (2012). *Taming the big data tidal wave: Finding opportunities in huge data streams with advanced analytics*. John Wiley and Sons.

Gerth, A. B., and Peppard, J. (2016). The dynamics of CIO derailment: How CIOs come undone and how to avoid it. *Bus. Horizons* 59 (1), 61–70. doi:10.1016/j.bushor.2015.09.001

Groysberg, B., and Lee, L.-E. (2009). Hiring stars and their colleagues: Exploration and exploitation in professional service firms. *Organ. Sci.* 20 (4), 740–758. doi:10.1287/orsc.1090.0430

Guler, I., and Nerkar, A. (2012). The impact of global and local cohesion on innovation in the pharmaceutical industry. *Strategic Manag. J.* 33 (5), 535–549. doi:10.1002/smj.957

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econ.* 93 (2), 345–368. doi:10.1016/s0304-4076(99)00025-1

Hendricks, K. B., Singhal, V. R., and Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *J. Oper. Manag.* 25 (1), 65–82. doi:10.1016/j.jom.2006.02.002

Henfridsson, O., Nandhakumar, J., Scarbrough, H., and Panourgias, N. (2018). Recombination in the open-ended value landscape of digital innovation. *Inf. Organ.* 28 (2), 89–100. doi:10.1016/j.infoandorg.2018.03.001

Hess, T., Matt, C., Benlian, A., and Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Q. Exec.* 15 (2), 123–139. doi:10.7892/boris.105447/

Hinings, B., Gegenhuber, T., and Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Inf. Organ.* 28 (1), 52–61. doi:10.1016/j.infoandorg.2018.02.004

Huaijin, Q., Xiuqin, C., and Yanxia, L. (2020). The impact of digital economy on corporate governance: From the perspective of information asymmetry and managers' irrational behavior. *Reform* (04), 50–64.

Ioanna, N., Pipina, K., Despina, C., Ioannis, S., and Dionysis, A. (2022). Stakeholder mapping and analysis for climate change adaptation in Greece. *Euro-Mediterranean J. Environ. Integration* 7 (3), 339–346. doi:10.1007/s41207-022-00317-3

Jamali, D., Safieddine, A. M., and Rabbath, M. (2008). Corporate governance and corporate social responsibility synergies and interrelationships. *Corp. Gov. Int. Rev.* 16, 443–459.

Jansen, J. J., Van Den Bosch, F. A., and Volberda, H. W. (2005). Managing potential and realized absorptive capacity: How do organizational antecedents matter? *Acad. Manag. J.* 48 (6), 999–1015. doi:10.5465/amj.2005.19573106

Jianfei, L., and Yun, G. (2019). The quality and innovation sustainability of corporate social responsibility information disclosure under financing constraints--data analysis of small and medium-sized board enterprises. *Sci. Technol. Prog. Countermeas.* 36 (11), 8.

Jimenez-Jimenez, D., and Sanz-Valle, R. (2008). Could HRM support organizational innovation? *Int. J. Hum. Resour. Manag.* 19 (7), 1208–1221. doi:10.1080/09585190802109952

Kane, G. C. (2017). Digital innovation lights the fuse for better health care outcomes. *MIT sloan Manag. Rev.* 59 (1).

Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., et al. (2016). Smart manufacturing: Past research, present findings, and future directions. *Int. J. Precis. Eng. Manuf. Green Technol.* 3 (1), 111–128. doi:10.1007/s40684-016-0015-5

Katmon, N., Mohamad, Z. Z., Norwani, N. M., and Farooque, O. A. (2019). Comprehensive board diversity and quality of corporate social responsibility disclosure: Evidence from an emerging market. *J. Bus. ethics* 157 (2), 447–481. doi:10.1007/s10551-017-3672-6

Khan, A., Muttakin, M. B., and Siddiqui, J. (2013). Corporate governance and corporate social responsibility disclosures: Evidence from an emerging economy. *J. Bus. ethics* 114 (2), 207–223. doi:10.1007/s10551-012-1336-0

Kim, G., Shin, B., Kim, K. K., and Lee, H. G. (2011). *Journal of the association for information IT capabilities, process-oriented dynamic capabilities, and firm financial performance*.

Kohtamäki, M., Partanen, J., Parida, V., and Wincent, J. (2013). Non-linear relationship between industrial service offering and sales growth: The moderating role of network capabilities. *Ind. Mark. Manag.* 42 (8), 1374–1385. doi:10.1016/j.indmarman.2013.07.018

La Rosa, F., Liberatore, G., Mazzi, F., and Terzani, S. (2018). The impact of corporate social performance on the cost of debt and access to debt financing for listed European non-financial firms. *Eur. Manag. J.* 36 (4), 519–529. doi:10.1016/j.emj.2017.09.007

Laforet, S. (2008). Size, strategic, and market orientation affects on innovation. *J. Bus. Res.* 61 (7), 753–764. doi:10.1016/j.jbusres.2007.08.002

Lau, C., Lu, Y., and Liang, Q. (2016). Corporate social responsibility in China: A corporate governance approach. *J. Bus. ethics* 136 (1), 73–87. doi:10.1007/s10551-014-2513-0

Lew, Y. K., Sinkovics, R. R., and Kuivalainen, O. (2013). Upstream internationalization process: Roles of social capital in creating exploratory capability and market performance. *Int. Bus. Rev.* 22 (6), 1101–1120. doi:10.1016/j.ibusrev.2013.03.001

Li, Y., and Fei, G. Z. (2023). Network embeddedness, digital transformation, and enterprise performance—the moderating effect of top managerial cognition. *Front. Psychol.* 14, 1098974. doi:10.3389/fpsyg.2023.1098974

Li, S., Gao, L., Han, C., Gupta, B., Alhalabi, W., and Almakdi, S. (2023). Exploring the effect of digital transformation on Firms' innovation performance. *J. Innovation Knowl.* 8 (1), 100317. doi:10.1016/j.jik.2023.100317

Liang, S., and Li, T. (2022). Can digital transformation promote innovation performance in manufacturing enterprises? The mediating role of R&D capability. *Sustainability* 14 (17), 10939. doi:10.3390/su141710939

Lindič, J., Baloh, P., Ribière, V. M., and Desouza, K. C. (2011). Deploying information technologies for organizational innovation: Lessons from case studies. *Int. J. Inf. Manag.* 31 (2), 183–188. doi:10.1016/j.ijinfomgt.2010.12.004

Lin-Hi, N., and Blumberg, I. (2018). The link between (not) practicing CSR and corporate reputation: Psychological foundations and managerial implications. *J. Bus. Ethics* 150 (1), 185–198. doi:10.1007/s10551-016-3164-0

Liu, D. Y., Chen, S. W., and Chou, T. C. (2011). Resource fit in digital transformation: Lessons learned from the CBC Bank global e-banking project. *Manag. Decis.* 49 (10), 1728–1742. doi:10.1108/00251741111183852

Lončar, D., Paunković, J., Jovanović, V., and Krstić, V. (2019). Environmental and social responsibility of companies cross EU countries–Panel data analysis. *Sci. Total Environ.*, 657, 287–296. doi:10.1016/j.scitotenv.2018.11.482

Matt, C., Hess, T., and Benlian, A. (2015). Digital transformation strategies. *Bus. Inf. Syst. Eng.* 57 (5), 339–343. doi:10.1007/s12599-015-0401-5

Melville, N., Kraemer, K., and Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Q.* 28 (2), 283–322. doi:10.2307/25148636

Meng, S., Su, H., and Yu, J. (2022). Digital transformation and corporate social performance: How do board independence and institutional ownership matter? *Front. Psychol.* 13, 915583. doi:10.3389/fpsyg.2022.915583

Moeuf, A., Lamouri, S., Pellerin, R., Tamayo-Giraldo, S., Tobon-Valencia, E., and Eburdy, R. (2020). Identification of critical success factors, risks and opportunities of Industry 4.0 in SMEs. *Int. J. Prod. Res.* 58 (5), 1384–1400. doi:10.1080/00207543.2019.1636323

Nollet, J., Filis, G., and Mitrokostas, E. (2016). Corporate social responsibility and financial performance: A non-linear and disaggregated approach. *Econ. Model.* 52, 400–407. doi:10.1016/j.econmod.2015.09.019

Parida, V., Westerberg, M., and Frishammar, J. (2012). Inbound open innovation activities in high-tech SMEs: The impact on innovation performance. *J. small Bus. Manag.* 50 (2), 283–309. doi:10.1111/j.1540-627x.2012.00354.x

Parsons, D., Gotlieb, C., and Denny, M. (1990). *Productivity and computers in Canadian banking*. University of Toronto—Department of Economics.

Porter, M. E., and Kramer, M. R. (2011). *Creating shared value: Harvard business review*. From the Magazine (January–February 2011).

Progiou, A., Liora, N., Sebos, I., Chatzimichail, C., and Melas, D. (2023). Measures and policies for reducing PM exceedances through the use of air quality modeling: The case of thessaloniki, Greece. *Sustainability* 15 (2), 930. doi:10.3390/su15020930

Rai, A., Patnayakuni, R., and Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Q.* 30, 225–246. doi:10.2307/25148729

Ren, Y., Li, B., and Liang, D. (2023). Impact of digital transformation on renewable energy companies' performance: Evidence from China. *Front. Environ. Sci.* 10, 2702. doi:10.3389/fenvs.2022.1105686

Rochford, L., and Rudelius, W. (1997). New product development process: Stages and successes in the medical products industry. *Ind. Mark. Manag.* 26 (1), 67–84. doi:10.1016/s0019-8501(96)00115-0

Rouse, M. J., and Daellenbach, U. S. (2002). More thinking on research methods for the resource-based perspective. *Strategic Manag. J.* 23 (10), 963–967. doi:10.1002/smj.256

Schultz, F., Castelló, I., and Morsing, M. (2013). The construction of corporate social responsibility in network societies: A communication view. *J. Bus. ethics* 115 (4), 681–692. doi:10.1007/s10551-013-1826-8

Schumpeter, J. A. (1982). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle (1912/1934)*, 1. Transaction Publishers, 244.

Scuotto, V., Santoro, G., Bresciani, S., and Del Giudice, M. (2017). Shifting intra-and inter-organizational innovation processes towards digital business: An empirical analysis of SMEs. *Creativity Innovation Manag.* 26 (3), 247–255. doi:10.1111/caim.12221

Sebastian, I., Mocker, M., Ross, J., Moloney, K., Beath, C., and Fonstad, N. (2017). How big old companies navigate digital transformation. *MIS Q. Exec.* 42, 150–154.

Sebos, I., Progiou, A. G., and Kallinikos, L. (2020). "Methodological framework for the quantification of GHG emission reductions from climate change mitigation actions," in *Strategic planning for energy and the environment*, 219–242.

Sebos, I. (2022). Fossil fraction of CO2 emissions of biofuels. *Carbon Manag.* 13 (1), 154–163. doi:10.1080/17583004.2022.2046173

Sorescu, A. B., Chandy, R. K., and Prabhu, J. C. (2003). Sources and financial consequences of radical innovation: Insights from pharmaceuticals. *J. Mark.* 67 (4), 82–102. doi:10.1509/jmkg.67.4.82.18687

Sosik, J. J., Gentry, W. A., and Chun, J. U. (2012). The value of virtue in the upper echelons: A multisource examination of executive character strengths and performance. *Leadersh. Q.* 23 (3), 367–382. doi:10.1016/j.leaqua.2011.08.010

Tippins, M. J., and Sohi, R. S. (2003). IT competency and firm performance: Is organizational learning a missing link? *Strategic Manag. J.* 24 (8), 745–761. doi:10.1002/smj.337

Un, C. A., and Asakawa, K. (2015). Types of R&D collaborations and process innovation: The benefit of collaborating upstream in the knowledge chain. *J. Prod. Innovation Manag.* 32 (1), 138–153. doi:10.1111/jpim.12229

Vij, S., and Farooq, R. (2016). Moderating effect of firm size on the relationship between IT orientation and business performance. *IUP J. Knowl. Manag.* 14 (4), 34–52.

White, M. (2012). Digital workplaces: Vision and reality. *Bus. Inf. Rev.* 29 (4), 205–214. doi:10.1177/0266382112470412

Wu, Z., Wang, X., Liao, J. Y., Hou, H., and Zhao, X. (2023). Evaluation of digital transformation to support carbon neutralization and green sustainable development based on the vision of "channel computing resources from the east to the west". *Sustainability* 15 (7), 6299. doi:10.3390/su15076299

Yeniyurt, S., Henke, J. W., and Yalcinkaya, G. (2014). A longitudinal analysis of supplier involvement in buyers' new product development: Working relations, inter-dependence, co-innovation, and performance outcomes. *J. Acad. Mark. Sci.* 42 (3), 291–308. doi:10.1007/s11747-013-0360-7

Zahra, S. A., and George, G. (2002). The net-enabled business innovation cycle and the evolution of dynamic capabilities. *Inf. Syst. Res.* 13 (2), 147–150. doi:10.1287/isre.13.2.147.90

Zhang, C., Chen, P., and Hao, Y. (2022). The impact of digital transformation on corporate sustainability-new evidence from Chinese listed companies. *Front. Environ. Sci.* 10, 1047418. doi:10.3389/fenvs.2022.1047418

Zheng, P., and Scase, R. (2013). The restructuring of market socialism in China: The contribution of an "agency" theoretical perspective. *Thunderbird Int. Bus. Rev.* 55 (1), 103–114. doi:10.1002/tie.21526

Zhu, Y., and Jin, S. (2023). COVID-19, digital transformation of banks, and operational capabilities of commercial banks. *Sustainability* 15 (11), 8783. doi:10.3390/su15118783

Zuanyong, Y., and Dian, W. (2021). "One belt, one road" corporate social responsibility, financing constraints and investment efficiency. *Finance Econ.* (02), 45–55.

Zuo, L., Strauss, J., and Zuo, L. (2021). The digitalization transformation of commercial banks and its impact on sustainable efficiency improvements through investment in science and technology. *Sustainability* 13 (19), 11028. doi:10.3390/su131911028

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 26 July 2023
DOI 10.3389/fenvs.2023.1225406

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Pengyu Chen,
Dankook University, Republic of Korea
Lev Mazelis,
Vladivostok State University of Economics and Service, Russia

*CORRESPONDENCE
Jiandong Liu,
jdliu9955@126.com

RECEIVED 22 May 2023
ACCEPTED 11 July 2023
PUBLISHED 26 July 2023

CITATION
Liu Z, Liu J, Yin Y and Zhu X (2023), Effects of digital economy and city size on green total factor productivity.
Front. Environ. Sci. 11:1225406.
doi: 10.3389/fenvs.2023.1225406

Effects of digital economy and city size on green total factor productivity

Zejie Liu, Jiandong Liu*, Yuanyuan Yin and Xianwen Zhu

School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China

Utilizing the digital economy's contribution to green total factor productivity is a key strategy for accelerating China's green growth, although more research is still needed to understand the mechanism of this influence. This study uses panel data from 282 Chinese prefecture-level cities from 2011 to 2019 to empirically assess the impact of the digital economy and city size on GTFP. First, GTFP overall exhibits an upward trend with excellent spatial correlation and minimal regional variation. Second, the findings demonstrate that, while surrounding locations' GTFP is not affected by the digital economy, local productivity can be improved. Third, the heterogeneity study demonstrates that the digital economy contributes more to local GTFP in the eastern region compared to the central and western regions, with the central region making the largest contribution to GTFP in the surrounding regions; the first, second, and third tier cities have more contributions from the digital economy to local and neighboring GTFP than the fourth and fifth tier cities. Fourth, city size positively modifies the relationship between the green total factor productivity and the digital economy. The western region is where the positive moderating effect of city size expansion is greatest. Moreover, compared to first-, second-, and third-tier cities, the fourth- and fifth-tier cities have a stronger beneficial moderating effect of city size increase. In light of this, we should focus on the growth of the digital economy, optimize city scale, and fully exploit the scale effect produced by the concentration of the digital industries and the spillover effect produced by the spread of the digital technology.

KEYWORDS

digital economy, city size, GTFP, spatial measurement, spatial spillover effects

1 Introduction

The level of green economic development is directly reflected in GTFP, and increasing GTFP is in line with the practical requirements of China's new development philosophy. China has made significant progress in its economic and social development since the reform and opening up, but it also faces a number of challenges, including environmental pollution, an aging population, an energy crisis, and high carbon emissions. Chinese digital economy has advanced to a new stage of deeper application, standardized development, and sharing for the benefit of everyone thanks to the deep integration of the digital economy and many fields in recent years. Accelerating the development of the digital economy is a significant way to address the challenging issues in the current development pattern, support Chinese high-quality development, and increase total factor productivity in this context as it is a key driving force for development in the new era. Therefore, one of the crucial academic themes of the present is investigating whether the digital economy can encourage the improvement of GTFP and by what mechanism it will boost GTFP.

Cities serve as the foundation of the national economy and are crucial to the advancement of sustainable and high-quality development. A significant factor in the process of the digital economy producing social repercussions is the breadth and depth of urban scale transformation. The future green and high-quality growth of Chinese cities will focus on developing the new green engine of the digital economy and urban scale transformation as well as exploring the new path of these factors that enable green development. In light of this, this paper explains how the digital economy and city scale affect GTFP and empirically analyzes the connection between the digital economy, city scale, and GTFP using panel data from 282 prefecture-level cities from 2011 to 2019. The goal is to provide a theoretical foundation for relevant departments to develop targeted policy measures in the context of modernization. On the basis of this, the paper's minor contributions are as follows. In order to analyze the respective roles and synergistic effects of the digital economy, city size, and GTFP in fostering GTFP growth, this article first integrates these three variables into a single analytical framework. Second, using spatial econometric models, 282 prefecture-level Chinese cities are utilized as empirical samples to examine the effects of the digital economy and city size on the GTFP.

2 Literature review

GTFP research is currently divided into two main areas. One of the elements is the measurement approach, in which researchers mostly use the SBM model-GML index to measure GTFP from an input-output perspective (Feng et al., 2018). The other aspect entails the research on the identification and role of the influencing factors that affect GTFP. The identified influencing factors can be categorized as economic development, ecological environment, and government policies. The economic development mainly includes market mismatch, technological innovation, OFDI, etc. According to empirical findings by Zhang et al. (2019), market mismatch hampered the expansion of GTFP in 33 countries along the Belt and Road from 1995 to 2012. Using panel data for the OECCD countries from 1996 to 2017, Wang H. et al. (2021) demonstrate that technical innovation has a strong positive impact on GTFP. Data from 21 European countries that took part in the Belt and Road Initiative from 2009 to 2018 are used by Xie and Zhang (2021), and the empirical findings indicate that China's OFDI helps these nations' GTFP increase. The ecological environment aspects are mainly related to environmental pollution and its management. The findings of Li et al. (2022) demonstrated that severe air pollution does not raise GTFP in agriculture. According to Tong et al. (2022), China's GTFP is greatly increased by stringent environmental rules. Further, government policies become an important basis for enhancing GTFP, such as the construction of national e-commerce demonstration cities, fiscal decentralization, carbon emission trading pilot, and pilot free trade zones, all of which have significant impacts on GTFP (Song et al., 2020; Cao et al., 2021; Wang A. et al., 2022; Yu et al., 2022).

Academics have focused their attention on the difficult economic activity of how to harness the force and rules of the digital economy to improve GTFP. Most research on the subject of the digital economy and GTFP agree that it has a good impact on the latter, although there are some variations between their conclusions, which primarily come from two points of view. One is that the development of GTFP can be directly influenced by the digital economy. Based on panel data from 108 cities in the Yangtze River Economic Zone from 2011 to 2019, the study by Hu and Guo (2022) demonstrates that the digital economy significantly increases GTFP. Second, the relationship between the digital economy and GTFP is U-shaped or inverted U-shaped. Meng and Zhao (2022) demonstrate that there is a specific threshold value for the impact of the digital economy on GTFP using panel data from 17 manufacturing industries from 2000 to 2014. The positive impact of the digital economy on GTFP is negligible before to exceeding the threshold, but it can dramatically increase GTFP after exceeding the barrier. According to Li et al. (2020), the encouragement of green technology advancement by the digital economy is the key source of the digital economy's impact on GTFP, which has a substantial U-shaped characteristic.

Cities serve as the fundamental building block of the national economy and are crucial to the high-quality growth of the digital economy. In the process of creating social consequences in the digital economy, the change in city size is crucial. City size and digital economy are interconnected and influence each other. On the one hand, the growth of the digital economy is based on city size. According to Pradhan et al. (2021), urbanization is a crucial foundation for the advancement of information and communication technology, which supports the growth of the digital economy. On the other side, the transformation of city size will be accelerated by the digital economy. The findings of Zhu and Chen (2022) demonstrate that the digital economy has a greater influence on urban space than urbanization. Academics have not yet reached consensus on the research findings about the connection between city size and GTFP, and there are three basic points of view. One is the promotion theory, which holds that increasing city size contributes to an increase in GTFP. The growth of city size is advantageous to the enhancement of GTFP, according to empirical findings from Peng et al. (2020) measurement of the level of GTFP in the nations that make up the Silk Road economic belt. The second is the suppression theory, which holds that increasing city size is bad for increasing GTFP. According to Xie et al. (2022), the mismatch of land resources brought on by rapid urban development prevents the growth of GTFP. There is a threshold for the contribution of city size expansion to GTFP, according to the third theory, which is nonlinear. The research by Tan et al. (2022) demonstrates that when the economic agglomeration is relatively modest, the impact of urban transportation infrastructure on GTFP change is not considerable, but it becomes clear as the agglomeration rises.

Although the literature now available is adequate, there are a number of issues. First, the present literature is mostly concerned with the mechanism and impact of the digital economy on GTFP at the local level; however, not enough studies have been done to pinpoint the precise mechanisms through which the digital economy influences GTFP at the local level of cities. Second, the existing studies on the external effects of the digital economy and city size assume that the relationship between the two factors and GTFP is linear. Yet, the spatial implications of the digital economy and city size on GTFP need for greater consideration in light of the spatial externality hypothesis. In order to provide workable policy recommendations, this study first integrates the digital economy, city size, and GTFP into a single analytical system for theoretical analysis. Then, it uses a spatial econometric model to empirically analyze the effect of the digital economy on GTFP and the moderating role of city size in this process.

3 Theoretical mechanisms and research hypotheses

3.1 Digital economy and GTFP

The digital economy is a critical component that offers a new strategic fulcrum for China's economic transition since it is redefining global factor resources, the global economic structure, and the global competitive environment. Thus, China's economy can change from being a factor-driven economy to an efficiency-driven and innovation-driven one, and it can exhibit a modern economic development path; consequently, the changes that affect power, efficiency, and quality provide a new growth path for GTFP.

First, the digital economy creates power shifts that impact GTFP through influencing developments in technology, models, and institutions (Chen, 2022b). The digital economy has fundamentally changed the way traditional sectors produce goods by leveraging cutting-edge technology in fields like big data, artificial intelligence, cloud computing, and high-end equipment manufacture. Innovation in digital technology increases the organic momentum of green economic development in addition to providing the technical foundation for data to become a revolutionary production technique and a key production element. Secondly, the digital economy via "Internet +" for the innovation of traditional industrial development mode, and for the promotion of digital recording, storage, interaction, and sharing of fundamental high-quality data resources across various industries, which indirectly improves productivity, promotes the quality and efficiency of traditional industries, and creates momentum for the intelligent and green development of industries. Finally, for the digital economy to develop, the government should facilitate the development of an environmental supervision system that is based on digital technology, which will effectively promote institutional innovation, accelerate the construction of a robust network that will transform China's economy into a digital economy, provide environmental support and policy support that is compatible with the form of the digital economy that the country will develop, encourage the development of a novel green and low-carbon development pattern and enlist the aid of institutional innovation funds that prioritize the improvement of GTFP.

Second, the digital economy encourages efficiency change and increases GTFP through improving production efficiency and factor allocation efficiency (Zhang et al., 2022). On the one hand, the economies of scale, scope, and long-tail effect of the digital economy can help businesses get around several institutional and technological constraints that prevent the improvement of production efficiency. Additionally, businesses can use digital technology to streamline operations, improve operational effectiveness, reduce resource waste, and cut expenses associated with transactions. As a result, business vitality is boosted, competitiveness is increased, and enterprise green transformation and development are accomplished. On the other hand, the digital economy has opened up the channels for the production factors' circulation; continually led the supply, value, and industrial chains, which made it possible to allocate resources efficiently using the internet; facilitated coordination and innovation among various industrial sectors; and yielded novel industrial forms such as the platform economy, sharing economy, "virtual" industrial parks, and industrial clusters; thus, the digital economy can help to further advance GTFP.

