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RESEARCH ARTICLE

Does the diffusion of digital technologies promote corporate green innovation? Empirical evidence from China

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ABSTRACT

To explore how the diffusion of digital technologies shapes corporate green innovation, this study uses panel data from A-share listed companies between 2007 and 2021. The empirical findings reveal that digital diffusion significantly enhances the quality, quantity, and efficiency of green innovation. The effects are heterogeneous across firms: in high-tech enterprises, digital diffusion primarily improves innovation quality, while in non-high-tech enterprises, it mainly boosts innovation quantity. Moreover, the positive effects are stronger in heavily polluting industries than in cleaner ones. Mechanism analysis suggests that digital diffusion advances green innovation by strengthening internal corporate capabilities—particularly in production, automation, R&D, and management. These enhanced capabilities lead to more efficient and higher-quality green innovation outcomes. Interestingly, the study uncovers an inverted U-shaped relationship between digital diffusion and the quantity of green innovation, implying that while early-stage diffusion stimulates innovation, its marginal benefits may decline after a certain threshold. This finding offers valuable insights into the stages of technological adoption and their varying impacts. The research provides strategic implications for both policymakers and corporate leaders. For governments, it underscores the need to balance support for digital infrastructure with regulation to avoid diminishing returns. For firms, especially those in high-pollution or low-tech sectors, the study highlights the importance of timing and scale in digital transformation strategies.

Keywords: digital technology diffusion; green technology innovation; green innovation quality; green innovation quantity; green innovation efficiency

1. Introduction

Industrialization and urbanization have long driven rapid economic growth but also led to severe energy consumption and environmental degradation. As the world’s largest manufacturing country and carbon emitter, China faces significant pressure in balancing growth and sustainability. The government's pledges to achieve “carbon peak” by 2030 and “carbon neutrality” by 2060 underscore the urgency of accelerating

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green development. In this context, the emergence and diffusion of digital technologies—such as big data, artificial intelligence, and cloud computing—are offering new pathways to enhance environmental governance and promote green innovation.

Recent policy initiatives, including the "Overall Layout Plan for Building Digital China" (2023) and the "Opinions on Accelerating the Comprehensive Green Transition" (2024), highlight the strategic integration of digital and green transformations. The Third Plenary Session of the 20th Central Committee of the Communist Party of China emphasized using digital intelligence to upgrade traditional industries, suggesting that the diffusion of digital technologies is not only a technological shift but also a key enabler of systemic green transformation. Against this backdrop, this study aims to examine a central research question: How does the diffusion of digital technologies affect the quality, quantity, and efficiency of corporate green innovation in China?

While green technology innovation is widely recognized as a fundamental driver of sustainable development[1,2], its underlying mechanisms in the digital era remain underexplored. Digital technologies can support energy optimization and pollution control[3,4], reduce emissions[5], and foster a circular economy[6]. Real-world cases—such as Huawei's use of intelligent inspection robots, or Shaanxi Blower Group's digital "Energy Interconnection Island" project—show how digital solutions can deliver measurable energy savings and emissions reductions. Despite these advancements, China's manufacturing sector continues to face bottlenecks due to escalating energy constraints and environmental pressures. Thus, identifying the mechanisms through which digital technology diffusion drives green innovation has become both a theoretical imperative and a practical necessity. Although prior studies have demonstrated that digital transformation can enhance green performance by improving resource allocation, optimizing R&D, and facilitating external knowledge acquisition[7,8], a clear gap remains in understanding how internal corporate capabilities mediate this relationship.

Specifically, this study builds on emerging literature that highlights dynamic and absorptive capabilities as important mediators of innovation outcomes[9,2], but moves beyond broad conceptualizations to examine four core internal capabilities—production, automation, R&D, and management. These dimensions are treated as distinct yet interrelated operational drivers that digital diffusion can strengthen, which in turn affect the quality, quantity, and efficiency of green innovation. This framework not only expands the theoretical understanding of internal capabilities but also addresses the empirical blind spot in identifying the operational levers of green innovation under digitalization.

Furthermore, existing research predominantly assumes a linear relationship between digital diffusion and green innovation. However, this study proposes and empirically tests a nonlinear (inverted U-shaped) effect of digital diffusion on the quantity of green innovation, suggesting that while early-stage diffusion boosts innovation, excessive digitalization may lead to diminishing or even negative returns due to implementation costs or technological rigidity.