Third, the digital economy fosters quality change by raising the quality of factors, goods, and services, leading to GTFP growth (Wang M. et al., 2021). The digital economy produces significant changes in production relations and lifestyles through data factorization and factor datafication; reshapes the factor input structure that characterizes the original economic system, which in turn enhances factor quality, facilitates the development of a novel model for developing the digital economy, which exhibits a multi-level structure, wide coverage, differentiation, and the rational division of labor among large, medium, and small enterprises; and promotes the development of China's green economy. Furthermore, the quality and mode of supply of goods and services have undergone significant changes as a result of the digital economy, which enables enterprises to transform their products and services using digitalization and to promote the mode of supply from single to multiple, the motive from management to service, the content from rough to fine, the mode from decentralized to collaborative, and the performance evaluation from closed to open; thus, enterprises provide consumers with more digital products and with personalized and customized services. Therefore, the digital economy responds to the growing desire for a better living and raises total green factor productivity.

Based on the aforementioned study, we put up the following hypothesis (Hypothesis 1): the digital economy helps to positively boost GTFP.

3.2 City size and GTFP

The major ways that city size influences GTFP are through the agglomeration economic effect caused by the concentration of production factors, the technology spillover effect caused by technological advancement, and the structure-driven effect caused by the modernization of industrial structures.

First, when a city's population changes, agglomeration-based economic effects frequently follow, having a significant impact on GTFP (Cheng et al., 2022). In the early stages of urbanization, factors of production such as industries, talents, capital, and innovation activities are heavily invested in urban construction, which generates agglomeration effects, and the city scale becomes rapidly widened, which offers strong support for the modernization of the urban industrial structure, technological advancement, and economic growth; hence, city size aids in the ongoing improvement of urban GTFP. However, as the scale of cities continues to expand, the congestion effect that modifies the urban scale inhibits the growth of GTFP, the population and industries over-concentrate in cities, and the disorderly expansion of the urban space occurs.

Second, variations in city size offer an essential conduit for the information diffusion that impacts technological innovation, which affects the expansion of GTFP (Wang KL. et al., 2022). In terms of cities and towns, as economic and population scales increase, people, businesses, and industries are more likely to share resources, information, and markets. The diversified and specialized clustering of industries also changes how factor inputs are shared, which supports the growth of the green economy. The expansion of cities on a suitable scale can improve the quality of the labor force, the quality of the innovation factors, and provide enough capital to support technical innovation and knowledge spillover, thereby promoting GTFP. The information spillover effect that influences technological innovation will be lessened by the chaotic growth of city size; as a result, the improvement of GTFP will not be assisted.

Third, changes in city size result in sophisticated industrial structures, and the rationalization and advancement of these structures have an impact on GTFP (Cheng and Jin, 2022). During scale expansion, cities can guide and adjust the general layout of industries based on their own factor endowments and competitive advantages. The concentration of production factors encourages the emergence and growth of numerous industrial parks, which encourages the transformation of the industrial structure from agriculture to industry and services, low-level to high-level, and quantitative to qualitative. It also encourages the development of the urban industrial structure, which encourages GTFP. The spatial planning and element resetting that characterize the process of urban scale change can assist industry complementarity and mutual support, modify and optimize the industrial distribution pattern, and promote the ongoing extension and expansion of the industrial chain. Additionally, it can support the efficient use of resources, ease the change of the city's old-new dynamics, allocate resources and spatial components in the best way possible, and assist the orderly transformation of the economic development mode. Consequently, element resetting and spatial planning support the rationalization of the change in urban scale. Hence, improving GTFP is facilitated by rationalizing the industrial structure.

Based on the aforementioned study, we put up the following hypothesis (Hypothesis 2): the improvement of GTFP is facilitated by a proper city scale.

3.3 Digital economy, city size, and GTFP

In general, as development levels rise, which have an impact on the digital economy, cities will get larger, which in turn will fuel the expansion of the digital economy; thus, the digital economy and city size are correlated. Four theories are primarily used to explain how digitalization and city size interact to affect GTFP.

According to the first theory, the digital infrastructure's characteristic leapfrogging promotes GTFP growth (Pan et al., 2022). Cities support the simultaneous development of urbanization and informatization, which widens and deepens the application scenarios of digital infrastructure, by creating digital infrastructure, scaling up communication network construction, and boosting the capacity of communication services; hence, the master plan for the optimization of city scale is affected. As a result, the foundation for the growth of the digital economy, which guarantees that people's lives are improved, is digital infrastructure. As a result, numerous fields will see an acceleration of the digital revolution, which will continuously improve digital governance, support the upgrading and transformation of the regional economy, and provide a strategic, ground-breaking, and essential foundation for increasing GTFP.

According to the second theory, GTFP is promoted by the accelerated improvement of digital industries' potential for innovation (Qiu et al., 2021). Regarding the digital economy, the expansion of city scale creates opportunities for innovation, and the improvement of digital industry innovation capacity accelerates the application of digital technology to traditional industries. This motivates real businesses to increase their investment in information technology, get past technical hurdles, improve their information analysis skills, and address industrial bottlenecks. The gradual maturity of businesses results in increased security and stability when it comes to the use of digital technology in the industrial and supply chains, whereas the city's innovation-driven development strategy, which supports the growth of the digital economy and its radiation-driven capability, adds additional vitality and momentum that can boost GTFP.

Third, increasing GTFP is facilitated by the acceleration of digital industrialization and industrial digitization (Zhang and Zhou, 2022). Industrial digitization is the use of digital technology by established industries to innovate and transform, whereas digital industrialization refers to the creation of new industries and economic sectors based on digital technology. The rapid growth of digital industrialization and industrial digitization encourages the fusion and expansion of traditional industries and digital technologies as well as the exact balancing of supply and demand, blurs the boundary between traditional industrial sectors, transforms the mode of coupling digital information and production factors, facilitates the release of the agglomeration economic effect and the urban growth potential that is occasioned by urban scale expansion, promotes the rational layout of traditional industries and digital industries in urban space, and assists cities in promoting GTFP through a thorough, high-quality development process.

According to the fourth theory, the digitalization of public services encourages urban growth. The digital transformation of public services promotes the enhancement of GTFP (Thanh, 2022). Public services are an essential building block for the development of green cities; however, the separation of administrative responsibilities across cities, competing interests, and high transaction costs impede their integration, which in turn has a detrimental effect on the improvement of GTFP. By taking the initiative to direct the diffusion and application of digital technology in public services, the government can support the digital transformation of urban public services, eliminate "fragmented governance" and administrative hurdles between cities, support the integration of public services between central and local governments, improve its capacity to transform the scale of cities, and reshape the administration and quality of public services, thus contributing to promote GTFP.

Based on the aforementioned study, we put up the following hypothesis (Hypothesis 3): the connection between digitalization and city size is beneficial to improving GTFP.

10.3389/fenvs.2023.1225406

4 Model setting and indicator construction

4.1 Measurement model setting

By constructing a spatial econometric model that takes into account the digital economy, city size, and GTFP, this study experimentally analyzes the relationship between the three. In order to decrease the potential endogenous influence of the dynamic change process of the variables on the estimation results, the dynamic spatial Durbin model is used in this research to conduct the empirical analysis. The specific model parameters are as follows:

$$\begin{aligned} gtfp_{i,t} &= \alpha + \rho W \times gtfp_{i,t} + \beta_1 gtfp_{i,t-1} + \beta_2 digital_{i,t} + \beta_3 X_{i,t} \\ &\quad + \theta_1 W \times \mathrm{digital}_{i,t} + \theta_2 W \times X_{i,t} + \mu_i + \eta_t + \varepsilon_{\mathrm{i,t}} \end{aligned} \tag{1}$$

Considering Eq. 1, the explanatory variable $gtfp_{i,t}$ denotes GTFP; the core explanatory variables $digital_{i,t}$ denote the digital economy; α、β、θ denotes the coefficient that should be estimated; $X_{i,t}$ denotes the control variables; and μ_i、η_t and ε_{it} represent individual fixed effects, time fixed effects, and error terms, respectively.

This research introduces the interaction term of the digital economy ($digital_{i,t}$) and city size ($scale_{i,t}$) based on Eq. 1 to investigate the interaction effect of the digital economy and city size on green total factor productivity.

$$\begin{aligned} gtfp_{i,t} &= \alpha + \rho W \times gtfp_{i,t} + \beta_1 gtfp_{i,t-1} + \beta_2 digital_{i,t} + \beta_3 scale_{i,t} \\ &\quad + \beta_4 X_{i,t} + \beta_5 digital_{i,t} \times scale_{i,t} + \theta_1 W \times \mathrm{digital}_{i,t} \\ &\quad + \theta_2 W \times scale_{i,t} + \theta_3 W \times X_{i,t} + \theta_3 W \times digital_{i,t} \times scale_{i,t} \\ &\quad + \mu_i + \eta_t + \varepsilon_{\mathrm{i,t}} \end{aligned} \tag{2}$$

4.2 Variable selection and measurement

4.2.1 Explained variable

We construct an SBM-Malmquist productivity index model ($gtfp_{i,t}$) to calculate GTFP, using variables for the labor force, the volume of capital inputs, and energy consumption (Fukuyama and Weber, 2010). First, the labor force is calculated by counting the number of employed people in each prefecture-level city during a given calendar year; second, capital input is calculated using the perpetual inventory method; and third, energy consumption is calculated by adding up all of the energy used by all prefecture-level cities during that same calendar year. The actual GDP of each prefecture-level city in a calendar year represents the expected output, and the emissions of industrial wastewater, industrial sulfur dioxide, and industrial smoke and dust in each prefecture-level city in calendar year represent the non-expected output. We determine the ratio of each city's total industrial output value to the total industrial output value of the province in which the city is located in order to account for missing data on energy or non-expected output indicators. After that, we multiply the total energy or non-expected output indicators of each provincial level by the number of cities that fall under its purview in order to obtain the data regarding energy or non-expected output indicators specific to each city.

4.2.2 Explanatory variable

Digital economy ($digital_{i,t}$) is the explanatory factors. First, we use four variables that are relevant to the growth of the internet: mobile phone penetration, related practitioners, related output, and internet penetration rate. Then, using data from Peking University's Digital Financial Inclusion Index, we incorporate the indicators of digital financial inclusion. Finally, we use the entropy weight approach to combine the five variables to create the digital economy development index.

4.2.3 Adjustment variable

City size ($scale_{i,t}$) is the adjustment variable. Nighttime lighting data is chosen as a proxy variable to estimate the size of the city. Furthermore, to increase the credibility of the results, the corrected DMSP-like OLS data are obtained by integrating DMSP–OLS and NPP–VIIRS data based on the administrative divisions that characterize China in a fixed year (2011), and nighttime lighting data are obtained based on the DMSP-like OLS data (Wu et al., 2021).

4.2.4 Control variables

1) Technological progress (tec) is expressed as the ratio of regional S&T expenditures to local GDP (unit: %). 2) Advanced industrial structure ($indgaoji$): the ratio of the tertiary industry output value to the secondary industry output value (unit: %) is utilized to express $indgaoji = \frac{P_3}{P_2}$, where P_2、P_3 denotes the output value of secondary and tertiary industries, and a high ratio indicates a highly advanced industrial structure. 3) Rationalization of industrial structure ($indheli$): the construction of $indheli = \sum_{I=1}^{n} \left(\frac{P_I}{P}\right) \ln\left(\frac{P_I}{L_I} / \frac{P}{L}\right)$ is based on the Thayer index, where P denotes the output value, I denotes the industry, L denotes the employment, and n denotes the number of industrial sectors, and a small value indicates a highly rational industrial structure. 4) Government intervention (gov) is expressed as the ratio of local fiscal expenditure to local GDP. 5) Regional openness ($open$) is expressed as the ratio of FDI to local GDP. 6) Environmental regulation (env): First, we standardize the index values of industrial wastewater, industrial sulfur dioxide, and industrial smoke; subsequently, we utilize the entropy weight method to determine the index weights; and, finally, we determine the comprehensive index of environmental regulation (unit: %) based on the reciprocal pertaining to the product of the weights and the standardized values, where a high comprehensive index score indicates strict environmental regulation.

4.3 Data sources

The China City Statistical Yearbook and the Digital Finance Research Center of Peking University provided the majority of the data that we used to measure the digital economy. We used the evening lighting data (DMSP/OLS and NPP/VIIRS) that the National Oceanic and Atmospheric Administration (NOAA) supplied from 2011 to 2019 to estimate the size of cities. The descriptive statistics for the variables are shown in Table 1.

TABLE 1 Descriptive statistics results.

Variable name	Symbols	Observations	Average value	Maximum value	Minimum value	Standard deviation
GTFP	*gtfp*	2,538	1.081	8.911	0.041	0.245
Digital Economy	*digital*	2,538	0.341	1.000	0.053	0.119
City Size	*scale*	2,538	7.909	58.518	0.130	9.423
Technological Advances	*tec*	2,538	0.003	0.063	0.000	0.004
Advanced Industrial Structure	*indgaoji*	2,538	0.923	13.477	0.094	0.548
Rationalization of Industrial Structure	*indheli*	2,538	0.271	3.839	0.000	0.221
Government Intervention	*gov*	2,538	0.157	1.936	0.003	0.118
Government Intervention	*open*	2,538	0.022	0.776	0.000	0.030
Environmental Regulation	*env*	2,538	0.108	0.328	0.082	0.015

TABLE 2 Annual average values of urban GTFP in China and regions, 2011 to 2019.

Year	National	East	Central	West	First, second and third tier cities	Fourth and fifth tier cities
2011	1.040	1.040	1.050	1.029	1.042	1.073
2012	1.032	1.021	1.038	1.042	1.022	1.039
2013	1.065	1.062	1.136	0.999	1.104	1.036
2014	1.031	1.020	1.093	1.051	1.021	1.039
2015	1.134	1.077	1.057	1.290	1.115	1.147
2016	1.093	1.156	1.100	0.994	1.159	1.045
2017	1.119	1.141	1.102	1.068	1.146	1.099
2018	1.128	1.127	1.150	1.108	1.147	1.114
2019	1.112	1.130	1.131	1.068	1.135	1.96

5 Regression results

5.1 Temporal characterization of GTFP

Table 2 displays the annual average GTFP values for the nation and individual cities from 2011 to 2019. Table 2 shows that there is a varying upward tendency in the annual average values of GTFP as a whole. By regions, the annual mean values of GTFP in eastern and central regions are higher than those in western regions, and the annual mean values of GTFP in first-, second- and third-tier cities are higher than those in fourth- and fifth-tier cities, demonstrating that areas with greater economic development are better able to increase GTFP than areas with lesser levels of economic development.

5.2 Spatial correlation analysis

Table 3 shows the Moran indices we developed to investigate the regional autocorrelation of the digital economy, city size, and GTFP. Table 3 shows that the global Moran index is significantly positive, with the exception of a few years. Consequently, there is a significant spatial relationship between the size of the city, the GTFP, and the digital economy, which emphasizes the requirement and sense of using a spatial econometric model to research this problem.

5.3 Trend analysis

We create 3D perspective views of the digital economy, city size, and GTFP using a "trend analysis" tool that was created using ArcGIS software; the corresponding images are shown in Figures 1–3. The Z-axis points to the properties, the Y-axis points to the north, and the X-axis points east. Figure 1's fitted curve for GTFP shows a decreasing East-West trend, and a "U"-shaped north-south curve shows that regional variations in GTFP are not significant. Figure 2's fitted curve for the digital economy shows a west-to-east growing tendency as well as a North-to-South increasing trend, both of which point to high levels of development in China's east and south. Figure 3 shows that the fitted curve for city size rises and

TABLE 3 Test results of the global Moran index.

Year	*gtfp*	*digital*	*scale*	Year	*gtfp*	*digital*	*scale*
2011	0.000	0.195***	0.469***	2016	0.044***	0.152***	0.453***
2012	0.041***	0.180***	0.451***	2017	0.051***	0.147***	0.463***
2013	0.008	0.180***	0.459***	2018	0.058***	0.152***	0.463***
2014	0.013	0.148***	0.453***	2019	0.009***	0.141***	0.468***
2015	0.234***	0.156***	0.453***				

Note: Robustness standard errors are placed within parentheses, where * indicates $p < 0.1$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$. The same below.

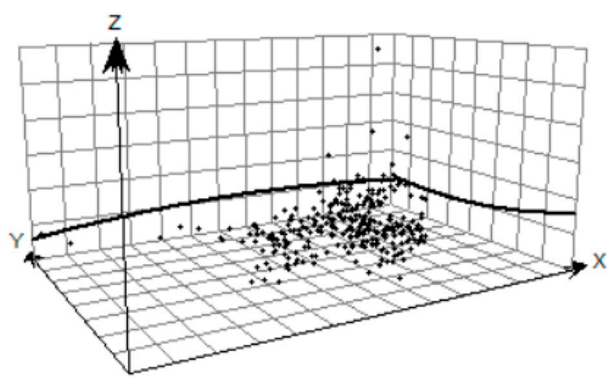


FIGURE 1
Trend analysis of GTFP.

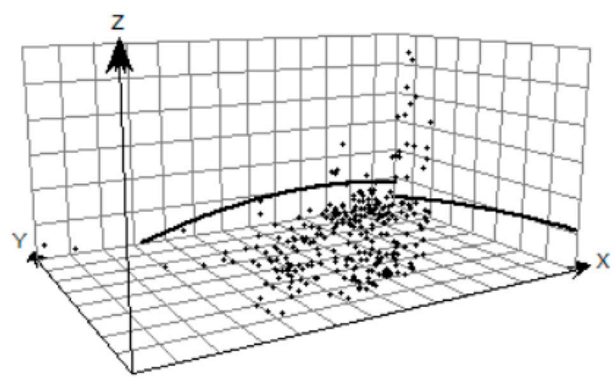


FIGURE 3
Trend analysis of city size.

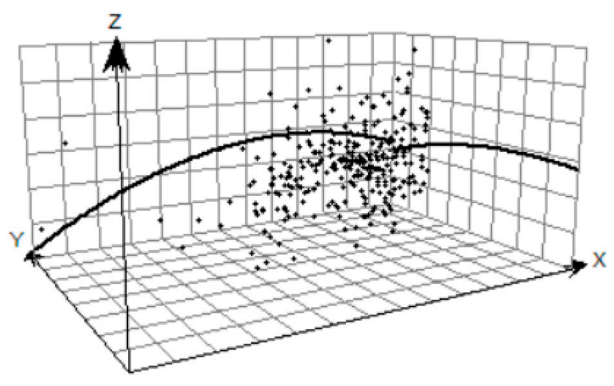


FIGURE 2
Trend analysis of the digital economy.

follows an East-West and North-South axis, indicating that the West and South of China have large cities.

5.4 Analysis of spatial measurement results

The geographic econometric correlation test is used in this paper to evaluate the appropriateness of applying the dynamic spatial Durbin model, and the specific outcomes are displayed in Table 4.

TABLE 4 Estimation results of spatial measurement correlation test.

Inspection	Value	Inspection	Value
VIF	1.35	Hausman	3.04*
$LR-lag$	10.08***	$LR-error$	10.85***
$Wald-lag$	10.09***	$Wald-error$	10.77***

There is no multicollinearity among the variables used for this paper, as shown by the VIF test findings in Table 4. The dynamic spatial Durbin model used in this work is known to be plausible based on the findings of the LR test and Wald test.

The findings of the spatial effect decomposition appear in columns 2 through 7, while the results of the dynamic spatial Durbin model based on the geographic distance matrix appear in the first column of Table 5. The results of Table 5's first column show that the estimated coefficient of GTFP ($L.gtfp$) in the lag period is significantly negative, showing that the GTFP in the prior period is not conducive to improving the GTFP in the subsequent period. The reason could be that issues with the city's construction process related to industrial development, ecological protection, technological advancement, and changes in spatial structure not only have an impact on the GTFP now but also pose a threat to it in the future, making it challenging to create a growth inertia for GTFP improvement. The estimated digital economy coefficient ($digital$) is significantly positive, showing that the growth of the local GTFP is

TABLE 5 Dynamic spatial Durbin model estimation results.

Variables	Estimated value	Short-term			Long-term		
		Direct effect	Indirect effects	Total effect	Direct effect	Indirect effects	Total effect
$L.gtfp$	−0.166*** (−8.43)						
$digital$	0.031* (1.73)	0.028 (1.58)	−0.125 (−0.78)	−0.098 (−0.59)	0.024 (1.62)	−0.096 (−0.82)	−0.072 (−0.59)
tec	0.214 (0.09)	0.487 (0.22)	2.171 (0.14)	2.658 (0.17)	0.410 (0.22)	1.538 (0.14)	1.948 (0.17)
$indgaoji$	0.019 (0.89)	0.015 (0.76)	−0.188 (−1.27)	−0.172 (−1.15)	0.013 (0.79)	−0.141 (−1.30)	−0.127 (−1.16)
$indheli$	0.074 (1.24)	0.069 (1.21)	−0.289 (−0.67)	−0.220 (−0.51)	0.060 (1.23)	−0.223 (−0.70)	−0.163 (−0.51)
gov	−0.126 (−1.49)	−0.117 (−1.40)	0.274 (0.48)	0.157 (0.27)	−0.101 (−1.41)	0.216 (0.51)	0.115 (0.27)
$open$	−0.005 (−0.02)	0.023 (0.08)	2.070 (0.82)	2.094 (0.82)	0.014 (0.05)	1.538 (0.82)	1.552 (0.82)
env	7.951*** (6.90)	7.975*** (7.16)	3.887 (0.35)	11.862 (1.05)	6.816 (7.18)	1.972 (0.24)	8.788 (1.06)
$W \times digital$	−0.083 (0.09)						
ρ	0.519 (9.85)						
$sigma^2$	0.084*** (37.47)						
R^2	0.0631						
N	2,256						

facilitated by the expansion of the digital economy, supporting hypothesis 1. The reason could be that by integrating the Internet with other industries, the digital economy can develop new business models and patterns for urban industrial development and structural upgrading, encourage the use of clean energy in cities, hasten the transition between old and new dynamics within cities, direct the clustering of high-tech businesses and high value-added services in cities, and encourage cities to optimize the form and scale of urban development. To support GTFP, cities should grow in size and scope (Chen, 2022a).

Among the control variables, the positive estimated coefficient of technological progress (tec) indicates that technological progress is conducive to GTFP, primarily because environmentally friendly technological advancement can greatly lessen the effects of using fossil fuels on the environment, increasing the output of green total factors (Wang H. et al., 2021; Wang M. et al., 2021). A positive coefficient of industrial structure advanced ($indgaoji$) indicates that industrial structure advanced is conducive to the improvement of GTFP, and a positive coefficient of industrial structure rationalization ($indheli$) indicates that industrial structure rationalization is conducive to the improvement of GTFP, the major justification for this is that modernizing the industrial structure encourages high-quality economic growth, which in turn encourages GTFP (Gu et al., 2022). The negative coefficient of government intervention (gov) indicates that government intervention inhibits the improvement of GTFP, the market's ability to allocate resources is constrained by excessive government intervention, which is harmful to increasing GTFP (Wu et al., 2021). The negative estimated coefficient of regional openness ($open$) indicates that the level of regional openness is not conducive to enhancing GTFP, primarily because improving regional openness by local governments may result in the introduction of polluting FDI, which is counterproductive to increasing the productivity of green total factors (Lin and Chen, 2018). The estimated coefficient of environmental regulation (env) is positive indicating that environmental regulation is conducive to increasing GTFP, primarily because implementing sensible and effective environmental regulation policies is a key strategy for boosting the productivity of green total factors (Cheng and Li, 2022).

Based on Table 5's direct, indirect, and total effects in the short and long terms, as well as the predicted spatial spillover effects of the main explanatory factors. The estimated coefficients of the spatial lag of the digital economy ($W \times digital$) are negative, and the short- and long-term direct effects of the digital economy ($digital$) are positive, but the indirect and total effects are negative, showing that the short-term and long-term effects of the digital economy are positive for improving local GTFP but negative for improving neighboring areas' GTFP. This suggests that, both immediately and over time, the digital economy helps to raise local GTFP but not surrounding GTFP. The development of the digital economy may be the cause because it encourages the deepening of data factors, removing barriers between industries, erasing geographic distinctions between cities, promoting the deep integration of the real and digital economies, igniting the interest of various market participants, and opening up the domestic integrated market, thus promoting the local. However, the growth of the local digital economy will take a significant quantity of production elements from nearby locations due to the siphon effect, which will restrict the improvement of GTFP in nearby locations.

5.5 Heterogeneity analysis

Based on the geography of their provinces, the 282 cities in this study were split into eastern, western, and central areas. The results are displayed in Table 6. Table 6 shows that the eastern region has

TABLE 6 Heterogeneity analysis of East, Central and West regions.

Variables	East	Central	West
L.gtfp	−0.172***	−0.154***	−0.274***
	(−5.73)	(−3.97)	(−7.48)
digital	0.120***	0.029	−0.019
	(4.15)	(0.67)	(-0.74)
$W \times digital$	0.271	0.798**	0.242
	(1.50)	(2.20)	(1.48)
ρ	0.080	0.302	0.361***
	(0.43)	(1.27)	(3.32)
$sigma^2$	0.086***	0.105***	0.064***
	(24.65)	(20.10)	(20.36)
Control variables	Control	Control	Control
R^2	0.118	0.115	0.169
N	960	640	656

TABLE 7 Heterogeneity analysis of city classification.

Variables	First, second and third tier cities	Fourth and fifth tier cities
L.gtfp	−0.172***	−0.242***
	(−5.61)	(−8.69)
digital	0.162***	0.0002
	(3.09)	(0.02)
$W \times digital$	0.301**	0.034
	(1.76)	(0.88)
ρ	0.010	0.054***
	(0.13)	(0.85)
$sigma^2$	0.162***	0.034***
	(24.54)	(28.72)
Control variables	Control	Control
R^2	0.101	0.146
N	952	1,304

the biggest positive digital economy (*digital*) coefficient, followed by the central region with the second largest, and the western region with the smallest and negative coefficient, additionally, the digital economy's favorable contribution the central region experiences the largest geographic spillover term ($W \times digital$), followed by the eastern region and the western region, demonstrating that the digital economy in the center region is more advantageous than that in the eastern and western regions to increase the GTFP of the surrounding regions. This may be due to the fact that eastern cities are better positioned than central and western cities to benefit from the "digital dividend" brought about by the growth of the digital economy. This will enable industrial upgrading, increase production efficiency, lessen resource mismatch, and reduce production costs, all of which will increase local GTFP. As the central region transitions from "central collapse" to "central rise," the growth of the digital economy can support that region's development potential and vitality. As a result, neighboring regions' GTFP will be increased more than in the eastern and western regions.

Table 7 displays the findings of the classification of 282 cities into Tier 1, 2, 3, 4 and 5 cities. According to Table 7, Tier 1, 2, and 3 cities have larger positive coefficients for digital economy (*scale*) and the spatial spillover term ($W \times scale$) than Tier 4 and 5 cities, indicating that Tier 1, 2, and 3 cities' development of the digital economy is more likely to increase GTFP locally and in nearby areas. This may be due to the fact that Tier 1, 2, and 3 cities have better economic development levels, population densities, technological innovation capacities, infrastructure, and transportation convenience than Tier 4 and 5 cities, making it simpler for Tier 1, 2, and 3 cities to create an environment in which the digital economy encourages urban GTFP improvement.

TABLE 8 Robustness tests.

Variables	(1)	(2)	(3)	(4)
L.gtfp		−0.161***		−0.173***
		(−5.89)		(−8.58)
digital	0.030	0.0331	0.030*	0.034*
	(1.36)	(1.54)	(1.77)	(1.86)
$W \times digital$			0.021	0.011
			(0.38)	(0.26)
Control variables	Control	Control	Control	Control
N	2,538	2,538	2,538	2,538

5.6 Robustness test

This paper conducts robustness tests using least squares estimation OLS, systematic GMM, static spatial Durbin model, and the use of economic distance matrix in four different ways. The specific results are displayed in columns (1)–(4) of Table 8 in the order in which they were obtained. Table 8 demonstrates that the estimated results of the primary explanatory variables are less different from the previous article in terms of coefficient values and significance, further demonstrating that the regression results of this paper are more reliable.

5.7 Test and analysis of interaction effects

Based on the previous work, this paper adds an interaction term between the two to investigate if the digital economy and city size

TABLE 9 Results of adjustment effects.

Variables	National	National	East	Central	West	First, second and third tier cities	Fourth and fifth tier cities
L.gtfp	−0.167***	−0.168***	−0.172***	−0.158***	−0.296***	−0.176***	−0.249***
	(−8.50)	(−8.57)	(−5.74)	(−4.07)	(−7.88)	(−5.76)	(−8.90)
digital	0.039**	0.013	0.108***	0.014	−0.033	0.148**	−0.007
	(2.19)	(0.61)	(2.91)	(0.23)	(−1.10)	(1.98)	(−0.40)
scale	0.014**	−0.032	−0.002	−0.013	−0.062	0.002	−0.016
	(2.38)	(−1.57)	(−0.08)	(−0.22)	(−0.73)	(0.05)	(−0.56)
$digital \times scale$		0.004**	0.001	0.002	0.006	0.001	0.003
		(2.34)	(0.62)	(0.41)	(0.85)	(0.28)	(0.93)
$W \times digital$	0.006	−0.00008	0.289	0.651	0.098	0.127	0.128**
	(0.09)	(−0.00)	(0.97)	(1.16)	(0.42)	(0.49)	(2.43)
$W \times scale$	−0.007	−0.024	−0.140	−0.257	−1.068	−0.219	0.263**
	(−0.80)	(−0.40)	(−0.74)	(−0.44)	(−1.54)	(−1.37)	(2.55)
$W \times digital \times scale$		0.002	0.008	0.023	0.090	0.015	−0.025***
		(0.29)	(0.50)	(0.44)	(1.42)	(1.17)	(−2.57)
ρ	0.537	0.535***	0.206	0.307	0.345	0.004	0.035
	(10.52)	(10.47)	(1.02)	(1.28)	(3.16)	(0.06)	(0.56)
$sigma^2$	0.084***	0.084***	0.085***	0.105	0.064***	0.160***	0.034
	(37.48)	(37.48)	(24.63)	(20.10)	(20.36)	(24.54)	(28.73)
Control variables	Control	Control	Control	Control	Control	Control	Control
R^2	0.095	0.098	0.128	0.118	0.102	0.109	0.156
N	2,256	2,256	960	640	656	952	1,304

have a synergistic impact on green total factor production. The precise findings are displayed in Table 9.

When the interaction term is removed from the results in column 1 of Table 9, the positive correlations for the city size (*scale*) and its spatial lag term ($W \times scale$) show that increasing city size is advantageous to enhancing GTFP, supporting Hypothesis 2. When we add the interaction term to the results in columns 2–7 of Table 9, we can see that the estimated coefficients of the interaction term between city scale and digital economy ($digital \times scale$) are all positive. This means that city scale has a positive moderating effect on the process of local GTFP improvement, and Hypothesis 3 is true. The positive coefficient is bigger in the fourth and fifth tier cities than in the first, second, and third tier cities, and it is biggest in the western region, second largest in the central region, and smallest in the eastern region. This might be because there are more fourth- and fifth-tier cities in the western region than in the eastern and central regions. The foundation and starting point for the digitization of the urban economy and urban scale optimization is the western region's expanding new urbanization. Additionally, the urban economy's digitalization lays the groundwork for the knowledge, technology, and other intensive industries to congregate in cities in terms of time, place, technology, and economy. In order to actualize the logical architecture of the digital industries and to activate the multiplier, competitiveness, and spillover effects of digital technology, city scale optimization is a key factor. A digital economy development environment with the qualities of universality, inclusiveness, high permeability, reproducibility, and convenience is made possible by the deepening integration between the digitalization of the urban economy and urban scale optimization. This environment is very helpful in promoting the green development of the urban economy and the enhancement of GTFP.

6 Conclusion and recommendations

This research experimentally examined the relationship between digital economy, city size, and GTFP using a spatial econometric model, based on the panel data of 282 prefecture-level cities in China from 2011 to 2019, and came to the following conclusion. First, GTFP exhibits a yearly rising trend generally, with excellent spatial correlation and minimal regional variation. Second, the digital economy is advantageous for improving local GTFP, but not for improving GTFP in nearby locations. Third, the eastern region's digital economy is more suited to boosting regional GTFP than the central and western regions' are, and the central region's digital economy is more suited than the eastern and western regions to boosting GTFP in the surrounding areas. Comparatively to fourth- and fifth-tier cities, the digital economy in first-, second-, and third-tier cities is more suited to boosting GTFP in the region and its surrounding areas. Fourth, additional research reveals that the city size of the digital economy can increase GTFP, with the western area moderating the influence of city size more positively than the eastern and central regions. Additionally, in terms of city size, the fourth and fifth tier cities moderated the effects more favorably than the first, second, and third tier cities.

Based on the findings discussed above, this study proposes the following suggestions. First, it is underlined how important it is for the growth of the digital economy and city scale optimization to support the promotion of GTFP enhancement. The development of digital economy can provide effective support for the green and low-carbon transformation of urban economy through scale effect, spillover effect, and universal sharing, and thus promote the growth of GTFP. Second, it is important to address the local conditions when addressing the effects of the city size and the digital economy on GTFP. To advance the GTFP, individual cities should execute distinct digital economy development strategies based on their level of economic growth and orderly encourage the fusion of the digital economy with new urbanization. Third, it is important to properly acknowledge the beneficial effects of optimizing city size in the process of the digital economy's influence on GTFP. It is essential to actively encourage the use of digital technology during the process of new urbanization construction because this gives cities a digital technology foundation to improve their capacity for green development, optimizing the scale of cities and encouraging the improvement of GTFP.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

ZL contributed to conception and design of the study. JL and YY conducted the data analysis, wrote the original draft. XZ edited the paper. All authors contributed to the article and approved the submitted version.

Funding

This research was funded by the Fundamental Research Funds for the Central Universities, Zhongnan University of Economics and Law (No. 202311020).

Acknowledgments

The authors would like to thank KetengEdit (https://www.ketengedit.com) for linguisticassistance during the preparation of this manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Cao, X., Deng, M., and Li, H. (2021). How does e-commerce city pilot improve green total factor productivity? Evidence from 230 cities in China. *J. Environ. Manage* 289, 112520. doi:10.1016/j.jenvman.2021.112520

Chen, P. (2022a). Is the digital economy driving clean energy development? New evidence from 276 cities in China. *J. Clean. Prod.* 372, 133783. doi:10.1016/j.jclepro.2022.133783

Chen, P. (2022b). Relationship between the digital economy, resource allocation and corporate carbon emission intensity: New evidence from listed Chinese companies. *Environ. Res. Commun.* 4 (7), 075005. doi:10.1088/2515-7620/ac7ea3

Cheng, Z., and Jin, W. (2022). Agglomeration economy and the growth of green total-factor productivity in Chinese Industry. *Socio-Econ Plan. Sci.* 83, 101003. doi:10.1016/j.seps.2020.101003

Cheng, Z., and Li, X. (2022). Do raising environmental costs promote industrial green growth? A quasi-natural experiment based on the policy of raising standard sewage charges. *J. Clean. Prod.* 343, 131004. doi:10.1016/j.jclepro.2022.131004

Cheng, Z., Li, X., Zhu, Y., and Wang, M. (2022). The effects of agglomeration externalities on urban green total-factor productivity in China. *Econ. Syst.* 47, 101025. doi:10.1016/j.ecosys.2022.101025

Feng, C., Huang, J. B., and Wang, M. (2018). Analysis of green total-factor productivity in China's regional metal industry: A meta-frontier approach. *Resour. Policy* 58, 219–229. doi:10.1016/j.resourpol.2018.05.008

Fukuyama, H., and Weber, W. L. (2010). A directional slacks-based measure of technical inefficiency. *Socio-Econ Plan. Sci.* 43 (4), 274–287. doi:10.1016/j.seps.2008.12.001

Gu, B., Liu, J., and Ji, Q. (2022). The effect of social sphere digitalization on green total factor productivity in China: Evidence from a dynamic spatial Durbin model. *J. Environ. Manage.* 320, 115946. doi:10.1016/j.jenvman.2022.115946

Hu, X., and Guo, P. (2022). A spatial effect study on digital economy affecting the green total factor productivity in the Yangtze River Economic Belt. *Environ. Sci. Pollut. Res.* 29 (60), 90868–90886. doi:10.1007/s11356-022-22168-9

Li, H., Tang, M., Cao, A., and Guo, L. (2022). Assessing the relationship between air pollution, agricultural insurance, and agricultural green total factor productivity: Evidence from China. *Environ. Sci. Pollut. Res.* 29 (52), 78381–78395. doi:10.1007/s11356-022-21287-7

Li, T., Han, D., Ding, Y., and Shi, Z. (2020). How does the development of the internet affect green total factor productivity? Evidence from China. *IEEE Access* 8, 216477–216490. doi:10.1109/access.2020.3041511

Lin, B., and Chen, Z. (2018). Does factor market distortion inhibit the green total factor productivity in China? *J. Clean. Prod.* 197, 25–33. doi:10.1016/j.jclepro.2018.06.094

Meng, F., and Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environ. Sci. Pollut. Res.* 29 (52), 79497–79515. doi:10.1007/s11356-022-21434-0

Pan, W., Xie, T., Wang, Z., and Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *J. Bus. Res.* 139, 303–311. doi:10.1016/j.jbusres.2021.09.061

Peng, Y., Chen, Z., Xu, J., and Lee, J. (2020). Analysis of green total factor productivity trend and its determinants for the countries along silk roads. *Growth Change* 51 (4), 1711–1726. doi:10.1111/grow.12435

Pradhan, R. P., Arvin, M. B., and Nair, M. (2021). Urbanization, transportation infrastructure, ict, and economic growth: A temporal causal analysis. *Cities* 115, 103213. doi:10.1016/j.cities.2021.103213

Qiu, W., Zhang, J., Wu, H., Irfan, M., and Ahmad, M. (2021). The role of innovation investment and institutional quality on green total factor productivity: Evidence from 46 countries along the "Belt and Road". *Environ. Sci. Pollut. Res.* 1-15, 16597–16611. doi:10.1007/s11356-021-16891-y

Song, K., Bian, Y., Zhu, C., and Nan, Y. (2020). Impacts of dual decentralization on green total factor productivity: Evidence from China's economic transition. *Environ. Sci. Pollut. Res.* 27, 14070–14084. doi:10.1007/s11356-020-07953-8

Tan, R., Pan, L., Xu, M., and He, X. (2022). Transportation infrastructure, economic agglomeration and non-linearities of green total factor productivity growth in China: Evidence from partially linear functional coefficient model. *Transp. Policy* 129, 1–13. doi:10.1016/j.tranpol.2022.09.027

Thanh, T. T. (2022). Effects of digital public services on trades in green goods: Does institutional quality matter? *J. Innov. Knowl.* 7 (1), 100168. doi:10.1016/j.jik.2022.100168

Tong, L., Jabbour, C. J. C., Najam, H., and Abbas, J. (2022). Role of environmental regulations, green finance, and investment in green technologies in green total factor productivity: Empirical evidence from Asian region. *J. Clean. Prod.* 380, 134930. doi:10.1016/j.jclepro.2022.134930

Wang, A., Hu, Y., Li, Y., Rao, S., and Lin, W. (2022a). Do pilot free trade zones improve the green total factor productivity? Evidence from a quasi-natural experiment in China. *Environ. Sci. Pollut. Res.* 29 (50), 75307–75321. doi:10.1007/s11356-022-21003-5

Wang, H., Cui, H., and Zhao, Q. (2021a). Effect of green technology innovation on green total factor productivity in China: Evidence from spatial durbin model analysis. *J. Clean. Prod.* 288, 125624. doi:10.1016/j.jclepro.2020.125624

Wang, K. L., Pang, S. Q., Zhang, F. Q., Miao, Z., and Sun, H. P. (2022b). The impact assessment of smart city policy on urban green total-factor productivity: Evidence from China. *Environ. Impact Asses* 94, 106756. doi:10.1016/j.eiar.2022.106756

Wang, M., Pang, S., Hmani, I., Hmani, I., Li, C., and He, Z. (2021b). Towards sustainable development: How does technological innovation drive the increase in green total factor productivity? *Sustain Dev.* 29 (1), 217–227. doi:10.1002/sd.2142

Wu, Y., Shi, K., Chen, Z., Liu, S., and Chang, Z. (2021). Developing improved time-series DMSP-OLS-like data (1992–2019) in China by integrating DMSP-OLS and SNPP-VIIRS. *IEEE Trans. Geosci. Remote Sens.* 60, 1–14. doi:10.1109/tgrs.2021.3135333

Xie, F., and Zhang, B. (2021). Impact of China's outward foreign direct investment on green total factor productivity in "Belt and Road" participating countries: A perspective of institutional distance. *Environ. Sci. Pollut. Res.* 28, 4704–4715. doi:10.1007/s11356-020-10849-2

Xie, R., Yao, S., Han, F., and Zhang, Q. (2022). Does misallocation of land resources reduce urban green total factor productivity? An analysis of city-level panel data in China. *Land use policy* 122, 106353. doi:10.1016/j.landusepol.2022.106353

Yu, Z., Mao, S., and Lin, Q. (2022). Has China's carbon emissions trading pilot policy improved agricultural green total factor productivity? *Agriculture* 12 (9), 1444. doi:10.3390/agriculture12091444

Zhang, C., Chen, P., and Hao, Y. (2022). The impact of digital transformation on corporate sustainability-new evidence from Chinese listed companies. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1047418

Zhang, C., and Zhou, W. (2022). New direction of sustainable urbanization: The impact of digital technologies and policies on China's *in situ* urbanization. *Buildings* 12 (7), 882. doi:10.3390/buildings12070882

Zhang, Q., Yan, F., Li, K., and Ai, H. (2019). Impact of market misallocations on green TFP: Evidence from countries along the Belt and Road. *Environ. Sci. Pollut. Res.* 26, 35034–35048. doi:10.1007/s11356-019-06601-0

Zhu, W., and Chen, J. (2022). The spatial analysis of digital economy and urban development: A case study in hangzhou, China. *Cities* 123, 103563. doi:10.1016/j.cities.2022.103563

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 10 August 2023
DOI 10.3389/fenvs.2023.1256052

Check for updates

OPEN ACCESS

EDITED BY
Evgeny Kuzmin,
Ural Branch of the Russian Academy of Sciences, Russia

REVIEWED BY
Maria Urbaniec,
Kraków University of Economics, Poland
Ángel Acevedo-Duque,
Autonomous University of Chile, Chile

*CORRESPONDENCE
Tao Fu,
futaowssy@163.com

RECEIVED 10 July 2023
ACCEPTED 02 August 2023
PUBLISHED 10 August 2023

CITATION
Fu T and Li J (2023), An empirical analysis of the impact of ESG on financial performance: the moderating role of digital transformation.
Front. Environ. Sci. 11:1256052.
doi: 10.3389/fenvs.2023.1256052

An empirical analysis of the impact of ESG on financial performance: the moderating role of digital transformation

Tao Fu* and Jiangjun Li

School of Urban Economics and Management, Beijing University of Civil Engineering and Architecture, Beijing, China

Introduction: Environmental, social, and governance (ESG) considerations have become increasingly important in the financial market and serve as concrete manifestations of sustainable development within a sector. Most corporate leaders have adopted ESG concerns as an important strategy to enhance their financial performance. Therefore, this study investigated whether ESG affects corporate financial performance, and if this relationship is moderated by digital transformation.

Method: We used A-share listed companies in China from 2015 to 2021 as samples to test this mechanism.

Results: Regression analysis showed that ESG positively and significantly affects corporate financial performance, and digital transformation drives this promoting effect. Furthermore, we found that the positive effect of current ESG on financial performance in the lag period will gradually weaken. Specifically, the heterogeneity test results show that the enhancement effect of ESG on financial performance is significant for non-state-owned companies but insignificant for state-owned companies; the same is true for companies located in the eastern region compared with those in the midwestern region. Finally, the enhancement effect of ESG on the financial performance of polluting firms is stronger than that on non-polluting firms.

Conclusion: These findings will be useful for firms and government departments in formulating relevant policies.

KEYWORDS

ESG, firm performance, digital transformation, moderating effect, sustainable development

1 Introduction

The concept of environmental, social, and governance (ESG) originated from responsible and ethical investment (Wang and Sarkis, 2017). Similar to social responsibility and ethics, ESG serves as a guide for corporate risk management and operations. Owing to its comprehensive effects in alignment with the current international focus on green, low-carbon, and sustainable development, ESG has become a research hotspot in the global economy and management field (Paradis and Schiehll, 2021; Finger and Rosenboim, 2022).

According to the Global Sustainable Investment Alliance (GSIA) report, global ESG assets under management reached $28.6 trillion in 2017, accounting for 30% of the total worldwide. On 15 June 2018, the China Securities Regulatory Commission (CSRC) issued a revised version of the Code of Corporate Governance for Listed Companies in China, explicitly requiring listed companies to disclose ESG information. For investors, ESG criteria have become a collection of principles that they can use to evaluate potential investments based on a company's operational activities. For enterprises, assuming responsibility for ESG issues has become a potential driving force for economic benefits. Although investing in ESG initiatives such as purchasing environmentally friendly equipment, protecting workers' rights, and practicing community responsibility, may significantly increase short-term costs, businesses can reap benefits over time from these sustainable investments and potentially successfully promote their products and enhance their reputations. Therefore, in this study, we aim to investigate how does ESG affects corporate financial performance.

As the ESG framework has become embedded into corporate development strategies and operational management processes, the relationship between ESG and financial performance has been extensively discussed in academic literature (Tarmuji et al., 2016; Minutolo et al., 2019). Enterprise ESG information disclosure can effectively alleviate information asymmetry and agency problems, thereby enhancing enterprises' information transparency and reducing financing costs (Fatemi et al., 2015). It can also establish a good corporate social responsibility image, strengthen a company's relationships with stakeholders, and enhance its reputation (Lian et al., 2023). However, the ESG concept in China remains in its early stages (Wang et al., 2023). In 2021, approximately 26% of Chinese listed companies independently published ESG reports. Although the disclosure rate of indicators in various dimensions have improved, problems with unbalanced and inadequate disclosures remain (Yang et al., 2023). Most companies currently face issues such as inadequate capabilities and high costs in ESG practices, which greatly reduce their intrinsic motivation to fulfill ESG obligations (Cong et al., 2023). Regulators and investors still encounter many difficulties in obtaining ESG data to use as a basis for decision-making (Zhang and Liu, 2022). Thus, in China, it is essential to promote ESG development, enhance the ability of companies to engage in ESG practices, and stimulate companies' intrinsic motivation.

The innovative development and application of digital information technologies, represented by artificial intelligence (AI), blockchain technology, cloud computing, and Big Data, provide effective technical means to enhance companies' ESG capabilities (Chen et al., 2022). First, digital technology integration with the real economy can reduce costs and improve efficiency in areas such as information collection, decision support, and operational management, while meeting companies' ESG information disclosure and market supervision needs (Sedunov, 2017; Lv and Xiong, 2022). Second, the efficiency and convenience of digital information technology are driving many companies to shift from traditional production models to digital intelligence development. Digital transformation reduces the costs of fulfilling social responsibility obligations and improves accountability efficiency, thereby providing a foundation for improving ESG performance (Bhandari et al., 2022). Therefore, we argue that digital transformation is an important factor requiring further consideration in the context of its role in the relationship between ESG and financial performance.

The contributions of our study are as follows. Firstly, previous research on the relationship between ESG and financial performance has mainly focused on developed counties, with less attention paid to developing countries. We used Chinese listed companies as research samples to verify this relationship, thus expanding the existing literature. Second, our study is among the first to use digital transformation as a moderating variable to investigate the relationship between ESG and financial performance. Furthermore, owing to variations in property rights, regional environments, and potential for environmental pollution, businesses are subject to different policy constraints. Thus, we classified firms into various groups based on their property rights, regions, and pollution levels, and analyzed how ESG practices affect their financial performance in different contexts. This study provides guidance for policymakers and companies to develop effective policies for green sustainable development to promote economic recovery in the post-pandemic era.

The remainder of this paper is organized as follows: Section 2 presents a literature review concerning ESG and financial performance, and then proposes the hypotheses. Section 3 includes the data, variables, and research model. The empirical analysis is presented in Section 4. Section 5 reports the results of the grouped regression, and Section 6, 7 present the discussion and conclusions, respectively.