The main contributions of this study are threefold:

First, it clearly defines and empirically tests the impact of digital technology diffusion on the quality, quantity, and efficiency of green innovation, providing timely insights for firms navigating digital transformation.

Second, it advances the literature by identifying internal corporate capabilities as key mediators, thus offering a more granular explanation of how digital technologies enable green innovation at the firm level. Third, by introducing the inverted U-shaped relationship, this study opens a new perspective on the stages of digital diffusion, uncovering that its marginal effects on green innovation are not constant but vary across different stages of adoption. This finding has important implications for both policy timing and strategic planning.

2. Hypotheses

China's industrial sector has long followed an old development model characterized by high energy consumption, high pollution, and high growth, which has pushed the environment close to its capacity limits. The new development philosophy advocates for low consumption, low emissions, and high output as the objectives of China's high-quality development [10-12]. The transformation of enterprises from using high-pollution, inefficient traditional technologies to adopting low-pollution, high-efficiency green technologies is key to achieving these high-quality development goals. However, the uncertainty risks and high sunk costs inherent in green innovation impose stricter demands on a company's internal management capabilities. In response to these challenges, the diffusion of digital technologies helps shift from "industrial management models" to "digital management models", fundamentally reshaping and transforming information structures, management practices, operational mechanisms, and production processes by integrating digital technologies into existing corporate management frameworks[13,14]. Due to the non-competitive nature of data, companies can not only use their own data resources but also share data resources and technologies from other firms within the industry [15], all of which support green innovation. This data sharing, facilitated by digital technologies, significantly reduces the costs of searching, transmitting, and tracking information [16], thereby fostering innovation in business models, products, and services[17,18].

The accessibility, universality, standardization, and scalability of digital technologies effectively accelerate the speed of technological diffusion. Digital platforms enhance the matching efficiency of innovation supply and demand[19]. The application and diffusion of digital technologies can promote corporate green innovation through information dissemination and knowledge spillover. On one hand, concerning the external drivers of corporate green innovation, the diffusion of digital technologies helps reduce information asymmetry between companies and financial institutions, thereby enhancing trust from financial institutions toward green innovation firms and alleviating their financing constraints[20]. On the other hand, regarding the internal drivers of corporate green innovation, the diffusion of digital technologies helps diminish the ambiguity surrounding green innovation activities, motivating R&D personnel to deeply integrate digital technologies with green innovation efforts, breaking away from traditional technological dependencies and boosting the momentum for corporate green innovation [4]. Based on the above analysis, this study proposes the following hypothesis:

Hypothesis 1: The diffusion of digital technologies within firms can promote corporate green innovation.

In terms of the mechanisms by which the diffusion of digital technologies promotes corporate green innovation, this study aims to analyze it from the perspective of internal capabilities, proposing hypotheses across four aspects: production levels, automation levels, R&D levels, and management levels. Generally, the theoretical logic of Hypothesis 2 is shown in **Figure 1**.

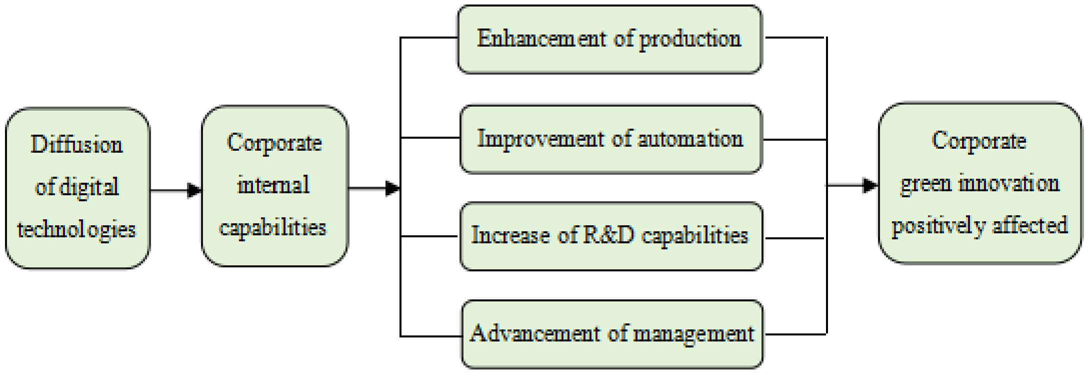

Figure 1. Mechanism of the impact of digital technology diffusion on corporate green innovation.