2 Literature review and hypotheses development

2.1 ESG and financial performance

The concept of ESG was first proposed in a report published by the United Nations Principles for Responsible Investment (UNPRI) in 2006 (Hoepner et al., 2021). The UNPRI argues that responsible investors should thoroughly consider the impact of ESG factors on investment value, view that has gained increasing prominence in investment choices worldwide.

Under the backdrop of the "dual carbon" goal, interest in the connection between corporate ESG and financial performance has been increasing among academics, practitioners, and international standard-setters (Abdi et al., 2022; Wang et al., 2022). Although consensus has been reached in the literature regarding the relationship between ESG and corporate performance, at present, the academic community generally holds the view that negative ESG events harm corporate performance (Krüger, 2015). From a sustainable development perspective, enterprises should concentrate on environmental protection and rational resource utilization to provides an excellent long-term development environment for promoting sustainable business development (Jeffrey et al., 2019). By creating a green, environmentally friendly corporate image through taking a long-term view of corporate development and not pursuing short-term benefits for immediate profit, companies may obtain long-term returns (Gao and Han, 2020). According to stakeholder theory, companies that can effectively manage their relationships with all stakeholders tend to achieve success, because this theory suggests that companies should not only be accountable to shareholders but also to creditors, employees, suppliers and customers, the government, the community, and the environment (Freeman, 1984). Stakeholder theory emphasizes the external corporate governance to maximize stakeholders' overall interests of, which, in turn, will lead to higher growth and benefits companies (Teplova et al., 2022). For example, satisfied employees are more motivated in their work and satisfied suppliers provide higher-quality raw materials. This allows a company to build a good reputation, thereby promoting performance improvement. Lev et al. (2010) noted that in consumer-sensitive industries, corporate charitable donations contribute to companies' future income. Carnini et al. (2022) found that timely disclosure of information through announcements is crucial for companies to achieve short-term success. Through ESG disclosure, companies can effectively enhance transparency and reduce information asymmetry, thereby enhancing investor confidence in their long-term investments in the company (Cui et al., 2018). Friede et al. (2015) summarized and analyzed over 2000 ESG-related studies and found that approximately 90% indicated a positive relationship between ESG and financial performance. Therefore, we proposed the following hypothesis:

H1. When a company performs well in terms of ESG, ESG can contribute to positive financial performance.

2.2 Digital transformation and ESG

Several studies have revealed that the application of digital technology significantly promotes economic development (Wong et al., 2021), boosts manufacturing upgrades, optimizes employment structures, enhances quality improvement, and fosters entrepreneurial activity (Papagiannidis et al., 2020). The value of digital transformation for enterprises reflects innovations and breakthroughs in not only production technology but also various aspects such as those concerning the environment, society, and corporate governance (Shimizu, 2020).

ESG practices have specific externalities that lead to insufficient investment. Company investment in environmental and social responsibility can consume corporate resources, resulting in financial expenses that damage shareholders' rights and interests, thereby weakening a firm's competitiveness (Friedman, 2007; Garcia and Orsato, 2020). However, resource constraints, outdated technology, and information asymmetry among stakeholders have limited the ability of many firms to enhance their ESG performance. Consequently, these firms face high costs when implementing ESG practices, and cannot be encouraged to improve them by insufficient incentives (Zhong et al., 2023). Digital transformation provides a viable solution to this problem (ElMassah and Mohieldin, 2020). First, digital transformation can promote enterprise technological innovation, particularly the innovation and application of green technology, thereby promoting companies' sustainable development. Second, by minimizing information asymmetry, digitalization can enhance enterprise information transparency and reduce transaction costs (Gouvea et al., 2022). This enables companies to improve their governance levels and fulfill their social responsibilities effectively. Finally, digital technology enhances resource allocation and utilization efficiency, thereby improving companies' decision-making and operational efficiency. Therefore, we propose the following hypothesis:

H2. Embracing digital transformation can help companies improve their ESG.

2.3 Moderating effect of digital transformation

In the post-pandemic era, enhancing management capabilities and improving the quality of business operations have become important aspects of exploring economic development in complex environments. As the public has gained awareness of Chat AI technology, many firms have invested in the digital transformation process (Ionascu et al., 2022). First, through digital technology, companies can collect, analyze, and monitor environmental data to better identify and address environmental risks, improve energy efficiency, and reduce emissions and waste. Second, based on stakeholder value reciprocity (Freeman, 1984) and the insurance mechanism of corporate social responsibility (Godfrey, 2005), business operators often strive for minimal costs yielding maximum returns. For example, some companies intentionally reduce the quality of their information disclosure (Luo et al., 2017) and selectively manipulate the disclosure language using pseudo-corporate social responsibility to push for stakeholder support if they have limited cognitive abilities. However, the characteristics of Big Data and blockchain technology, such as recordability and traceability, effectively address this issue with information asymmetry (Nambisan et al., 2019) and increase public supervision of corporations. Digital technologies and automated processes can also reduce human resources, change how production factors are combined, and improve supply chain relationships, customer relationship management, and marketing effectiveness. These factors can reduce operational costs and increase profit margins and returns on investment for businesses. Therefore, we propose the following hypothesis.

H3. The effect of ESG on financial performance is more prominent when the degree of digital transformation is high.

3 Materials and methods

3.1 Data collection

Based on data availability, we selected Chinese A-share listed companies from 2015 to 2021 as our samples. We screened and processed the samples based on the following exclusion criteria: 1) listed financial companies, 2) ST and *ST companies, 3) companies with a debt-to-asset ratio greater than 1, and 4) samples with missing data. To avoid interference from outliers in the results of the empirical analysis, all continuous variables were winsorized at the 1% and 99% quantiles. Finally, we obtained a total of 15,710 unbalanced panel datapoints from 2,256 listed companies.

TABLE 1 Description of variables.

Type	Variable	Symbol	Variable definition
Dependent	Financial performance	ROA	Net profit divided by average total assets
Independent	ESG	ESG	According to ESG rating "C-AAA", 9-grade ratings are assigned 1–9
	Regional nature	province	1 If the firm's registered location is in the eastern region; 0 if the registered location is in the mid-western region
	Property rights	SOE	1 If the listed firm is a state-owned firm; otherwise, the value is 0
	Pollution nature	pollute	1 If the listed firm pollutes the environment; otherwise, the value is 0
Moderator	Digital transformation	DTB	A score assigned to the degree of digital transformation based on digitalization keywords obtained from annual reports of listed companies
Control	Firm size	size	The logarithm of total assets
	Debt level	debt	The logarithm of total liabilities divided by total assets
	Operating leverage	lev	The logarithm of fixed assets total divided by total assets
	Firm age	age	The logarithm of (the current year minus the year the company established and then add 1)
	Cash flow	cash	Cash holdings divided by total assets
	Equity restriction ratio	balance	The stockholding ratio of the second to the tenth largest stockholder divided by the stockholding ratio of the largest stockholder
	Executive compensation	wage	The logarithm of the annual salary of directors, supervisors, and executives
	Regional development level	GDP	GDP of the province where the company is located

*We classified B6, B7, B8, B9, B10, B11, C15, C17, C18, C19, C22, C25, C26, C27, C28, C29, C30, C31, C32, D44 as pollution enterprises and others as non-pollution enterprises based on the industry code.

The ESG data were collected using the Huazheng ESG rating system sourced from the Wind Information Financial Terminal Database. All other financial data were obtained from the China Stock Market and Accounting Research (CSMAR) database and National Bureau of Statistics. We used Excel and Stata15 for data processing and model estimation.

3.2 Variables and measures

3.2.1 Financial performance

As a representative accounting-based performance measure, return on assets (ROA) reflects resource allocation effciency more accurately than other accounting information (Zabri et al., 2016). Therefore, consistent with Kim and Lee (Kim and Lee, 2020), we selected ROA as the dependent variable. The mutually influential relationship between ESG and financial performance has been widely debated; therefore we analyzed financial data for t, t+1, and t+2 years to investigate this lagging effect.

3.2.2 ESG

To measure ESG performance, we adopted the ESG rating system developed by Huazheng, consistent with Xie and Lu, (2022), which provides quarterly ESG ratings categorized into nine grades, As follows from high to low: AAA, AA, A, BBB, BB, B, CCC, CC, and C. We assigned ESG grades ranging from 1-9 based on these ratings; for example, ESG = 1 when the ESG rating is C, ESG = 2 when the rating is CC, ESG = 3 when the rating is CCC, and ESG = 4 when the rating is B. Higher scores represent higher ESG performance, whereas lower scores represent lower ESG performance. We used annual average ESG scores as a measure of a firm's ESG performance. In an additional analysis, we selected the Wind ESG_1 rating as an alternative explanatory variable to ensure the robustness of our findings.

3.2.3 Digital transformation

Listed companies' annual reports provide their annual summary review and future outlook; therefore, text analysis and word frequency statistics of these reports are meaningful and feasible measures of corporate digital transformation. Thus, referring to Wu et al. (2021), we used text analysis and word frequency statistics to measure corporate digital transformation, utilizing Python to deeply mine the "digitalization" content in listed companies; annual reports and construct a digital list including five dimensions: including "AI technology," "Big Data technology," "cloud computing technology," "blockchain technology," and "digital technology application." Then, based on the digital list, we used the "jieba" word segmentation tool in Python for text analysis and word frequency statistics. Finally, we logarithmically measured each company's degree of digital transformation.

3.2.4 Control variables

To control for other factors that could affect the empirical findings, we selected eight indicators identified from previous research as control variables: firm size (size), debt level (debt), operating leverage (lev), firm age (age), cash holding level (cash), equity restriction ratio (balance), executive compensation (wage), and regional development level (GDP). In addition, we included year and industry-fixed effects in the model. Table 1 presents definitions and descriptions of these variables.

TABLE 2 Description statistics.

Variable	N	Mean	Median	S.D.	Min.	Max.
ROA	15710	3.322	3.304	6.589	−25.81	21.23
ESG	15,10	4.035	4	1.113	1	6.250
DTB	15710	19.84	9	29.89	0	169
size	15710	4.152	3.983	1.302	1.545	8.045
debt	15710	3.656	3.775	0.561	1.852	4.481
lev	15710	2.605	2.872	1.193	−1.907	4.242.
age	15710	3.058	3.091	0.245	2.398	3.638
cash	15710	0.163	0.138	0.107	0.0170	0.548
balance	15710	0.951	0.729	0.788	0.0520	3.871
wage	15710	6.370	6.332	0.699	4.745	8.344
GDP	15710	50944	41781	30726	3703	124370

3.3 Research design

To examine the effects of ESG levels on firms' financial performance, Eq. 1 is established to test H1:

$$ROA_{i,t} = \alpha_0 + \alpha_1 ESG_{i,t} + \sum Controls_{i,t} + \sum IND + \sum YEAR + \varepsilon_{i,t} \tag{1}$$

where ROA is the financial performance of the dependent variable, ESG is the company's ESG performance of the independent variable, and Controls represents each control variable.

To test the moderating effect of ESG on financial performance, Eqs 2, 3 are established based on Eq. 1:

$$ESG_{i,t} = \beta_0 + \beta_1 DTB_{i,t} + \sum Controls_{i,t} + \sum IND + \sum YEAR + \varepsilon_{i,t} \tag{2}$$

$$\begin{aligned} ROA_{i,t} = \alpha_0 + \alpha_1 ESG_{i,t} + \alpha_2 DTB_{i,t} + \alpha_3 ESG_{i,t} \times \alpha_4 DTB_{i,t} \\ + \sum Controls_{i,t} + \sum IND + \sum YEAR + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In these equations, DTB represents the digital transformation of the moderating variable. Eq. 2 focuses on checking whether digital transformation has an impact on ESG performance, and Eq. 3 analyzes whether digital transformation plays a moderating role.

4 Empirical results

4.1 Descriptive statistics

Table 2 displays descriptive statistics for the variables of interest, including ESG, financial performance (measured by ROA), and digital transformation. The mean ROA is 3.322, with a standard deviation of 6.589 and a range from −25.81 to 21.23, demonstrating significant variability across companies. The mean and median of ESG are 4.035 and 4, respectively, with a minimum value of 1 and a maximum of 6.250, signifying wide variation in ESG performance across listed companies. Digital transformation ranges from 0 to 169, indicating that some companies have not yet implemented the process. We assessed the variance inflation factor to check for multicollinearity and found an average of 1.12 (ranging from 1.01 to 1.14), which suggests that multicollinearity is unlikely to significantly impact our results.

4.2 Correlation analysis

Table 3 presents the results of the correlation analysis of all variables in this study. The correlation coefficients are below 0.6 for all variables, indicating distinct differentiation among them (Zheng et al., 2022). Notably, a significantly positive correlation coefficient is observed between the dependent variable ROA and independent variable ESG ($\beta = 0.2168$, $p < 0.01$), suggesting a positive association between ESG performance and corporate financial performance.

4.3 Regression results

4.3.1 ESG and financial performance

Table 4 displays the regression results for all study variables. H1 posits that an increase in ESG performance leads to improved corporate financial performance. The results support this hypothesis, in that ESG performance has a significant and positive effect on ROA ($\alpha = 0.894$, $p < 0.01$), indicating that high ESG performance leads to better financial performance. To ensure the credibility of our study, we tested the robustness of our findings by implementing lags of one and two periods for our explained variable (ROA) in Model (1). The results show that the positive regression coefficients of ESG performance remain significant even with the lag treatment. This indicates that ESG performance has a consistent positive effect on financial improvement. Furthermore, by applying the lag method, we investigated the relationship between the two, which helps account for potential endogeneity issues. This approach indicates that our findings are unlikely to be significantly affected by endogeneity.

4.3.2 Digital transformation and ESG

Table 5 reports the regression results of the impact of digital transformation on ESG performance as captured by Eq. 2. The coefficient of ESG is positive and significant at the 1% level ($\beta = 2.518$, $p < 0.01$), supporting H2. This indicates that digital transformation significantly enhances corporate ESG performance. Furthermore, the regression analysis for control variables also aligns with our expectations. Size, debt, level, cash, wage, and GDP all show a strong correlation with digital transformation.

4.3.3 Moderating effect of Digital transformation

Table 6 presents the results of the test of the moderating effect of digital transformation (DTB) on the relationship between ESG and financial performance. The coefficient of ESG*DTB is the focus of this study. The regression results in column (2) show that the coefficient of the interaction term (ESG*DTB) is significantly positive ($\beta = 0.001$, $p < 0.05$), suggesting that digital transformation has a significant positive moderating effect between ESG and financial performance, supporting H3.

TABLE 3 Correlation matrix.

Variable	ROA	ESG	Size	Debt	Lev	Age	Cash	Balance	Wage	GDP
ROA	1.0000									
ESG	0.2168***	1.0000								
size	0.0935***	0.3200***	1.0000							
debt	−0.2488***	−0.0049	0.4588***	1.0000						
lev	0.0206***	−0.0374***	−0.0414***	−0.0280***	1.0000					
age	−0.0398***	0.0028	0.1068***	0.1200***	−0.0928***	1.0000				
cash	−0.0123	0.0078	0.0068	−0.0054	−0.0118	−0.1579***	1.0000			
balance	0.0077	0.0062	0.0208***	0.0275***	0.0031	−0.0410***	−0.0293***	1.0000		
wage	−0.0016	0.0304***	0.0540***	−0.0146	0.0149	0.0004	0.0052	0.0961***	1.0000	
GDP	−0.0109	0.0071	0.0218***	−0.0044	0.0070	0.0429***	−0.0127	0.0681***	0.1471***	1.0000

***$p < 0.05$.

TABLE 4 Regression results for the impact of ESG on financial performance.

Variable	1) ROA_t	2) ROA_{t+1}	3) ROA_{t+2}
ESG	0.894***	0.872***	0.741***
	(0.047)	(0.054)	(0.064)
size	1.041***	0.503***	0.444***
	(0.045)	(0.052)	(0.061)
debt	−3.998***	−2.411***	−2.034***
	(0.100)	(0.114)	(0.130)
lev	0.130***	0.440***	0.642***
	(0.041)	(0.047)	(0.054)
age	−0.565***	−0.323	0.190
	(0.205)	(0.234)	(0.268)
cash	−1.199***	−1.888***	−1.655***
	(0.463)	(0.529)	(0.609)
balance	0.113*	0.100	0.121
	(0.062)	(0.071)	(0.081)
wage	−0.203***	−0.173**	−0.115
	(0.071)	(0.082)	(0.094)
GDP	−0.000**	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)
_cons	12.950***	7.821***	4.488***
	(0.857)	(0.990)	(1.145)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	15,710	13,430	11,187
R^2	0.138	0.068	0.051

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 5 Regression results for the impact of digital transformation on ESG.

Variable	1) DTB
ESG	2.518***
	(0.251)
size	−0.550**
	(0.235)
debt	−2.248***
	(0.520)
lev	−5.248***
	(0.214)
age	0.214
	(1.061)
cash	−8.089***
	(2.393)
balance	0.095
	(0.323)
wage	3.526***
	(0.371)
GDP	0.000*
	(0.000)
_cons	11.715***
	(4.464)
Year	YES
Industry	YES
N	15710
R^2	0.052

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 6 Moderating effect.

Variable	1) ROA	2) ROA
ESG	0.894***	0.905***
	(0.047)	(0.070)
ESG*DTB		0.001**
		(0.001)
size	1.041***	2.889***
	(0.045)	(0.144)
debt	−3.998***	−5.359***
	(0.100)	(0.181)
lev	0.130***	−0.881***
	(0.041)	(0.107)
age	−0.565***	−8.384***
	(0.205)	(0.819)
cash	−1.199***	0.181
	(0.463)	(0.658)
balance	0.113*	0.110
	(0.062)	(0.134)
wage	−0.203***	−0.015
	(0.071)	(0.147)
GDP	−0.000**	−0.000
	(0.000)	(0.000)
_cons	12.950***	38.100***
	(0.857)	(2.145)
Year	Yes	Yes
Industry	Yes	Yes
N	15,710	15,710
R^2	0.138	0.139

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5 Robustness check and heterogeneity analysis

5.1 Robustness check

To further validate the reliability of the research results and examine the stability of the model, we conducted a robustness check by replacing Huazheng's ESG ratings with ESG_1 scores from Wind (MSCI). Wind's ESG_1 scores are widely used in investment portfolios and decisions. The score ranges from 0 to 10, indicating a company's ESG performance, with 10 indicating the highest ESG performance and 0 indicating the lowest. The rating criteria include risk management, anti-corruption measures, labor standards, and community relations. Table 7 shows the regression results of ESG_1 on financial performance, including the current period and one and two lagging periods. As the table shows, the estimated coefficient of ESG_1 is 0.843, which is significant at the 1% level. When ROA lags by one or two periods, the estimation coefficient of ESG_1 remains significant at the 1% level ($\beta1 = 0.800, p < 0.01$; $\beta2 = 0.677$, $p < 0.01$). This is consistent with the main regression results; thus, the results are robust.

TABLE 7 Replacement of independent variable.

Variable	1) ROA_t	2) ROA_{t+1}	2) ROA_{t+2}
ESG_1	0.843***	0.800***	0.677***
	(0.044)	(0.050)	(0.059)
_cons	13.248***	8.188***	4.842***
	(0.853)	(0.985)	(1.138)
Controls	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	15,710	13,430	11,187
R^2	0.139	0.068	0.051

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5.2 Heterogeneity analysis

A company's property rights directly affects its business decisions and risk controls. Different property rights may lead to significant differences in the degree of emphasis on and management of ESG, which in turn affect financial performance. Additionally, given China's vast territory, there are significant variations in policy environments and sociocultural backgrounds across regions, affecting companies' ESG investment and management practices. Furthermore, environmental pollution has become a global concern and grouping companies based on pollution levels can help explore the impact of environmental protection on ESG. Therefore, we conducted group testing on the samples according to property rights, regions, and whether they cause environmental pollution.

5.2.1 Impact of property rights

Company ownership is a significant factor affecting ESG performance, resource allocation, and decision-making (Singh and Chen, 2018). Companies with different property rights experience different effects on fulfilling their social responsibilities. Therefore, we divided the sample into state-owned and non-state-owned companies, to examine how different types of companies' ESG performance affects their financial performance. As shown in columns (1) and (2) of Table 8, the ESG coefficient of state-owned companies is not significant, whereas that of non-state-owned companies is 0.217 and significant at the 5% level. Since state-owned companies are often subject to government administrative intervention and bear multiple responsibilities, such as economic development and employment, they often have a good reputation in terms of social image (Li and Li, 2022). However, the multiple responsibilities of state-owned companies make their operations and

TABLE 8 Regression results in different groups.

Variable	1) State-owned	2) Non-state-owned	3) Eastern	4) Mid-western	5) Polluting	6) Non-polluting
ESG	0.136	0.217**	0.212**	0.146	0.459**	0.158**
	(0.101)	(0.093)	(0.085)	(0.117)	(0.208)	(0.073)
size	2.970***	2.888***	2.805***	3.142***	2.545***	2.970***
	(0.224)	(0.187)	(0.175)	(0.252)	(0.415)	(0.154)
debt	−5.255***	−5.417***	−5.158***	−5.777***	−4.572***	−5.454***
	(0.273)	(0.240)	(0.218)	(0.323)	(0.516)	(0.193)
lev	−1.193***	−0.661***	−0.893***	−0.881***	−1.042***	−0.865***
	(0.165)	(0.142)	(0.132)	(0.186)	(0.275)	(0.117)
age	−6.073***	−9.644***	−8.020***	−8.672***	−9.169***	−8.283***
	(1.198)	(1.112)	(1.068)	(1.381)	(3.447)	(0.846)
cash	0.283	0.125	−0.229	1.014	−0.592	0.348
	(1.061)	(0.842)	(0.806)	(1.144)	(2.257)	(0.690)
balance	0.030	0.118	0.015	0.297	−0.233	0.147
	(0.238)	(0.163)	(0.163)	(0.238)	(0.405)	(0.142)
wage	−0.243	0.149	0.019	−0.106	−0.204	0.034
	(0.219)	(0.199)	(0.186)	(0.241)	(0.429)	(0.158)
GDP	−0.000***	0.000*	−0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	34.509***	39.199***	36.317***	40.046***	43.910***	36.953***
	(3.131)	(2.863)	(2.721)	(3.738)	(10.197)	(2.157)

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

decision-making process relatively complex. Simultaneously, the policy environment and market competition often make it difficult for state-owned companies to compare themselves with non-state-owned companies in terms of profits and performance (Li and Xia, 2018). Therefore, good ESG performance hardly brings more economic benefits to state-owned companies. In contrast, non-state-owned companies have traditionally been more profit-oriented and often regard social responsibility and environmental protection as secondary factors. However, this situation is changing, and an increasing number of non-state-owned companies are beginning to pay attention to ESG performance, making it easier for them to enhance their corporate reputation, attract outstanding talent, and achieve better performance.

5.2.2 Impact of regions

China has regional disparities in economic development levels and institutional environments. The eastern region boasts higher economic development levels, a better institutional environment, and stricter government regulations, leading eastern enterprises to place greater emphasis on ESG performance to reduce supervision and public pressures (Cong et al., 2023). Moreover, the region's economic prosperity, coupled with government access to abundant financial resources, allows for policy support such as funding and tax breaks for socially responsible companies, further incentivizing companies to improve their ESG performance. However, in the midwestern regions, the government attaches much more importance to economic benefits than to ESG. The lack of financial resources also increases the cost to enterprises for improving ESG performance, resulting in a low level of enterprise ESG investment (Yan et al., 2023). Therefore, we divided the full sample into two sub-samples according to regions, including the eastern and midwestern regions. Beijing, Hebei, Liaoning, Tianjin, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan are located in the eastern region, whereas the remaining areas are considered to be in the midwestern region. As shown in columns (3) and (4) of Table 8, the regression coefficient of companies in midwestern region is not significant, whereas that in the eastern region is significant at the 5% level.

5.2.3 Impact of pollution

According to Hamori et al. (2022), environmental governance is the most important ESG component. Protecting the environment is not only a moral responsibility but also plays a crucial role in the long-term sustainable development of corporations and maintaining a stable socio-economic environment. Corporations in different industries have different attitudes toward environmental governance. Considering the differences within industries, we categorized corporations into two types based on the relevant regulations of the environmental information disclosure guidance for listed companies. We defined enterprises engaged in power generation, steel, cement, electrolytic aluminum, coal, metallurgy, chemical engineering, petrochemicals, building materials, paper-making, brewing, pharmaceuticals, fermentation, textiles, tanning, and mining as polluting enterprises, whereas the remainder are non-polluting enterprises. Columns (5) and (6) of Table 8 show that the regression coefficients of polluting and non-polluting enterprises are 0.459 and 0.158, respectively, and both are significant at the 5% level. This implies that the relationship between ESG and financial performance is stronger for polluting enterprises than for non-polluting enterprises. As polluting enterprises face greater public pressure in terms of their production and operations, they must demonstrate superior ESG performance to cope with external criticism, which brings more opportunities and challenges to their operations (Yu and Xiao 2022). Furthermore, in the context of increasingly stringent environmental requirements, polluting enterprises must take more environmental measures to avoid possible fines, making them more focused on ESG performance. In contrast, the industry characteristics and business models of non-polluting companies are less related to environmental issues; therefore, the improvement of their ESG has a relatively small promoting effect on their financial performance. Meanwhile, with the support of the "greenwashing strategy," non-polluting companies may only need to conduct superficial green marketing without taking action, which may weaken this promoting effect.

6 Discussion

The COVID-19 pandemic has caused significant disruptions to the global economy and accelerated the digitalization trend, resulting in risks and challenges for many businesses. Consequently, ESG considerations have become critical factors in enterprises' long-term development.

Our study generated several interesting findings. The results shown in Tables 3, 4 indicate that a company's ESG performance can act as a catalyst to improve its overall performance, thereby supporting H1. One noteworthy finding was the positive impact of ESG on corporate performance, which extended from the current year to the second and third years and demonstrated a lasting effect. For example, companies that integrate ESG principles into their strategies tend to attract a wider range of investors who prioritize sustainability and social responsibility. This can lead to increased capital flow and enhanced financial performance. Furthermore, ESG practices can help companies manage more effectively and efficiently environmental and social risks, potentially mitigating legal, regulatory, and reputational costs that could adversely impact financial performance. ESG practices can also contribute to better cost management, employee retention, and innovation, leading to more sustainable long-term growth prospects. These results are consistent with those of previous studies. Chang and Lee (2022) found that performance will improve when organizations increase their investment in sustainable development. Using data on Bangladesh's manufacturing industry, Zhou et al. (2023) found that companies with better ESG performance tend to have more sustainable and innovative performance. However, most enterprises face difficulties in implementing ESG. For example, to report on ESG issues, companies may need to collect and analyze vast amounts of data. This can be time consuming and expensive, especially for companies that lack the necessary resources or expertise.

We further identified a positive relationship between ESG and digital transformation (H2), which is in line with the findings of prior studies by Zhong et al. (2023) and others. As Table 6 shows, digital transformation moderates the relationship between ESG and financial performance (H3). Zhong noted out that digitalization by enterprises creates value beyond economic impact, also encompassing social and environmental benefits. Lu et al. (2022) concluded that ESG disclosure is crucial for companies' decision-making. Digital financial inclusion also plays a crucial role in motivating companies to disclose their ESG performance. Belousova et al. (2022) found that minimizing the negative environmental impact of digital business services companies can deliver greater positive value to client performance. Unfortunately, however, the impact of ESG factors on financial performance may vary depending on sector, market, and institutional constrains.

Thus, the samples were divided into different groups. As shown in Table 8, the positive effect of the ESG level on financial performance varies by company ownership type, region, and degree of pollution. These findings imply that non-state-owned companies may have greater incentives to improve their ESG practices and transparency because of heightened competition and scrutiny from investors and stakeholders. Compared with those in the midwestern region, companies in the eastern region may be more committed to ESG practices to meet global standards and stakeholder expectations given the presence of large international corporations and industry leaders in the region. Finally, companies with high pollution levels face greater scrutiny and public pressure to enhance their ESG practices due to the negative impact of their operations on the environment and society. These results could help companies and the government formulate more effective ESG strategies to improve finance performance, and provide investors and stakeholders with a better understanding of the potential benefits of investing in companies with strong ESG practices.

7 Conclusion

ESG is a critical factor in sustainable corporate development and is an important indicator of corporate social responsibility. We utilized unbalanced panel data of 2256 Chinese-listed companies from 2015 to 2021 to analyze the effects of ESG on corporate financial performance. Specifically, our findings demonstrate that the level of ESG performance, as tested by Huazheng, positively influences corporate performance. Moreover, our research found that digital transformation can regulate and moderate the relationship between ESG and financial performance to ensure sustainable growth for companies. Deeper research showed that the positive impact of ESG varies depending on ownership type, region, and degree of pollution.

Our study makes theoretical contributions by extending the existing literature on the relationship between ESG and financial performance, with China as the research object. China, the largest developing country, has gradually included finance and ESG in its national policies and issued a series of policies and standards. Therefore, this study has a guiding significance for ESG development and research in developing countries. For example, although sustainable development is a broad focus in Vietnam (Luu, 2019), most Vietnamese companies are still profit-oriented and lack regulatory and technical support for ESG practices and performance. The Indonesian government encourages companies to focus on ESG issues (Huang et al., 2022); however, the country lacks supervision and implementation norms, resulting in significant gaps in its ESG practices. Although the Pakistani government has formulated ESG strategies and policies, the country's long-term economic development and investment have tended to focus on traditional industries (Shahzad et al., 2020); therefore, ESG is relatively underdevelopment in Pakistan. Furthermore, this study explored the relationship between ESG and financial performance and fills gaps in the literature by using digital transformation as a moderating variable for the first time, given the leapfrog improvement in productivity promoted by digital technology.

This study has several practical implications for firms and government. First, to promote sustainable economic development, regulatory authorities should strengthen the guidance and supervision of ESG practices and information disclosure. Our study shows that ESG implementation can improve corporate performance. Therefore, enterprises should actively participate in ESG practices. Second, the application of digital technology has brought significant changes to industrial development. Companies should use digitalization as a tool to address the risks and challenges of the information age. Digital transformation can not only improve enterprises' resource utilization efficiency but also reduce their environmental and social impact, thereby enhancing their ability for sustainable development.

Our study has some limitations that require future research. First, our research did not focus on specific industries, although various industries are affected by distinct factors, such as policy environments, market sizes, and user behaviors. Therefore, we will focus on specific industries for an in-depth analysis, such as exploring the concrete mechanisms of the impact of ESG practices on financial performance in the energy industry. Second, considering difficulties in data collection, we only focused on listed companies that have disclosed ESG information. Non-listed and small and medium-sized enterprises play a significant role in Chinese economic development, serving as major sources of employment and providing consumers with valuable and innovative goods and services. Future studies should consider small and medium-sized enterprises and explore which of the three components of ESG has the greatest impact on their financial performance.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

TF: Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Visualization, Writing–original draft. JL: Conceptualization, Funding acquisition, Supervision, Writing–review and editing.

Funding

This work was supported by CITIC Reform and Development Research Foundation (H21319), the General Projects of Science and Technology Plan of Beijing Municipal Commission of Education (KM202110016006), and Beijing Advanced Innovation Center for Future Urban Design, Beijing University of Civil Engineering and Architecture (UDC2019021424).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Abdi, Y., Li, X., and Càmara-Turull, X. (2022). Exploring the impact of sustainability (ESG) disclosure on firm value and financial performance (FP) in airline industry: The moderating role of size and age. *Environ. Dev. Sustain.* 24 (4), 5052–5079. doi:10.1007/s10668-021-01649-w

Belousova, V., Bondarenko, O., Chichkanov, N., Lebedev, D., and Miles, I. (2022). Coping with greenhouse gas emissions: Insights from digital business services. *Energies* 15 (8), 2745. doi:10.3390/en15082745

Bhandari, K. R., Ranta, M., and Salo, J. (2022). The resource-based view, stakeholder capitalism, ESG, and sustainable competitive advantage: The firm's embeddedness into ecology, society, and governance. *Bus. Strategy Environ.* 31 (4), 1525–1537. doi:10.1002/bse.2967

Carnini, P. S., Ciaburri, M., Magnanelli, B. S., and Nasta, L. (2022). Does ESG disclosure influence firm performance? *Sustainability* 14 (13), 7595. doi:10.3390/su14137595

Chang, Y. J., and Lee, B. H. (2022). The impact of ESG activities on firm value: Multi-level analysis of industrial characteristics. *Sustainability* 14 (21), 14444. doi:10.3390/su142114444

Chen, G., Han, J., and Yuan, H. (2022). Urban digital economy development, enterprise innovation, and ESG performance in China. *Front. Environ. Sci.* 10, 955055. doi:10.3389/fenvs.2022.955055

Cong, Y., Zhu, C., Hou, Y., Tian, S., and Cai, X. (2023). Does ESG investment reduce carbon emissions in China? *Front. Environ. Sci.* 10, 977049. doi:10.3389/fenvs.2022.977049

Cui, J., Jo, H., and Na, H. (2018). Does corporate social responsibility affect information asymmetry? *J. Bus. Ethics.* 148 (3), 549–572. doi:10.1007/s10551-015-3003-8

ElMassah, S., and Mohieldin, M. (2020). Digital transformation and localizing the sustainable development goals (SDGs). *Ecol. Econ.* 169, 106490. doi:10.1016/j.ecolecon.2019.106490

Fatemi, A., Fooladi, I., and Tehranian, H. (2015). Valuation effects of corporate social responsibility. *J. Bank. Financ.* 59, 182–192. doi:10.1016/j.jbankfin.2015.04.028

Finger, M., and Rosenboim, M. (2022). Going ESG: The economic value of adopting an ESG policy. *Sustainability* 14 (21), 13917. doi:10.3390/su142113917

Freeman, R. E. (1984). *Strategic management: A stakeholder approach*. Boston: Pitman.

Friede, G., Busch, T., and Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *J. Sustain. Finance Invest* 5 (4), 210–233. doi:10.1080/20430795.2015.1118917

Friedman (2007). The social responsibility of business is to increase its profits. *Corp. Ethics Corp. Gov.*, 173–178. doi:10.1007/978-3-540-70818-6_14

Gao, Y., and Han, K. S. (2020). Managerial overconfidence, CSR and firm value. *Asia Pac. J. Acc. Econ.* 29, 1600–1618. doi:10.1080/16081625.2020.1830558

Garcia, A. S., and Orsato, R. J. (2020). Testing the institutional difference hypothesis: A study about environmental, social, governance, and financial performance. *Bus. Strateg. Environ.* 29 (8), 3261–3272. doi:10.1002/bse.2570

Godfrey, P. C. (2005). The relationship between corporate philanthropy and shareholder wealth: A risk management perspective. *Acad. Manage. Rev.* 30 (4), 777–798. doi:10.5465/amr.2005.18378878

Gouvea, R., Li, S., and Montoya, M. (2022). Does transitioning to a digital economy imply lower levels of corruption? *Thunderbird Int. Bus. Rev.* 64 (3), 221–233. doi:10.1002/tie.22265

Hamori, S., - Yue, X. G., Yang, L., and Crabbe, M. J. (2022). Editorial: ESG investment and its societal impacts. *Front. Environ. Sci.* 10, 1088821. doi:10.3389/fenvs.2022.1088821

Hoepner, A. G., Majoch, A. A., and Zhou, X. Y. (2021). Does an asset owner's institutional setting influence its decision to sign the principles for responsible investment? *J. Bus. Ethics.* 168 (2), 389–414. doi:10.1007/s10551-019-04191-y

Huang, P. T. B., Yang, C. C., Inderawati, M. M. W., and Sukwadi, R. (2022). Using modified delphi study to develop instrument for ESG implementation: A case study at an Indonesian higher education institution. *Sustainability* 14 (19), 12623. doi:10.3390/su141912623

Ionascu, I., Ionascu, M., Nechita, E., Săcărin, M., and Minu, M. (2022). Digital transformation, financial performance and sustainability: Evidence for European union listed companies. *Amfiteatru Econ.* 24 (59), 94–109. doi:10.24818/EA/2022/59/94

Jeffrey, S., Rosenberg, S., and McCabe, B. (2019). Corporate social responsibility behaviors and corporate reputation. *Soc. Responsib. J.* 15 (3), 395–408. doi:10.1108/SRJ-11-2017-0255

Kim, B., and Lee, S. (2020). The impact of material and immaterial sustainability on firm performance: The moderating role of franchising strategy. *Tour. Manage* 77, 103999. doi:10.1016/j.tourman.2019.103999

Krüger, F. (2015). *Corporate storytelling: Theorie und empirie narrativer public relations in der unternehmenskommunikation*. Berlin, Germany: Springer-Verlag, 107.

Lev, B., Petrovits, C., and Radhakrishnan, S. (2010). Is doing good good for you? How corporate charitable contributions enhance revenue growth. *Strategy Manag. J.* 31 (2), 182–200. doi:10.1002/smj.810

Li, A., and Xia, X. (2018). Are controlling shareholders influencing the relationship between CSR and earnings quality? Evidence from Chinese listed companies. *Emerg. Mark. Financ. Tr.* 54 (5), 1047–1062. doi:10.1080/1540496X.2018.1434070

Li, J., and Li, S. (2022). Environmental protection tax, corporate ESG performance, and green technological innovation. *Front. Environ. Sci.* 10, 982132. doi:10.3389/fenvs.2022.982132

Lian, Y., Li, Y., and Cao, H. (2023). How does corporate ESG performance affect sustainable development: A green innovation perspective. *Front. Environ. Sci.* 11, 430. doi:10.3389/fenvs.2023.1170582

Lu, Y., Wang, L., and Zhang, Y. (2022). Does digital financial inclusion matter for firms' ESG disclosure? Evidence from China. *Front. Environ. Sci.* 10, 1029975. doi:10.3389/fenvs.2022.1029975

Luo, X. R., Wang, D., and Zhang, J. (2017). Whose call to answer: Institutional complexity and firms' CSR reporting. *Acad. Manage. J.* 60 (1), 321–344. doi:10.5465/amj.2014.0847

Luu, T. T. (2019). CSR and customer value co-creation behavior: The moderation mechanisms of servant leadership and relationship marketing orientation. *J. Bus. Ethics.* 155, 379–398. doi:10.1007/s10551-017-3493-7

Lv, P., and Xiong, H. (2022). Can FinTech improve corporate investment efficiency? Evidence from China. *Res. Int. Bus. Finance.* 60, 101571. doi:10.1016/j.ribaf.2021.101571

Minutolo, M. C., Kristjanpoller, W. D., and Stakeley, J. (2019). Exploring environmental, social, and governance disclosure effects on the S&P 500 financial performance. *Bus. Strategy Environ.* 28 (6), 1083–1095. doi:10.1002/bse.2303

Nambisan, S., Wright, M., and Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Res. Policy.* 48 (8), 103773. doi:10.1016/j.respol.2019.03.018

Papagiannidis, S., Harris, J., and Morton, D. (2020). WHO led the digital transformation of your company? A reflection of it related challenges during the pandemic. *Int. J. Inf. Manage.* 55, 102166. doi:10.1016/j.ijinfomgt.2020.102166

Paradis, G., and Schiehll, E. (2021). ESG outcasts: Study of the ESG performance of sin stocks. *Sustainability* 13 (17), 9556. doi:10.3390/su13179556

Sedunov, J. (2017). Does bank technology affect small business lending decisions? *J. Financ. Res.* 40 (1), 5–32. doi:10.1111/jfir.12116

Shahzad, M., Qu, Y., Javed, S. A., Zafar, A. U., and Rehman, S. U. (2020). Relation of environment sustainability to csr and green innovation: A case of Pakistani manufacturing industry. *J. Clean. Prod.* 253, 119938. doi:10.1016/j.jclepro.2019.119938

Shimizu, K. (2020). Digital transformation of work and ESG: Perspectives on monopoly and fair trade. *Risk Gov. Control Financial Mark. Institutions* 10 (3), 75–82. doi:10.22495/rgcv10i3p6

Singh, j. n., and Chen, G. C. (2018). State-owned enterprises and the political economy of state-state relations in the developing world. *Third World Q.* 39 (6), 1077–1097. doi:10.1080/01436597.2017.1333888

Tarmuji, I., Maelah, R., and Tarmuji, N. H. (2016). The impact of environmental, social and governance practices (ESG) on economic performance: Evidence from ESG score. *Int. J. Financ. Econ.* 7 (3), 67–74. doi:10.18178/ijtef.2016.7.3.501

Teplova, T., Sokolova, T., Gubareva, M., and Sukhikh, V. (2022). The multifaceted sustainable development and export intensity of emerging market firms under financial constraints: The role of ESG and innovative activity. *Complexity* 2022, 1–20. doi:10.1155/2022/3295364

Wang, L., Fan, X., Zhuang, H., Liu, A., Wu, Z., Wang, Q., et al. (2023). ESG disclosure facilitator: How do the multiple large shareholders affect firms' ESG disclosure? Evidence from China. *Front. Environ. Sci.* 11, 83–100. doi:10.1089/3dp.2021.0055

Wang, Y., Wang, H. Y., Xue, S., Li, F., and He, Y. (2022). Greening of tax system and corporate ESG performance: A quasi-natural experiment based on the environmental protection tax law. *J. Financ. Econ.* 48 (09), 47–62. doi:10.3390/mi14010047

Wang, Z., and Sarkis, J. (2017). Corporate social responsibility governance, outcomes, and financial performance. *J. Clean. Prod.* 162, 1607–1616. doi:10.1016/j.jclepro.2017.06.142

Wong, W. C., Batten, J. A., Ahmad, A. H., Mohamed-Arshad, S. B., Nordin, S., and Adzis, A. A. (2021). Does ESG certification add firm value? *Financ. Res. Lett.* 39, 101593. doi:10.1016/j.frl.2020.101593

Wu, F., Hu, H. Z., Lin, H. Y., and Ren, X. Y. (2021). Digital transformation of enterprises and capital market performance: Empirical evidence from Stock liquidity. *J. Manag. World* 37 (07), 130–144+10. doi:10.19744/j.cnki.11-1235/f.2021.0097

Xie, H. J., and Lu, X. (2022). Responsible multinational investment: ESG and Chinese OFDI. *Econ. Res. J.* 57 (03), 83–99.

Yang, Y., Xu, G., and Li, R. (2023). Official turnover and corporate ESG practices: Evidence from China. *Environ. Sci. Pollut. R.* 30 (18), 51422–51439. doi:10.1007/s11356-023-25828-6

Yan, Y. Z., Cheng, Q. W., Huang, M. L., Lin, Q. H., and Lin, W. H. (2023). Government environmental regulation and corporate ESG performance: Evidence from natural resource accountability audits in China. *Int. J. Env. Pub. He.* 20 (1), 447. doi:10.3390/ijerph20010447

Yu, X. L., and Xiao, K. T. (2022). Does ESG performance affect firm value? Evidence from a new ESG-scoring approach for Chinese enterprises. *Sustainability* 14 (24), 16940. doi:10.3390/su142416940

Zabri, S. M., Ahmad, K., and Wah, K. K. (2016). Corporate governance practices and firm performance: Evidence from top 100 public listed companies in Malaysia. *Procedia Econ. Financ.* 35, 287–296. doi:10.1016/S2212-5671(16)00036-8

Zhang, D., and Liu, L. (2022). Does ESG performance enhance financial flexibility? Evidence from China. *Sustainability* 14 (8), 11324. doi:10.3390/su141811324

Zheng, J., Khurram, M. U., and Chen, L. (2022). Can green innovation affect ESG ratings and financial performance? Evidence from Chinese GEM listed companies. *Sustainability* 14 (14), 8677. doi:10.3390/su14148677

Zhong, Y., Zhao, H., and Yin, T. (2023). Resource bundling: How does enterprise digital transformation affect enterprise ESG development? *Sustainability* 15 (2), 1319. doi:10.3390/su15021319

Zhou, S., Rashid, M. H. U., MohdZobair, S. A., Sobhani, F. A., and Siddik, A. B. (2023). Does ESG impact firms' sustainability performance? The mediating effect of innovation performance. *Sustainability* 15 (6), 5586. doi:10.3390/su15065586

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 16 February 2024
DOI 10.3389/fenvs.2023.1268286

Check for updates

OPEN ACCESS

EDITED BY
Paul Terhemba Iorember,
Nile University of Nigeria, Nigeria

REVIEWED BY
Bruce Iortile Iormom,
University of Mkar, Nigeria
Ojonugwa Usman,
Istanbul Commerce University, Türkiye

*CORRESPONDENCE
Victoria Akberdina,
akberdina.vv@uiec.ru

RECEIVED 27 July 2023
ACCEPTED 13 December 2023
PUBLISHED 16 February 2024

CITATION
Akberdina V, Lavrikova Y and Vlasov M (2024), Environmental financing: does digital economy matter?
Front. Environ. Sci. 11:1268286.
doi: 10.3389/fenvs.2023.1268286

Environmental financing: does digital economy matter?

Victoria Akberdina[1,2]*, Yulia Lavrikova[1,2] and Maxim Vlasov[1,2]

[1]Institute of Economics of the Ural Branch of the Russian Academy of Sciences, Ekaterinburg, Russia, [2]Institute of Economics and Management, Ural Federal University Named After the First President of Russia B. N. Yeltsin, Ekaterinburg, Russia

Sustainable development and ecological restoration are a common goal pursued by countries around the world to mitigate the collision between economic growth and the environment. Digital economy has been rather instrumental in settling this type of conflict. The study is intended to identify the relationship between digital financing and environmental financing by assessing the specificities of their temporal and industry-specific dynamics, as well as to determine the side effects that the digital economy has in terms of current environmental investments and costs. The special attention is paid to the effect of the digital economy on both total environmental financing and its components, namely, environmental investment and current environmental protection costs. The authors come up with two indicators to evaluate the impact of the digital economy, these are digital financing (direct impact) and digital capital (indirect impact). To calculate these indicators, the authors' own method is developed. The impact of the digital economy on environmental financing was tested using the least squares method with clustering of annual standard deviation and individual fixed effects. The research data were retrieved from the Federal State Statistics Service (Rosstat) of the Russian Federation for 2012–2022. Our findings show that digital financing exerts a significant positive effect on environmental financing, which indicates that two dynamic processes in the economy—digital transformation and introduction of advanced environmental digital technologies—are synchronized. The authors prove that digital investments stimulate a comparable increase in environmental investment due to the effects created by digital technologies penetrating into environmental protection technologies. We demonstrate that the level of digitalization of the population, companies and the state assessed through the digital capital index has a positive effect on environmental financing. The results of the study are of use in the sphere of public policy.

KEYWORDS

sustainable development, digital economy, environmental financing, ecological restoration, digital capital

1 Introduction

Accelerated economic growth entails significant environmental problems associated with increasing pollution and depletion of resources. In the 21st century, anthropogenic pressure has turned into the main threat to human health, survival and development across the world. Sustainable development and ecological restoration have become, therefore, a common goal that all nations are striving for to mitigate the conflict between economic growth and the environment (Lu et al., 2017; Liang and Yang, 2019). Solving environmental problems and preventing new ones require companies and the states to invest significant amounts of financial resources. One of the most pressing issues of environmental protection, therefore, is the search for funding. The financial mechanism of nature management characterizes the state environmental policy, which means both direct financing of environmental protection measures at the expense of the state budget, and a set of tools to stimulate private investors.

However, sustainable development is not the only trend of the 21st century. Total digitalization has underlain the economic transition from one technological paradigm to another through the massive use of digital and information and communication technologies for boosting efficiency and competitiveness. To some extent, the digital economy has resolved the conflict between economic development and environmental pollution (Limna et al., 2022; Meng and Zhao, 2022).

The extensive use of digital technologies encourages the transformation and modernization of many traditional sectors of the economy, which eases the burden on the environment and resources, and reduces energy intensity. At the same time, digital technologies utilized in the environmental protection sphere allow providing more accurate assessments of the environmental impact and more reliable forecasts. The development of digital technologies opens up a plethora of opportunities for tackling environmental problems: from creating services for efficient waste management, searching for EV charging stations, monitoring systems and collecting climate change observation data to systems capable of preventing environmental risks and predicting environmental disasters.

A considerable number of scholarly publications scrutinize the role of digital technologies in reducing global emissions. Researchers analyze industry-specific features and the ownership structure and introduce them into their models, focus on spatial aspects of digital technologies' influence, conduct research using data from various countries, regions, and cities. In this context, environmental indicators such as air and water pollution, waste generation and energy consumption are used as dependent variables. In general, the impact of the digital economy on environmental financing has been understudied.

In our research, we want to focus specifically on the issues of financing environmental and digital transitions. If digitalization and sustainable development as synchronous processes are always considered together (through specific technologies that affect each other), then no one has studied the synchronization of financing of these processes. And we see in this a number of problems that have been overlooked by researchers. For example, environmental financing, as well as digital financing, represent government and corporate expenses. But the decision to finance these processes relates to different areas—for example, in companies these are different budgets located within different areas of strategy, and in the government, these are completely different departments with their own budgets and strategies. Since financing decisions are made by different responsible groups, it is quite difficult to talk about full synchronization of digital transformation and sustainable development. In addition, we intuitively believe that the propensity for digital financing is higher than the propensity for environmental financing, since digital transformation directly affects productivity and income. Therefore, if we can prove the connection between these financial flows, it will open up new opportunities for the implementation of stimulating mechanisms of public policy. This is our research motivation.

The foregoing explains the purpose of the study, which is to identify the relationship between digital financing and environmental financing by assessing the specificities of their temporal and industry-specific dynamics, as well as to determine the side effects that the digital economy has in terms of current environmental investments and costs.

In the study, we address the following research questions:

1. Does digital financing affect environmental financing? Can we affirm that the dynamic transformation of the economy is synchronized?
2. If it is, does digital investment stimulate a comparable increase in environmental investment due to the effects created by digital technologies penetrating into environmental protection technologies?
3. Is the impact of the digital economy on environmental financing dependent on the overall level of digital transformation of companies, population and the state?

We see the only limitation of the study related to the lack of separate statistical accounting. State statistical services do not single out the costs of implementing digital environmental technologies as part of environmental financing in a separate line, nor do they allocate costs for digital technologies aimed at environmental protection as part of digital financing. We will propose a solution to this problem in the Section 4.

To answer these questions, we use evidence from the Russian Federation. Similar to other nations, the country pays great attention to sustainable development, while the unfavorable state of the environment there is among the main constraints upon long-term development. According to the Environmental Security Strategy of the Russian Federation until 2025 (approved on 19 April 2017), over 70% of the population live in poor environmental conditions and are exposed to a substantial negative impact of manufacturing, transport and other industries. In recent years, green issues, such as environmental protection and the rational use of natural resources, have been high on the agenda in the country. The Russian government actively finances environmental protection activities and creates conditions for public-private partnerships to develop in this area by transferring part of the financial burden to partner companies and private investors. This is especially true for the costs incurred in collection and disposal of waste and wastewater treatment (Table 1).

Source: Federal law of 5 December 2022 No. 466-FZ "On the federal budget for 2023 and the 2024–2025 planning period". Available at https://www.consultant.ru/document/cons_doc_LAW_433298/(accessed on 30 May 2023).

In Russia, the primary document guiding the digitalization of the environment is the Strategic Direction for Digital Transformation of Ecology and Nature Management, which was approved on 8 December 2021. This document outlines several technologies that will be implemented to enhance environmental management. Artificial intelligence will be employed to analyze monitoring data, predict hazardous weather conditions and forest fire risks, automate real-time decision-making, and identify flora and fauna in complex environments. Remote sensing of the Earth and the use of unmanned aerial vehicles will be utilized for surveying, planning efficient resource utilization, protecting

TABLE 1 Russian government expenditure on environmental protection from the federal budget in 2023 and for the 2024–2025 planning period, thousands of rubles.

	2023	2024	2025
Environmental protection - total	352,164,590.9	319,276,310.0	261,872,095.6
Waste collection, disposal and wastewater treatment	13,072,478.1	19,062,954.5	2,046,368.6
Protection of flora and fauna and their habitat	16,833,745.4	17,120,771.7	12,106,573.0
Applied scientific research in the field of environmental protection	1,122,323.1	1,091,259.6	1,129,065.5
Other issues in the field of environmental protection	321,136,044.3	282,001,324.2	246,590,088.5

natural resources and the environment, and monitoring climate change. The Internet of Things (IoT) will play a crucial role in the development of the Federal Service for Hydrometeorology and Environmental Monitoring (Roshydromet) observation network program, improving the efficiency of data collection and transmission from stationary and mobile observation points. Big data and analytical data processing will be used to accumulate, store, analyze, and process data within federal state information systems and digital platforms. Additionally, the concept of a digital twin will be employed to update and create a comprehensive database of natural objects, including ecosystems such as subsoil, bodies of water, forests, and wildlife habitats. This will enable better understanding and management of these natural resources. Overall, these technological advancements aim to enhance environmental monitoring, resource management, and conservation efforts in Russia.

Another solution to environmental problems is the development of geographic information systems (GISs) that are designed to collect, analyze, store and graphically interpret spatial and temporal data, as well as attributive information about the objects presented in the GIS. Owing to these systems, it is possible to rationally manage resources and, by applying new means and methods of data processing, to optimize and control their use both at the regional and federal levels.

Digital technologies are also used to automate decision-making and managerial processes in the field of environmental and natural resources management. In this framework, it is planned to create a unified federal state information system for environmental monitoring that will contain data on the state of natural objects and environmental pollution. In addition, new data analysis methods will be pioneered to more accurately and quickly assess the environmental situation and forecast possible ecological problems. The government plans to implement full digital transformation of the environmental sector. Thus, the Strategic Direction for Digital Transformation of Ecology and Nature Management is an important step towards environmental security and sustainable development in Russia.

The present study consists of the following parts. Section 2 provides a literature review to find out the conceptual and logical relationship between the indicators under analysis. In Section 3, we elaborate on research design and theoretical hypothesis. The details about the models, variables and data resources are given in Section 4. Section 5 contains the modelling outcomes and economic rationale for them. Section 6 summarizes the research results.

2 Literature review

2.1 Digital economy and sustainable development

Digital economy is an economic concept that views digital knowledge as a key factor of production and looks at modern information and communication networks as the main carrier of digital knowledge (Purnomo et al., 2022). The digital economy plays a crucial role in mitigating market imperfections, improving economic efficiency and optimizing the industrial structure. The existing definitions of the concept of digital economy are summarized by a number of researchers (Williams, 2021; Zhang et al., 2021). The core characteristics of the digital economy are systematized in (Borremans et al., 2018; Ding et al., 2021). The digital economy consists of three main components: digital infrastructure, digital technologies in economic sectors, and e-commerce. Digital infrastructure ensures the connectivity of economic agents; digital technologies and solutions transform virtually all aspects of production and consumption; and e-commerce includes the exchange of economic resources using platforms and reduces transaction costs (Akberdina and Barybina, 2022). It is worth noting that the development level of the digital economy directly correlates with the level of the material sphere. The digital economy is a superstructure over the material sector of the economy and allows increasing the efficiency of any interaction. Hence, if digital technologies are introduced in the context of the insufficient development of material production, the cumulative economic effect of digitalization will not be of decisive importance.

The digital economy in a country covers information technology, software, mobile communications, and data transmission. There is quite a lot of studies on various aspects of the digital economy in Russia (Akberdina, 2018; Basaev, 2019; Ziyadullaev et al., 2019; Belokurova et al., 2020; Gureev et al., 2020; Vlasov, 2020; Rudyk et al., 2022). The researchers note that the digital economy in Russia is developing at a high pace, transforming industries and markets and penetrating into education and intellectual activity. At that, the digital inequality of the regions and the low share of their own digital technologies serve as development constraints.

Sustainable development, green economy, circular economy and ESG-concept are the components of a worldview advocating that a just economy should be built in accordance with both social and environmental dimensions, since the economy and the environment have a tremendous mutual influence on each other (Söderholm, 2020;

D'amato & Korhonen, 2021). These concepts share a common thesis that a low-carbon, resource-efficient and socially inclusive economy should improve human wellbeing and social justice, while significantly reducing environmental threats and resource scarcity (Bouchoucha, 2021; Xie et al., 2023). The bibliometric analysis indicates that there is an upward trend in the number of research in the field of green economy, circular economy and sustainable development; however, there are country-specific differences in terminology (Ali et al., 2021). At that, all researchers tend to believe that the efficient use of resource, the circular economy, innovation, social integration, ecosystem protection, *etc.*, contribute to the coordinated development of the economy, society and the environment and the achievement of sustainable development (Ozkan et al., 2023).

Sustainability and the green economy in Russia are also deeply investigated (Bobylev and Solovyeva, 2017; Zhironkin et al., 2017; Popkova et al., 2018; Karieva et al., 2020; Tulupov et al., 2020; Lavrikova et al., 2021; Kuznetsova et al., 2022; Tagaeva et al., 2022). The researchers highlight that Russia is rich in natural resources, which has historically formed an evolution model based on commodity exports. To shift to a new paradigm of economic development, the concept of sustainability with a balanced set of economic, social and environmental components should be included in the strategic documents underlying the country's long-term development.

Researchers typically sharing similar views within each subject area, however, express serious disagreements on the *impact the digital economy has on sustainable development* (Adeshola et al., 2023). On the one hand, extensive studies have shown that the digital economy and the green economy develop in sync and positively influence each other (Wu et al., 2018; Kostoska and Kocarev, 2019; Vinuesa et al., 2020). Some works analyze the overall impact of the digital economy on the total productivity of green factors of production. Researchers emphasize that information technology can increase labor productivity and promote economic growth, which are in a positive correlation with the total productivity of green factors of production (Niebel, 2018; Nguyen et al., 2020; Wang et al., 2021; Wang et al., 2022c). A number of publications put the emphasis on the relationship between digitalization and energy consumption and conclude that digital technologies cause a decrease in energy intensity (Mughal et al., 2022; Sun, 2022). For example, it was found that with a 1% increase in the digital economy index, the number of developments in the new energy domain increases by an average of 0.2% (Wang et al., 2022a). Additionally, the digital economy not only creates conditions for clean energy to develop in countries with high carbon emissions (Wang et al., 2022b), but also helps to optimize the energy structure, increase energy efficiency (Li et al., 2021; Nikitaeva and Dolgova, 2022; Pierli et al., 2022; Xue et al., 2022; Akberdina et al., 2023) and reduce energy consumption.

On the other hand, a fairly large part of works is devoted to the inverse relationship between the digital economy and environmental pollution. For instance, researchers demonstrate that there are certain contradictions between smart digital cities and sustainable development goals (Martin et al., 2018), note that digitalization is not yet proved to be essential for reducing energy consumption and greenhouse gas emissions (Jin et al., 2018), and assume that digital equipment causes a lot of damage to the environment during production, maintenance and disposal (Kuntsman and Rattle, 2019). The main argument for the inverse relationship between the digital economy and reducing the burden on the environment is the fact that the use of digital technologies (big data, in particular) increases energy consumption (Van Heddeghem et al., 2014; Zhou et al., 2018). The researchers claim that the share of digital infrastructure in the national energy consumption can reach up to 10%–15%.

2.2 Environmental financing

Sufficient funding is a vital prerequisite for a significant improvement in the state of the environment. Strictly speaking, sustainable development should be carried out amid the simultaneous progress in financial instruments. To handle this problem, various financing models are implemented (Cui et al., 2021; Sinha et al., 2021). Environmental protection funding was initially the state's responsibility; however, in recent years, this function has been transferred to public-private partnerships leaving the state in charge of financing the relevant infrastructure (Ho and Park, 2019). In addition to PPP, the state actively encourages private investors to invest in environmental protection by providing tax incentives, grants and subsidies. Traditionally, there are two types of private investors—institutional and individual (Zhou et al., 2020; Akomea-Frimpong et al., 2022). Institutional investors are commercial banks, insurance companies, pension and public funds. Private capital is provided by interested companies. Recently, the market for green loans (Su et al., 2022) and green bonds (Tolliver et al., 2020) has been formed in the institutional segment. The evolution of the digital economy has led to the emergence of a new type of investor, i.e., crowdfunding platforms to finance environmental expenditures (Böckel et al., 2021).

In various studies, the term "environmental finance" is used as a synonym for such concepts as "green finance" (Muganyi et al., 2021; Meo and Zhao, 2022), "ecological finance" (Kihombo et al., 2021; Lee et al., 2022), "sustainable finance" (Develay and Giamporcaro, 2023) or "clean technology finance" (Madaleno et al., 2022). Originally, the term referred to the environmental economics paradigm and environmental investment. However, with the development of direct and derivative financing instruments, the growing impact of environmental problems and the tightening of environmental regulations (Cao et al., 2021; Feng et al., 2022) the scope of the term's application has gradually expanded. Hence, the concept of environmental finance will be evolving adding new research aspects over time.

Publications on environmental financing in the Russian Federation cover the full range of issues identified above, focusing on the development of a green financial market and green risks (Ziyadin et al., 2019; Tulupov et al., 2020; Tyuleneva & Moldazhanov, 2020; Altunina and Alieva, 2021).

2.3 Digital capital

The existing literature on the digital economy primarily deals with measuring its level and effects. Currently, there is no single measurement method for selecting and evaluating indicators of the digital economy. Researchers mainly evaluate the digital economy and related indicators in terms of their specific tasks. The details of these methods are beyond the scope of the given study, but it is sufficient to refer to review articles (Bukht and Heeks, 2017). We are going to consider one of the indicators of the digital economy, namely, digital capital. This phenomenon is less popular among researchers if compared to the digital economy, and there are significant differences in studies with respect to the approaches used.

The first approach addresses digital capital from the perspective of an individual and in close connection with social and cultural capital (Resnick, 2004; Seale, 2012). These studies lie in the field of sociology and explore the extent to which people are involved in the use of digital technologies. Digital capital is interpreted as an individual's digital technology ecosystem that determines how a user interacts with digital technologies. This characterizes the conditions for effective interaction between an individual and digital technologies, which he/she needs for their wellbeing in a digital society. The ability to purchase digital gadgets and software is a subset of an individual's economic capital, and the material exchange takes place in areas where ICTs are used. Digital capital manifests itself in cultural capital in the form of digital skills, knowledge and competencies (Park and Park, 2017; Vartanova and Gladkova, 2020).

The second approach examines digital capital in the context of companies' intangible assets (Crouzet and Eberly, 2019; Ayyagari et al., 2020; McGrattan, 2020; Tambe et al., 2020; Wu et al., 2020). Firms invest in both manufacturing and digital equipment to enhance their production capacity. ICT equipment (servers, routers, online shopping platforms and basic Internet software) acts as a tangible part of digital capital. In order to benefit from new technologies, digital-focused companies not only require investments in digital technologies but also in intangible assets. These intangible assets include staff training, new decision-making structures, and new business models to generate profits from digital activities (Eisfeldt and Papanikolaou, 2013; Bughin and Manyika, 2018). These investments often result in higher overall costs compared to the costs of digital technologies alone. These intangible assets make up the intangible part of digital capital. Similar to other forms of capital, digital capital can depreciate over time and needs to be replenished through additional investments. However, unlike tangible assets, the value of the intangible part of digital capital is closely tied to a specific company and is influenced by external economic conditions. As a result, the value of intangible assets tends to fluctuate more strongly than the value of tangible ICT assets, which are more easily exchangeable and have active secondary markets. As digital capital becomes an increasingly crucial component of a company's overall capital reserves, differences in digital capital among firms can explain variations in the performance of new digital-focused companies compared to older firms. These differences in digital capital can be attributed to the accumulated reserves and variations in the marginal costs of investing in digital capital. In summary, the presence and management of digital capital play a significant role in determining the success and performance of digital-focused firms in comparison to traditional firms (Tambe et al., 2020).

The third approach to investigating digital capital lies in the field of the regional economy and characterizes the extent to which digital capital of a country or region is formed. The existing studies in this domain are not numerous. A number of publications on the assessment of the country's digital capital as a combination of digital technologies and digital competencies explore its relationship with socio-economic and demographic characteristics such as income, age, education level, and place of residence, *etc.* (Ragnedda, 2018; Ragnedda et al., 2020). The techUK trade association holds a regular study of the Local Digital Capital Index (LDC Index) in the UK regions (LDCI, 2021; LDCI, , 2022). This index incorporates eight components, these are digital skills, digital technologies, data ecosystems, digital infrastructure, finance and investment, research and innovation, trade support, and cooperation. The LDC Index evaluates the impact that digital technologies can exert on the region, demonstrates its strengths and sets the direction for further development. The Index can be applied when formulating public policy to address a range of issues faced by the region and the entire country. The LDC Index also provides data to regional innovation ecosystems, including industry, government, universities and the public.

2.4 Research gap

Despite the fact that the mutual impact of digitalization and sustainable development is being studied in depth, the issues of the relationship of financial flows underlying these processes have not been investigated. Our research should fill this gap, initiate such research, and substantiate the directions for clarifying public policy.

3 Research design and theoretical hypothesis

Environmental financing consists of two components—environmental investment and current environmental protection costs. Environmental investment is investment in equipment, technologies and new facilities in a particular period to insure environmental protection. Current environmental protection costs cover annual costs incurred in many areas of environmental protection, such as expenditures on the current control of the production and consumption wastes circulation, on the maintenance of the fixed capital for environmental purposes, and R&D expenditures as far as they relate to nature protection.

We will assess the impact of the digital economy on environmental financing using two indicators, these are digital financing and digital capital. Digital financing includes digital investment, current digital costs, and digital competence costs. To calculate digital capital, we adopt the aforementioned approach, but offer our own index methodology described in Section 3 'Methods and Data'.

We believe that the mechanism for linking the digital economy and environmental financing can be represented as follows (Figure 1):

1. The effect of the digital economy on environmental financing is assessed through digital financing. Digital economy is manifested through digital technologies that are put in new equipment purchased through investments in environmental protection, as well as the associated expenses for digital competencies and the ongoing costs of maintaining digital infrastructure.

H1. The higher the share of digital financing in a company, region or country, the more likely it is that environmental financing will cover

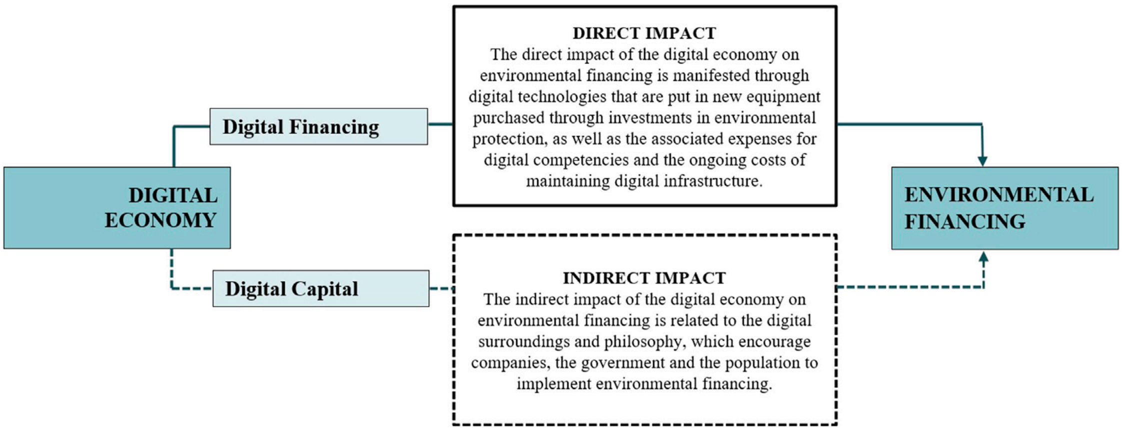


FIGURE 1
Direct and indirect impact of the digital economy on environmental financing.

expenses on new digital environmental protection technologies, and the larger the total amount of environmental financing.

Since any investments depend on companies' financial situation, profitability and risk, their dynamics will be unidirectional if investments are aimed at technological changes. Investments and current operating expenses are of a different nature, and their dynamics is determined by different factors. This thesis allows us to come up with another two hypotheses.

H2. A positive relationship of digital financing is stronger with environmental investment and weaker with current environmental protection costs.

H3. There is a strong positive relationship between digital investment and environmental investment, and the positive relationship of current digital costs and digital competence costs with environmental investment is weaker.

2. The indirect effect of the digital economy on environmental financing is associated with the formation of the necessary digital environment and worldview that stimulate companies, the state and the population to engage in environmental financing. To assess the strength of the relationship, the 'digital capital' indicator is used.

H4. Digital capital has a positive effect on environmental financing due to the cumulative synergistic effect of digitalization of the population, companies and the state.

H5. Effect of digital capital on environmental investment is more positive whereas its effect on current environmental protection costs is less positive.

4 Methods and data

4.1 Model's construction

According to the above theoretical analysis and study design, to test the impact of the digital economy on environmental financing, we will use the least squares method (LSM) with clustering of annual standard deviation and individual fixed effects. Figure 2 presents the set of the tested models.

Hypothesis H1. is tested using model M1:

$$\boldsymbol{EF_{it} = \alpha_0 + \alpha_1 DF_{it} + \alpha_2 C_t + \varepsilon_{it}} \tag{1}$$

where EF_{it} denotes environmental financing of industry i in time period t; DF_{it} is digital financing of industry i in time period t; C_t is a vector of control variables in time period t; ε_t denotes random term; α_1 and α_2 are the coefficients to be estimated.

To test hypothesis H2, models M1.1 and M1.2 are used, respectively:

$$\boldsymbol{EI_{it} = \beta_0 + \beta_1 DF_{it} + \beta_2 C_t + \mu_{it}} \tag{2}$$

$$\boldsymbol{CEPC_{it} = \gamma_0 + \gamma_1 DF_{it} + \gamma_2 C_t + \delta_{it}} \tag{3}$$

where EI_{it} denotes environmental investment of industry i in time period t; $CEPC_{it}$ is current environmental protection costs of industry i in time period t; DF_{it} is digital financing of industry i in time period t; C_t denotes a vector of control variables in time period t; μ_t and δ_t are random terms; β_1, β_2, γ_1 and γ_2 are the coefficients to be estimated.

Hypothesis H3. is tested using model M1.1.1:

$$\boldsymbol{EI_{it} = \rho_0 + \rho_1 DI_{it} + \rho_2 CDC_{it} + \rho_3 DCC_{it} + \rho_4 C_t + \tau_{it}} \tag{4}$$

where EI_{it} denotes environmental investment of industry i in time period t; DI_{it} denotes digital investment of industry i in time period t; CDC_{it} is current digital costs of industry i in time period t; DCC_{it} is digital competence costs of industry i in time period t; C_t denotes a vector of control variables in time period t; τ_t is random term; ρ_1, ρ_2, ρ_3 and ρ_4 are the coefficients to be estimated.

For testing hypothesis H4, model M2 is designed:

$$\boldsymbol{EF_{it} = \chi_0 + \chi_1 DC_t + \chi_2 C_t + \omega_{it}} \tag{5}$$

where EF_{it} denotes environmental financing of industry i in time period t; DF_{it} is digital capital in time period t; C_t is a vector of control variables in time period t; ω_t denotes random term; χ_1 and χ_2 are the coefficients to be estimated.

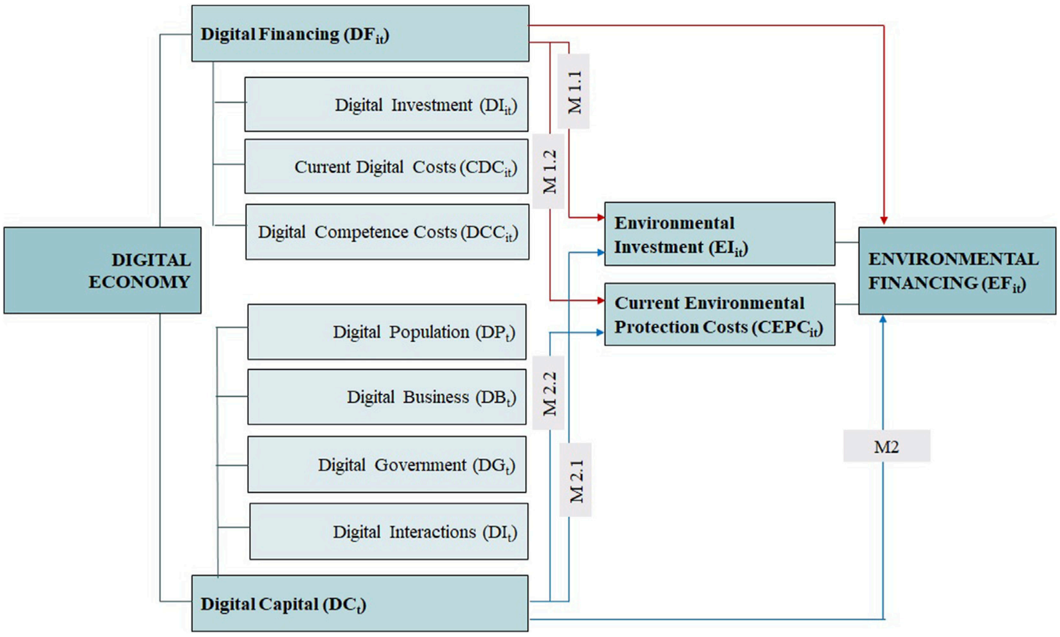


FIGURE 2
A set of models of the impact of the digital economy on environmental financing.

As indicated above, we offer our own index methodology to evaluate digital capital:

$$\boldsymbol{DC_t = \sqrt[4]{DP_t \cdot DB_t \cdot DG_t \cdot DI_t}} \tag{6}$$

where DC_t is digital capital index in time period t; DP_t is digital population index in time period t; DB_t is digital business index in time period t; DG_t denotes digital government index in time period t; DI_t is digital interaction index in time period t.

Similar approach to integrating sub-indices into a composite index produced a positive outcome in the case of the digital space index (Akberdina et al., 2022).

The first sub-index DP_t describes digital competencies of the population that are assessed through the following indicators: the number of mobile broadband Internet access subscribers per 100 population, the share of households with broadband Internet access, the share of the population that are active Internet users, the number of graduates in the program Computer Science and Computer Technology per 10,000 population, and the share of people employed in the ICT sector in the total number of the employed.

The second sub-index DB_t is related to the level of companies' digital transformation. The following indicators are applied to assess it: the share of organizations that provided additional training for employees in the field of ICT, the volume of investments in ICT, the share of organizations using Internet access at a speed of at least 2 Mbps, the share of organizations having special software to manage the procurement of goods (works, services), the share of organizations having special software to manage the sales of goods (works, services), the share of organizations using ERP systems, the share of organizations using CRM systems, and the share of organizations using electronic document management systems.

The third sub-index DG_t shows the extent to which digital technologies have penetrated the sphere of public administration and is assessed using the following indicators: the share of public authorities and local governments using the Internet at a speed of more than 256 Kbps, the share of public authorities and local self-governments with a data transfer rate of at least 2 Mbps, the share of public authorities and local self-governments using electronic digital signature means, and the share of public authorities and local self-governments utilizing electronic document management systems.

The fourth sub-index DI_t reflects the extent to which the interactions between the population, companies and the state are digitized. The following indicators are applied to assess it: the share of public authorities and local governments using automatic data exchange, the share of public authorities and local governments providing access to databases, the share of orders for state and municipal needs placed via electronic trading platforms, the share of the e-document management system in the interaction between public authorities, the share of organizations using the Internet to receive certain types of state and municipal services, the share of organizations using electronic data interchange between internal and external information systems, the share of organizations placing orders for goods (works, services) on the Internet, the share of organizations receiving orders for goods (works, services) via the Internet, the share of organizations using digital platforms, the share of the population using the Internet to get state and municipal services, and the share of the population using the Internet to order goods and (or) services.

The indicators of the sub-indices were normalized. The maximum value for each indicator over a period of time was equated to one, and the values for the remaining years were normalized in relation to it.

TABLE 2 Description of PBI_t variables.

Type	Name	Code	Measure unit	Data path
Dependent	Environmental Financing	EF_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/Rashod_oxr.xls
Dependent	Environmental Investment	EI_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/Zatrat_2022.xls
Dependent	Current Environmental Protection Costs	$CEPC_{it}$	rubles	https://rosstat.gov.ru/storage/mediabank/oxr_zatr_4.xls
Independent	Digital Financing	DF_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/3-inf_2015(1)(1).rar
Independent	Digital Investment	DI_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/3-inf_2016(1)(1).rar
Independent	Current Digital Costs	DCC_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/3-inf_2017(1)(1).rar
				https://rosstat.gov.ru/storage/mediabank/3-inf_2018(3).rar
Independent	Digital Competence Costs	CDC_{it}	rubles	https://rosstat.gov.ru/storage/mediabank/3-inf_2019.rar
				https://rosstat.gov.ru/storage/mediabank/3-inf_2020(2).rar
				https://rosstat.gov.ru/storage/mediabank/3-Inf_2021.rar
Independent	Digital Capital Index	DC_t	index	calculated
Independent	Digital Population Index	DP_t	normalized value	https://rosstat.gov.ru/storage/mediabank/monitor.xlsx
Independent	Digital Business Index	DB_t	normalized value	https://rosstat.gov.ru/storage/mediabank/monitor.xlsx
				https://rosstat.gov.ru/storage/mediabank/Ikt_org(1).xlsx
Independent	Digital Government Index	DG_t	normalized value	https://rosstat.gov.ru/storage/mediabank/monitor.xlsx
Independent	Digital Interaction	DI_t	normalized value	https://rosstat.gov.ru/storage/mediabank/monitor.xlsx
Control	GDP *per capita*	GDP_t	rubles	https://rosstat.gov.ru/storage/mediabank/VVP_na_dushu_s1995-2022.xls
Control	Research and Development Costs	$R\&D_t$	rubles	https://rosstat.gov.ru/storage/mediabank/nauka-5.xlsx
Control	Private Business Investments	PBI_t	rubles	https://rosstat.gov.ru/storage/mediabank/Invest-fs.xls

Finally, hypothesis H5 is tested using models M1.2 and M2.2:

$$\boldsymbol{EI_{it} = \nu_0 + \nu_1 DC_t + \nu_2 C_t + \varphi_{it}} \tag{7}$$

$$\boldsymbol{CEPC_{it} = \eta_0 + \eta_1 DC_t + \eta_2 C_t + \psi_{it}} \tag{8}$$

where EI_{it} is environmental investment of industry i in time period t; $CEPC_{it}$ denotes current environmental protection costs of industry i in time period t; DC_t is digital capital in time period t; C_t is a vector of control variables in time period t; φ_t and ψ_t are random terms; ν_1, ν_2, η_1 and η_2 are the coefficients to be estimated.

4.2 Variables and data sources

Based on the research purpose and data availability, we have developed dependent variables, main independent variables, control variables, and intermediate variables. Their specific values, calculation methods and data sources are presented in Table 2.

The study used data from the Federal State Statistics Service of the Russian Federation (Rosstat) on environmental protection expenditures for 2012–2022 by industry, including investment and current costs. In the research, the data are given by types of industry-specific economic activity—in aggregate (sections B, C, D, E according to the OKVED-2 classifier [OKVED-2 is the Russian National Classifier of Types of Economic Activity]) and in detail (industry sectors—decimal codes according to the OKVED-2 classifier).

To perform regression modeling of the relationship between environmental financing and digital financing, the data for 2015–2021 were taken, since the statistics on digitalization by type of industry expenses has been collected only since the approval of the state program Digital Economy of the Russian Federation. To carry out the regression assessment of the relationship between environmental financing and digital capital, data for 2012–2022 were used. The indicators for calculating the digital capital index and sub-indices are presented in the Consolidated Monitoring of the Development of the Information Society in the Russian Federation, provided by the Federal State Statistics Service of the Russian Federation.

5 Results and discussion

5.1 Digital financing and environmental financing

The first group of the research models dealt with the direct relationship between digital financing and environmental financing. Table 3 presents empirical results based on panel data for 31 Russian industries for 7 years (2015–2021). As we can see, the main model M1 (Eq. 1) gives quite good results: the regression coefficient of the impact of digital financing (DF_{it}) on environmental financing (EF_{it}) is positive and passed the test for significance at the 1% level.

We suppose that in this case the effect of digital technologies penetrating into environmental protection technologies is triggered.

TABLE 3 Effects of the digital economy on environmental financing.

Independent	Model 1	Model 1.1	Model 1.2	Model 1.1.1	Model 2	Model 2.1	Model 2.2
	EF_{it}	EI_{it}	$CEPC_{it}$	EI_{it}	EF_{it}	EI_{it}	$CEPC_{it}$
DF_{it}	0.423*** (12.07)	0.739*** (42.19)	0.290*** (3.13)	—	—	—	—
DI_{it}	—	—	—	0.428*** (54.33)	—	—	—
DCC_{it}	—	—	—	0.107*** (9.78)	—	—	—
CDC_{it}	—	—	—	0.239*** (11.04)	—	—	—
DC_t	—	—	—	—	0.018*** (10.73)	0.139*** (22.16)	0.007*** (1.25)
GDP_t	0.008*** (10.12)	0.009*** (11.56)	0.011*** (21.01)	0.007*** (12.77)	0.007*** (3.13)	0.006*** (3.45)	0.007*** (2.11)
$R\&D_t$	0.001*** (6.01)	0.001*** (7.12)	0.001*** (1.12)	0.001*** (5.17)	0.001*** (0.12)	0.004*** (0.17)	−0.001*** (0.11)
PBI_t	0.003*** (18.47)	0.003*** (33.56)	0.003* (12.85)	0.007** (28.19)	0.007** (8.42)	0.007** (10.01)	−0.012** (1.76)
const	0.042 (2.08)	0.019 (2.89)	0.007 (1.18)	0.029 (2.12)	0.097** (7.44)	1.307** (12.06)	0.059** (2.06)
R^2	0.815	0.854	0.561	0.848	0.712	0.789	0.442
N	217	217	217	217	341	341	341

Note: $***p < 0.01$, $**p < 0.05$, $*p < 0.10$; the values in parentheses are t values.

Digital technologies such as the Internet, the IoT, artificial intelligence, big data, digital twins, *etc.*, are widely used in environmental protection, which changes resource consumption patterns, pollution reduction, and higher energy efficiency. These technologies are instrumental in analyzing big data obtained through environmental monitoring, automating management decision-making in real time, and predictive forecasting of potentially hazardous natural phenomena and objects. Owing to the use of GISs, Earth space sensing data and unmanned observation, it possible to control landfills, identify flora and fauna objects, *etc.* The effect of the digital economy is also evident when solving any engineering and environmental problem. Software for design and automation of technological preparation of production is of great importance for cleaner production to progress. Increasingly scrupulous attention is paid to the latest achievements in artificial intelligence and neural networks applied to produce optimal technological solutions, i.e., to optimize resource consumption, reduce emissions of harmful substances, and cut down energy consumption.

On the other hand, there is a substitution effect: outdated production technologies are replaced by new digital solutions, which ultimately leads to a significant decrease in environmental pollution and resource savings in industry. This, in turn, reduces the need for environmental facilities construction funding and lowers current environmental protection costs. For example, industrial robots replace human labor for automated production, intelligent design improves the efficiency of allocation of production factors and productivity. Digital technologies also contribute to reducing the volumes of raw materials required. With electronic sensors of various sizes, virtually any change in the production system's operating state can be monitored. This allows not only tracking CO_2 emissions, but also controlling the level of emissions related to the company's entire value chain. The effects of penetration and substitution are manifested in different growth rates of digital financing and environmental financing. As evidenced by the case of Russia, digital financing is increasing annually at a faster pace than environmental financing. This led to the fact that over 7 years the share of digital financing in GDP increased 1.8 times, while the rise in the share of environmental financing in GDP was only 1.3 times (Figure 3). This absolutely does not mean that the digital economy in Russia is prioritized over sustainable development; this is merely a manifestation of the abovementioned effects. Thus, we can conclude that hypothesis H1 has been confirmed.

Models M1.1 and M1.2 (Eqs 2, 3) were developed to test hypotheses about the impact of digital financing on the elements of environmental financing, namely, environmental investment and current environmental protection costs. Table 3 demonstrates the situation that we had predicted. There is a sustainable positive relationship between digital financing (DF_{it}) and environmental investment (EI_{it}). At the same time, when evaluating the relationship between digital financing (DF_{it}) and current environmental protection costs ($CEPC_{it}$), we can see that the regression coefficient is a positive number of 0.290, but it fails the test for significance indicating that there is no relationship between the indicators.

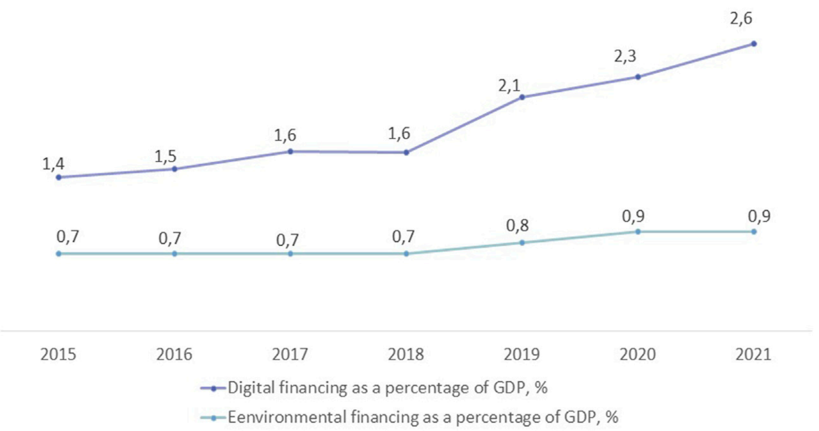


FIGURE 3
Digital financing and environmental financing as a percentage of GDP in the Russian Federation, %.

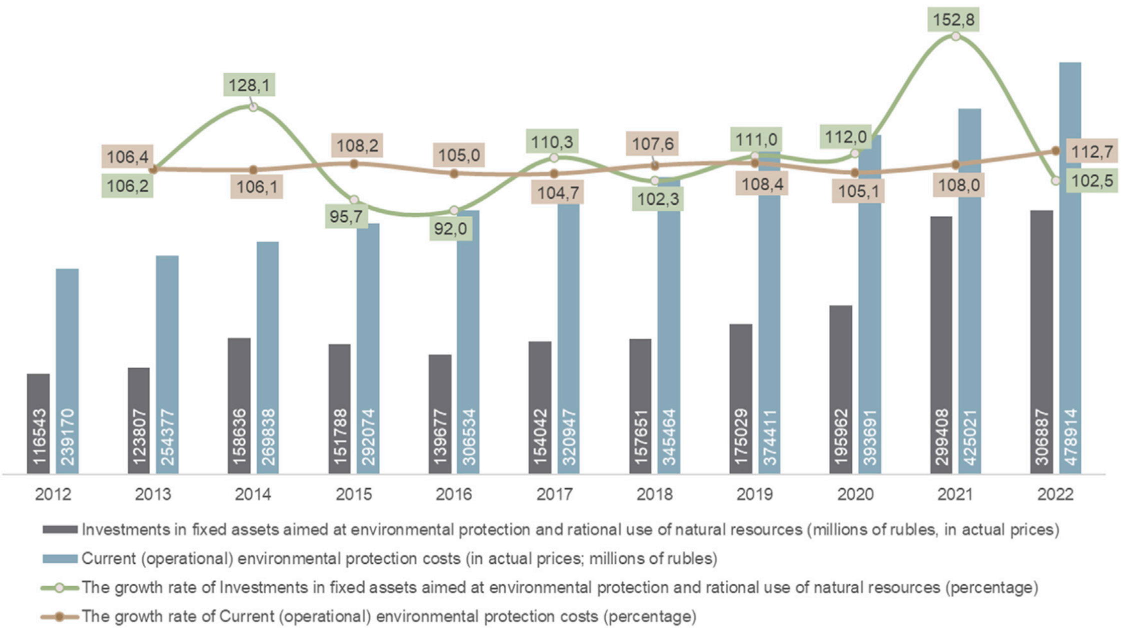


FIGURE 4
Dynamics of environmental investment and current environmental protection costs in the Russian Federation.

We argue that environmental investment and current environmental protection costs are of a different nature and determined by different factors. This is clearly illustrated in Figure 4.

The dynamic graphs of environmental investment and current environmental protection costs are configured in a completely manner. Current environmental protection costs are related to production volumes and resource consumption. Digital technologies have little effect on the costs associated with previous technological solutions. We believe that environmental investment is determined by the willingness of companies to invest and the availability of sufficient funding. Any investment in technology, therefore, will have unidirectional dynamics and a close statistical relationship. These arguments, in our view, support hypothesis H2.

Model M1.1.1 (Eq. 4) is a variation of model M1.1 and supposed to reveal the relationship of environmental investment (EI_{it}) with digital financing components, such as digital investment (DI_{it}), current digital costs (DCC_{it}) and digital competence costs (CDC_{it}). All the independent variables exert a positive effect on environmental investment, but only digital investment is of high significance, which confirms hypothesis H3. Digital financing is unevenly distributed across different industries. Our study has shown that 75% of the funds allocated for digitalization were distributed between 10 industries (in OKVED, industry covers more than 30 types of activities). Among the sectors leading in investment in industry digitalization are the energy industry, production of petroleum products, gas and oil production, metallurgy and production of metal products, electronics and machine tool

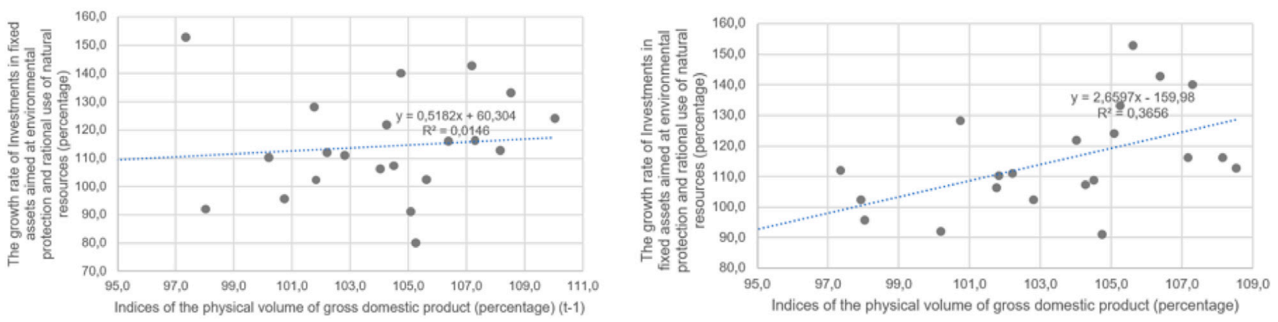


FIGURE 5
Dependence of environmental investment and GDP with a 1-year lag and without a time lag.

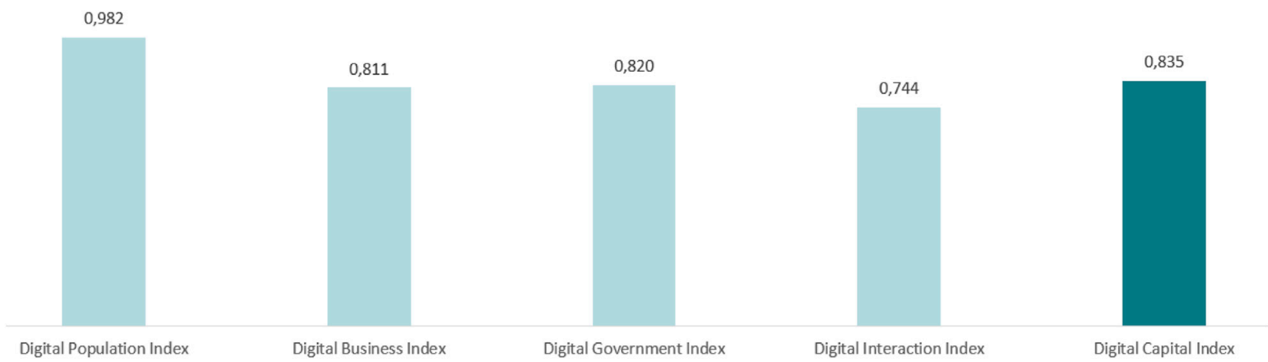


FIGURE 6
The digital capital index and its components in the Russian Federation in 2022.

manufacturing. At that, it is these industries that generate the main investment inflow in new environmental technologies and set environmental goals.

However, we prove that there is a relationship between environmental investment and GDP, but it is rather weak. Moreover, this relationship is significant only in the regression without a time lag, while a 1-year lag notably worsens the regression values (Figure 5).

In 2021, we analyzed the structure of digital financing in Russia. Of the total funds allocated for digital transformation in industry, 72% were directed to internal expenses, such as the purchase of information and communication equipment, software, staff training, *etc.* The remaining 28% of the budget was allocated to external expenses, such as digital equipment rental, software, technical support, and database access. The internal costs of digital transformation were involved in the acquisition of digital machinery and equipment, and 40.2% of these were associated with the purchase of computers and office equipment. However, the share of digital production equipment purchases remained small. Software accounted for 22% of the total domestic digitalization budget in 2021. Employee training comprised just 3% of all internal digital transformation spending. In industry, there are practically no costs incurred in the formation of digital context. Thus, the internal funds for digital transformation exceed the external ones, and most of them are aimed at purchasing hardware and software. Employee training and creating digital context in industry remain less significant expenses.

5.2 Digital capital and environmental financing

In the second part of our study of the relationship between the digital economy and environmental financing, we applied the digital capital index, for which we had previously proposed a definition and an assessment method. The digital capital index characterizes the environment, where technological segments of traditional industries develop. To assess the impact of the digital capital index (DC_t) on environmental financing (EF_{it}), we substantiated model M2 (Eqs 5, 6) and related models M2.1 and M2.2 (Eqs 7, 8), i.e., the impact of the index on environmental investment (EI_{it}) and current environmental protection costs ($CEPC_{it}$). The results of modelling are presented in Table 3. As can be seen, the regression coefficients and their significance are worse than models including digital financing; however, there is an overall positive relationship. Models M2 and M2.1 showed a more significant statistical relationship, which can be due to the fact that current environmental protection costs are in principle insensitive to anything other than production volumes.

The digital capital index has an indirect impact due to the cumulative synergistic effect of digitalization of the population, companies and the state. As follows from Figure 6, in 2022 the digital capital index in Russia was 0.835 out of the maximum possible value of 1. If the digital population index is close enough to the maximum value, and the digital business index and the digital government index are 18%–19% behind the maximum value, then the digital interaction index remains at a relatively low level of 0.744. With the growing importance of factors affecting the digital interaction index (e.g., the share of companies receiving orders via the Internet, the share of companies using digital platforms, the share of the population using the Internet to order goods and services, *etc.*), its contribution to the digital capital index will increase, so will the importance of the environmental financing index. These arguments support hypotheses H4 and H5.

6 Discussion

Digital transformation is a key factor for Russia in changing the technological structure of the economy and preserving the environment. Considering the importance of the digital economy in ensuring sustainable development, the present research has focused on the role of the digital economy in not only reducing the anthropogenic load on the environment, but in environmental financing, which, among other things, characterizes the technological renewal of this area. Having conducted the study, we answered the posed questions and arrived at the following conclusions.

Firstly, we found that digital financing has a significant positive impact on environmental financing, which indicates that the two dynamic processes in the economy—the digital transformation of the economy and the introduction of the latest digital technologies in the field of environmental protection—are synchronized. Digital technologies can be used to create innovative solutions aimed at reducing emissions of harmful substances and improving the environmental efficiency of production. For example, the use of sensors and the control system can help improve air and water quality, as well as reduce greenhouse gas emissions.

Secondly, we proved that digital investment stimulates a comparable increase in environmental investment due to the effects of digital technologies penetrating into environmental technologies. Investment in digital technologies has the potential to improve environmental monitoring, analyze pollution and resource efficiency data, and work out innovative solutions to lessen adverse environmental impacts.

Thirdly, we demonstrated that the level of digitalization of the population, companies and the state and the strengthening of the digital environment for interactions have a favorable effect on environmental financing. We introduced the digital capital index and traced the logic of its impact on environmental financing. It was found that digital involvement of the population stimulates the dissemination of information and awareness of sustainable development methods and environmentally friendly technologies; it also encourages active participation in crowdfunding platforms in support of environmental initiatives. Digital technologies in public administration can be used to create platforms for monitoring and managing various aspects of environmental protection, such as air, water and soil quality. This makes it possible to quickly detect problems and take action to resolve them, thus, minimizing the negative impact on the environment. Digitalization of production business processes allows the optimal use of material and human resources, granting the industry the opportunities to achieve sustainable development goals.

7 Discussion

The findings of our study are of special interest for public authorities. By creating conditions for a deep digital transformation of the economy, governments generate a significant demand for digital financing, which in turn increase the penetration of digital technologies into the field of ecology and stimulates environmental financing. One of the domains, where these results can be of use, is the development of the renewable energy sector. Digital technologies can make production processes and the use of renewable energy sources significantly more efficient. For example, sensors and the monitoring system allow optimizing the operation of solar and wind power plants, analyzing energy production data and predicting the consumption level. This will enhance the efficiency of using renewable energy sources and mitigate the negative impact on the environment.

Moreover, digital financing can contribute to the introduction of eco-friendly projects and initiatives. By attracting investments via digital platforms, the state can support the development and implementation of new technologies aimed at reducing greenhouse gas emissions, improving air and water quality, and the sustainable use of natural resources. Such projects may include the design of energy efficient technologies, the creation of waste management systems and sustainable agriculture.

Another fundamental aspect of digital financing is to ensure financial inclusion and access to financial services for all segments of the population. Digital platforms can provide small and medium-sized businesses and the population with limited financial resources with access to loans, investments and other financial instruments. This will improve the economic situation in regions and raise the standard of living of the population.

Thus, the results of our study can be widely used in public policy. The progress in digital financing and environmental financing can contribute to the sustainable development of the economy, reduce the damaging effect on the environment and boost the living standards of the population. The state should actively support and accelerate the development of digital technologies and eco-friendly projects to ensure a sustainable future for all.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

VA: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing–original draft, Writing–review and editing. YL: Conceptualization, Funding acquisition, Methodology, Resources, Writing–review and editing. MV: Data curation, Investigation, Visualization, Writing–review and editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. The research funding from the Ministry of Science and Higher Education of the Russian Federation Ural Federal University Program of Development within the Priority-2030 Program is gratefully acknowledged.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Adeshola, I., Usman, O., Agoyi, M., Awosusi, A. A., and Adebayo, T. S. (2023). "Digitalization and the environment: the role of information and communication technology and environmental taxes in European countries," in *Natural resources forum* (Oxford, UK: Blackwell Publishing Ltd).

Akberdina, V., and Barybina, A. (2022). "Digital platform for regional industry: prerequisites and functionality," in *Digital transformation in industry: digital twins and new business models* (Cham: Springer International Publishing), 109–120. doi:10.1007/978-3-030-94617-3_9

Akberdina, V., Naumov, I., and Krasnykh, S. (2022). "Regional digital space and digitalisation of industry: spatial econometric analysis," in International scientific conference on Digital Transformation in Industry: Trends, Management, Strategies, Cham (Springer Nature Switzerland), 7–19. doi:10.1007/978-3-031-30351-7_2

Akberdina, V., Strielkowski, W., Linder, N., Kashirin, S., and Shmeleva, L. (2023). Information technology and digital sufficiency for building the sustainable circular economy. *Energies* 16 (3), 1399. doi:10.3390/en16031399

Akberdina, V. V. (2018). Digitalization of industrial markets: regional characteristics. *Manag.* 9 (6), 78–87. doi:10.29141/2218-5003-2018-9-6-8

Akomea-Frimpong, I., Adeabah, D., Ofosu, D., and Tenakwah, E. J. (2022). A review of studies on green finance of banks, research gaps and future directions. *J. Sustain. Finance Invest.* 12 (4), 1241–1264. doi:10.1080/20430795.2020.1870202

Ali, E. B., Anufriev, V. P., and Amfo, B. (2021). Green economy implementation in Ghana as a road map for a sustainable development drive: a review. *Sci. Afr.* 12, e00756. doi:10.1016/j.sciaf.2021.e00756

Altunina, V. V., and Alieva, I. A. (2021). Current trends in the development of a green finance system: methodology and practice. *Balt. Reg.* 13 (2), 64–89. doi:10.5922/2079-8555-2021-2-4

Ayyagari, M., Demirgüç-Kunt, A., and Maksimovic, V. (2020). The rise of star firms: intangible capital and competition. Available at https://ssrn.com/abstract=3230154 (accessed on May 30, 2023).

Basaev, Z. V. (2019). The digitalisation of the economy: Russia in the context of global transformation. *World New Econ.* 12 (4), 32–38. doi:10.26794/2220-6469-2018-12-4-32-38

Belokurova, E. V., Pizikov, S. V., Petrenko, E. S., and Koshebayeva, G. K. (2020). "The institutional model of building the digital economy in modern Russia," in *Digital economy: complexity and variety vs. Rationality* (Springer International Publishing), 64–70. 9. doi:10.1007/978-3-030-29586-8_8

Bobylev, S. N., and Solovyeva, S. V. (2017). Sustainable development goals for the future of Russia. *Stud. Russ. Econ. Dev.* 28, 259–265. doi:10.1134/S1075700717030054

Böckel, A., Hörisch, J., and Tenner, I. (2021). A systematic literature review of crowdfunding and sustainability: highlighting what really matters. *Manag. Rev. Q.* 71, 433–453. doi:10.1007/s11301-020-00189-3

Borremans, A. D., Zaychenko, I. M., and Iliashenko, O. Y. (2018). "Digital economy. IT strategy of the company development," in MATEC Web of Conferences (St. Petersburg, Russia: EDP Sciences) 170. 01034. doi:10.1051/matecconf/201817001034

Bouchoucha, N. (2021). The effect of environmental degradation on health status: do institutions matter? *J. Knowl. Econ.* 12 (4), 1618–1634. doi:10.1007/s13132-020-00680-y

Bughin, J., and Manyika, J. (2018). Measuring the full impact of digital capital. Available at: https://www.mckinsey.com (accessed on May 30, 2023).

Bukht, R., and Heeks, R. (2017). Defining, conceptualising and measuring the digital economy. *Dev. Inf. Work. Pap.* 68. doi:10.2139/ssrn.3431732

Cao, S., Nie, L., Sun, H., Sun, W., and Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: evidence from China's regional economies. *J. Clean. Prod.* 327, 129458. doi:10.1016/j.jclepro.2021.129458

Chen, X., Despeisse, M., and Johansson, B. (2020). Environmental sustainability of digitalization in manufacturing: a review. *Sustainability* 12 (24), 10298. doi:10.3390/su122410298

Crouzet, N., and Eberly, J. C. (2019). *Understanding weak capital investment: the role of market concentration and intangibles (No. w25869).* Cambridge, United Kingdom: National Bureau of Economic Research. doi:10.3386/w25869

Cui, L., Duan, H., Mo, J., and Song, M. (2021). Ecological compensation in air pollution governance: China's efforts, challenges, and potential solutions. *Int. Rev. Financial Analysis* 74, 101701. doi:10.1016/j.irfa.2021.101701

D'amato, D., and Korhonen, J. (2021). Integrating the green economy, circular economy and bioeconomy in a strategic sustainability framework. *Ecol. Econ.* 188, 107143. doi:10.1016/j.ecolecon.2021.107143

Develay, E., and Giamporcaro, S. (2023). "Sustainable finance and the role of corporate governance in preventing economic crimes," in *Sustainable finance and financial crime* (Cham: Springer International Publishing), 267–287. doi:10.1007/978-3-031-28752-7_14

Ding, C., Liu, C., Zheng, C., and Li, F. (2021). Digital economy, technological innovation and high-quality economic development: based on spatial effect and mediation effect. *Sustainability* 14 (1), 216. doi:10.3390/su14010216

Eisfeldt, A. L., and Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *J. Finance* 68 (4), 1365–1406. doi:10.1111/jofi.12034

Feng, S., Zhang, R., and Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Struct. Change Econ. Dyn.* 61, 70–83. doi:10.1016/j.strueco.2022.02.008

Gureev, P. M., Degtyareva, V. V., and Prokhorova, I. S. (2020). "National features of forming a digital economy in Russia," in *Artificial intelligence: anthropogenic nature vs. Social origin* (Springer International Publishing), 13–20. doi:10.1007/978-3-030-39319-9_2

Ho, V. H., and Park, S. K. (2019). ESG disclosure in comparative perspective: optimizing private ordering in public reporting. *U. Pa. J. Int'l L.* 41, 249. Available at https://ssrn.com/abstract=3470991 (accessed on May 30, 2023).

Jin, S. T., Kong, H., Wu, R., and Sui, D. Z. (2018). Ridesourcing, the sharing economy, and the future of cities. *Cities* 76, 96–104. doi:10.1016/j.cities.2018.01.012

Karieva, E., Akhmetshina, L., and Mottaeva, A. (2020). "Green economy in the world and in Russia: preconditions and prospects," in E3S Web of Conferences (Les Ulis, France: EDP Sciences) 217. 07008. doi:10.1051/e3sconf/202021707008

Kihombo, S., Ahmed, Z., Chen, S., Adebayo, T. S., and Kirikkaleli, D. (2021). Linking financial development, economic growth, and ecological footprint: what is the role of technological innovation? *Environ. Sci. Pollut. Res.* 28 (43), 61235–61245. doi:10.1007/s11356-021-14993-1

Kostoska, O., and Kocarev, L. (2019). A novel ICT framework for sustainable development goals. *Sustainability* 11 (7), 1961. doi:10.3390/su11071961

Kuntsman, A., and Rattle, I. (2019). Towards a paradigmatic shift in sustainability studies: a systematic review of peer reviewed literature and future agenda setting to consider environmental (Un) sustainability of digital communication. *Environ. Commun.* 13 (5), 567–581. doi:10.1080/17524032.2019.1596144

Kuznetsova, S. N., Kozlova, E. P., Kuznetsov, V. P., and Tsymbalov, S. D. (2022). ""Green" economy as a trend in the socio-economic development of Russia," in *Business 4.0 as a subject of the digital economy* (Cham: Springer International Publishing), 671–674. doi:10.1007/978-3-030-90324-4_108

Lavrikova, Y. G., Buchinskaia, O. N., and Wegner-Kozlova, E. O. (2021). Greening of regional economic systems within the framework of sustainable development goals. *Econ. Regions* 17 (4), 1110–1122. doi:10.17059/ekon.reg.2021-4-5

LDCI (2022). Local digital capital index for 2022. Available at: https://www.creativelancashire.org/files/library/LDCI-Report-2022-Final.pdf (accessed on May 30, 2023).

Lee, C. C., Li, X., Yu, C. H., and Zhao, J. (2022). The contribution of climate finance toward environmental sustainability: new global evidence. *Energy Econ.* 111, 106072. doi:10.1016/j.eneco.2022.106072

Li, Y., Yang, X., Ran, Q., Wu, H., Irfan, M., and Ahmad, M. (2021). Energy structure, digital economy, and carbon emissions: evidence from China. *Environ. Sci. Pollut. Res.* 28, 64606–64629. doi:10.1007/s11356-021-15304-4

Liang, W., and Yang, M. (2019). Urbanization, economic growth and environmental pollution: evidence from China. *Sustain. Comput. Inf. Syst.* 21, 1–9. doi:10.1016/j.suscom.2018.11.007

Limna, P., Kraiwanit, T., and Siripipatthanakul, S. (2022). The growing trend of digital economy: a review article. *Int. J. Comput. Sci. Res.* 6, 1–11. Available at https://ssrn.com/abstract=4183686 (accessed on May 30, 2023).

Lu, Z. N., Chen, H., Hao, Y., Wang, J., Song, X., and Mok, T. M. (2017). The dynamic relationship between environmental pollution, economic development and public health: evidence from China. *J. Clean. Prod.* 166, 134–147. doi:10.1016/j.jclepro.2017.08.010

Madaleno, M., Dogan, E., and Taskin, D. (2022). A step forward on sustainability: the nexus of environmental responsibility, green technology, clean energy and green finance. *Energy Econ.* 109, 105945. doi:10.1016/j.eneco.2022.105945

Martin, C. J., Evans, J., and Karvonen, A. (2018). Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in Europe and North America. *Technol. Forecast. Soc. Change* 133, 269–278. doi:10.1016/j.techfore.2018.01.005

McGrattan, E. R. (2020). Intangible capital and measured productivity. *Rev. Econ. Dyn.* 37, S147–S166. doi:10.1016/j.red.2020.06.007

Meng, F., and Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: from a perspective of global value chain. *Environ. Sci. Pollut. Res.* 29 (52), 79497–79515. doi:10.1007/s11356-022-21434-0

Meo, M. S., and Abd Karim, M. Z. (2022). The role of green finance in reducing CO2 emissions: an empirical analysis. *Borsa Istanb. Rev.* 22 (1), 169–178. doi:10.1016/j.bir.2021.03.002

Muganyi, T., Yan, L., and Sun, H. P. (2021). Green finance, fintech and environmental protection: evidence from China. *Environ. Sci. Ecotechnology* 7, 100107. doi:10.1016/j.ese.2021.100107

Mughal, N., Arif, A., Jain, V., Chupradit, S., Shabbir, M. S., Ramos-Meza, C. S., et al. (2022). The role of technological innovation in environmental pollution, energy consumption and sustainable economic growth: evidence from South Asian economies. *Energy Strategy Rev.* 39, 100745. doi:10.1016/j.esr.2021.100745

Nguyen, T. T., Pham, T. A. T., and Tram, H. T. X. (2020). Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *J. Environ. Manag.* 261, 110162. doi:10.1016/j.jenvman.2020.110162

Niebel, T. (2018). ICT and economic growth–Comparing developing, emerging and developed countries. *World Dev.* 104, 197–211. doi:10.1016/j.worlddev.2017.11.024

Nikitaeva, A., and Dolgova, O. (2022). "Digital technologies and circular value chains for sustainable development," in International scientific conference on Digital Transformation in Industry: Trends, Management, Strategies, Cham (Springer Nature Switzerland), 169–179. doi:10.1007/978-3-031-30351-7_14

Ozkan, O., Coban, M. N., Iortile, I. B., and Usman, O. (2023). Reconsidering the environmental Kuznets curve, pollution haven, and pollution halo hypotheses with carbon efficiency in China: a dynamic ARDL simulations approach. *Environ. Sci. Pollut. Res.* 30 (26), 68163–68176. doi:10.1007/s11356-023-26671-5

Park, S., and Park, S. (2017). Understanding digital capital within a user's digital technology ecosystem. *Digit. Cap.*, 63–82. doi:10.1057/978-1-137-59332-0_4

Pierli, G., Murmura, F., and Bravi, L. (2022). "Digital transformation and sustainability. A systematic literature review," in International scientific conference on Digital Transformation in Industry: Trends, Management, Strategies, Cham (Springer Nature Switzerland), 83–99. doi:10.1007/978-3-031-30351-7_8

Popkova, E. G., Bogoviz, A. V., and Ragulina, J. V. (2018). "Technological parks, "green economy," and sustainable development in Russia," in *Exploring the future of Russia's economy and markets: towards Sustainable Economic Development* (Moscow, Russia: Emerald Publishing Limited), 143–159. doi:10.1108/978-1-78769-397-520181008

Purnomo, A., Susanti, T., Rosyidah, E., Firdausi, N., and Idhom, M. (2022). Digital economy research: thirty-five years insights of retrospective review. *Procedia Comput. Sci.* 197, 68–75. doi:10.1016/j.procs.2021.12.119

Ragnedda, M. (2018). Conceptualizing digital capital. *Telematics Inf.* 35 (8), 2366–2375. doi:10.1016/j.tele.2018.10.006

Ragnedda, M., Ruiu, M. L., and Addeo, F. (2020). Measuring digital capital: an empirical investigation. *New Media & Soc.* 22 (5), 793–816. doi:10.1177/1461444819869604

Resnick, P. (2004). "Impersonal sociotechnical capital, ICTs, and collective action among strangers," in *Transforming enterprise: the economic and social implications of information technology*. Editors W. H. Dutton, B. Kahin, and R. O'Callaghan (Cambridge, MA: MIT Press).

Rudyk, N. V., Niyazbekova, S. U., Yessymkhanova, Z. K., and Toigambayev, S. K. (2022). "Development and regulation of the digital economy in the context of competitiveness," in *Cooperation and sustainable development* (Springer International Publishing), 167–174. doi:10.1007/978-3-030-77000-6_20

Seale, J. (2012). When digital capital is not enough: reconsidering the digital lives of disabled university students. *Learn. Media Technol.* 38 (3), 256–269. doi:10.1080/17439884.2012.670644

Sinha, A., Mishra, S., Sharif, A., and Yarovaya, L. (2021). Does green financing help to improve environmental & social responsibility? Designing SDG framework through advanced quantile modelling. *J. Environ. Manag.* 292, 112751. doi:10.1016/j.jenvman.2021.112751

Söderholm, P. (2020). The green economy transition: the challenges of technological change for sustainability. *Sustain. Earth* 3 (1), 6. doi:10.1186/s42055-020-00029-y

Su, C. W., Umar, M., and Gao, R. (2022). Save the environment, get financing! How China is protecting the environment with green credit policies? *J. Environ. Manag.* 323, 116178. doi:10.1016/j.jenvman.2022.116178

Sun, H. (2022). What are the roles of green technology innovation and ICT employment in lowering carbon intensity in China? A city-level analysis of the spatial effects. *Resour. Conservation Recycl.* 186, 106550. doi:10.1016/j.resconrec.2022.106550

Tagaeva, T. J. O., Gilmundinov, V. M., Kazantseva, L. K., and Sinigaeva, D. D. (2022). «Green» economy and «green» investments in Russia IOP conference series: Earth and environmental science. *IOP Publ.* 962 (No. 1), 012035. doi:10.1088/1755-1315/962/1/012035

Tambe, P., Hitt, L., Rock, D., and Brynjolfsson, E. (2020). *Digital capital and superstar firms (No. w28285).* Cambridge, United Kingdom: National Bureau of Economic Research. doi:10.3386/w28285

Tolliver, C., Keeley, A. R., and Managi, S. (2020). Policy targets behind green bonds for renewable energy: do climate commitments matter? *Technol. Forecast. Soc. Change* 157, 120051. doi:10.1016/j.techfore.2020.120051

Tulupov, A. S., Mudretsov, A. F., and Prokopiev, M. G. (2020). Sustainable green development of Russia. *Complex Syst. Innovation Sustain. Digital Age* 1, 135–140. doi:10.1007/978-3-030-44703-8_15

Tyuleneva, T., and Moldazhanov, M. (2020). "The use of environmental taxation instruments in order to ensure sustainable development of mining region," in E3S Web of Conferences (Les Ulis, France: EDP Sciences) 174. 04061. doi:10.1051/e3sconf/202017404061

Van Heddeghem, W., Lambert, S., Lannoo, B., Colle, D., Pickavet, M., and Demeester, P. (2014). Trends in worldwide ICT electricity consumption from 2007 to 2012. *Comput. Commun.* 50, 64–76. doi:10.1016/j.comcom.2014.02.008

Vartanova, E. L., and Gladkova, A. A. (2020). Digital capital within the context of the intangible capitals concept. Mediascope 1. Available at http://www.mediascope.ru/2614 (accessed on May 30, 2023).

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., et al. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nat. Commun.* 11 (1). doi:10.1038/s41467-019-14108-y

Vlasov, M. (2020). "Digitalization of intellectual activity: Russian case," in Proceedings of the 16th European Conference on Management Leadership and Governance, ECMLG 2020, 266–274. doi:10.34190/ELG.20.020

Wang, H., Cui, H., and Zhao, Q. (2021). Effect of green technology innovation on green total factor productivity in China: evidence from spatial durbin model analysis. *J. Clean. Prod.* 288, 125624. doi:10.1016/j.jclepro.2020.125624

Wang, J., Wang, B., Dong, K., and Dong, X. (2022a). How does the digital economy improve high-quality energy development? The case of China. *Technol. Forecast. Soc. Change* 184, 121960. doi:10.1016/j.techfore.2022.121960

Wang, J., Wang, K., Dong, K., and Shahbaz, M. (2022b). How does the digital economy accelerate global energy justice? Mechanism discussion and empirical test. *Energy Econ.* 114, 106315. doi:10.1016/j.eneco.2022.106315

Wang, J., Wang, W., Ran, Q., Irfan, M., Ren, S., Yang, X., et al. (2022c). Analysis of the mechanism of the impact of internet development on green economic growth: evidence from 269 prefecture cities in China. *Environ. Sci. Pollut. Res.* 1, 9990–10004. doi:10.1007/s11356-021-16381-1

Williams, L. D. (2021). Concepts of digital economy and industry 4.0 in intelligent and information systems. *Int. J. Intelligent Netw.* 2, 122–129. doi:10.1016/j.ijin.2021.09.002

Wu, J., Guo, S., Huang, H., Liu, W., and Xiang, Y. (2018). Information and communications technologies for sustainable development goals: state-of-the-art, needs and perspectives. *IEEE Commun. Surv. Tutorials* 20 (3), 2389–2406. doi:10.1109/COMST.2018.2812301

Wu, L., Hitt, L., and Lou, B. (2020). Data analytics, innovation, and firm productivity. *Manag. Sci.* 66 (5), 2017–2039. doi:10.1287/mnsc.2018.3281

Xie, S., Li, T., and Cao, K. (2023). Analysis of the impact of carbon emission control on urban economic indicators based on the concept of green economy under sustainable development. *Sustainability* 15 (13), 10145. doi:10.3390/su151310145

Xue, Y., Tang, C., Wu, H., Liu, J., and Hao, Y. (2022). The emerging driving force of energy consumption in China: does digital economy development matter? *Energy Policy* 165, 112997. doi:10.1016/j.enpol.2022.112997

Zhang, W., Zhao, S., Wan, X., and Yao, Y. (2021). Study on the effect of digital economy on high-quality economic development in China. *PloS One* 16 (9), e0257365. doi:10.1371/journal.pone.0257365

Zhironkin, S., Gasanov, M., Barysheva, G., Gasanov, E., Zhironkina, O., and Kayachev, G. (2017). "Sustainable development vs. post-industrial transformation: possibilities for Russia," in E3S Web of Conferences (Les Ulis, France: EDP Sciences) 21. 04002. doi:10.1051/e3sconf/20172104002

Zhou, X., Tang, X., and Zhang, R. (2020). Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China. *Environ. Sci. Pollut. Res.* 27, 19915–19932. doi:10.1007/s11356-020-08383-2

Zhou, X., Zhou, D., and Wang, Q. (2018). How does information and communication technology affect China's energy intensity? A three-tier structural decomposition analysis. *Energy* 151, 748–759. doi:10.1016/j.energy.2018.03.115

Ziyadin, S., Streltsova, E., Borodin, A., Kiseleva, N., Yakovenko, I., and Baimukhanbetova, E. (2019). Assessment of investment attractiveness of projects on the basis of environmental factors. *Sustainability* 11 (9), 2544. doi:10.3390/su11092544

Ziyadullaev, N. S., Zoidov, K. K., and Usmanov, D. I. (2019). "Analysis and forecasting of the likely development of the digital economy in modern Russia," in *The cyber economy: opportunities and challenges for artificial intelligence in the digital workplace*, 203–214. doi:10.1007/978-3-030-31566-5_22

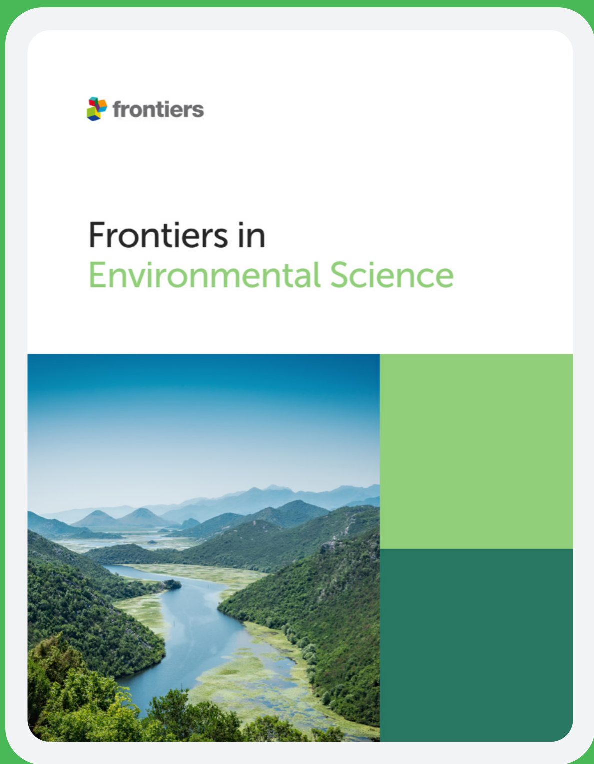
Frontiers in
Environmental Science

Explores the anthropogenic impact on our natural world

An innovative journal that advances knowledge of the natural world and its intersections with human society. It supports the formulation of policies that lead to a more inhabitable and sustainable world.

Discover the latest Research Topics

See more →



Frontiers

Avenue du Tribunal-Fédéral 34
1005 Lausanne, Switzerland
frontiersin.org

Contact us

+41 (0)21 510 17 00
frontiersin.org/about/contact