As illustrated in **Figure 1**, this study constructs a theoretical model to examine how the diffusion of digital technologies promotes corporate green innovation through the development of internal capabilities. The model is grounded in Dynamic Capability Theory and the Technology–Organization–Environment (TOE) framework, which together provide a comprehensive foundation for understanding the mechanisms by which firms respond to technological transformation in pursuit of sustainable development. Dynamic Capability Theory posits that firms must continually integrate, reconfigure, and renew internal and external resources to adapt to rapidly changing environments. In this context, the diffusion of digital technologies is conceptualized as a critical external driver that compels firms to build and enhance dynamic capabilities in order to maintain competitive advantage. The four internal capabilities depicted in the model—production, automation, R&D, and management—represent distinct yet interrelated domains through which firms mobilize their adaptive responses. Specifically, the enhancement of production capacity, measured through total factor productivity (TFP), reflects improvements in resource allocation, energy efficiency, and process optimization; the advancement of automation indicates the substitution of manual processes with intelligent systems and real-time operational controls; the increase in R&D capability captures firms' absorptive and innovative capacity in integrating digital knowledge into green technological development; and the improvement of management capability reflects digital empowerment in decision-making, coordination, and sustainability-oriented governance. Together, these capabilities function as mediating mechanisms that transform the potential of digital diffusion into tangible green innovation outcomes.

The TOE framework complements this analysis by contextualizing the diffusion process within the broader technological, organizational, and environmental landscape. From a technological perspective, the scalability and interoperability of digital technologies accelerate diffusion and knowledge spillover. From an organizational standpoint, firms' readiness in terms of infrastructure, human capital, and innovation culture affects their ability to leverage digital tools. Environmentally, external pressures such as regulatory mandates, industry competition, and stakeholder demands shape firms' strategic orientation toward green innovation. This framework underscores that the impact of digital technology diffusion on green innovation is not homogeneous, but rather contingent upon the interaction of internal capabilities and external conditions. By integrating dynamic capability theory with the TOE framework, the model provides a more nuanced and operationalizable explanation of how digital technology diffusion affects green innovation. It extends existing literature by identifying specific internal capability pathways through which technological change is internalized and translated into sustainable innovation performance. This theoretical structure not only enhances the explanatory depth of the model but also provides a robust basis for hypothesis development and empirical testing.

Production level serves as a comprehensive indicator that can be measured using TFP. Existing research has found that the development of the digital economy can significantly enhance the green TFP of the manufacturing sector[21]. The digital economy positively impacts green TFP through industrial structure upgrades and reducing distortions in factor markets[22]. The use of digital technologies such as artificial intelligence can improve both TFP and labor productivity[23]. Many studies have also highlighted the substitution effect of digital technologies on human factors[24], which contributes to improved production efficiency[25-28]. The increased density of robot usage has been shown to promote TFP growth[23,28]. Furthermore, the diffusion of digital technologies enhances production efficiency, optimizes the structure of production factors, and reduces carbon emission intensity[29]. The application and diffusion of digital technologies create data capital, which can empower other production factors and promote technological innovation within enterprises.[30,31]

The diffusion of digital technologies allows information and scientific knowledge to enter the production system in the form of data elements, which serve three main purposes: (1) driving technological and process innovation to enhance innovation capabilities, (2) reducing production costs and increasing efficiency, and (3) improving resource utilization and reducing pollution emissions. These factors facilitate the optimization and greening of the corporate product structure, balancing short-term and long-term interests while aligning economic, social, and ecological benefits for high-quality development. This process ultimately enhances corporate TFP, representing overall technological progress. The application and diffusion of digital technologies can significantly improve the marginal productivity of various production factors, thereby promoting TFP growth and fostering green innovation. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2a: The diffusion of digital technologies within firms can enhance their TFP, thereby promoting green technology innovation.

Research has shown that the integration of robots into production processes enhances automation levels, thereby improving productivity [32]. The application and diffusion of digital technologies introduce more advanced production techniques and equipment, driving enterprises to transition from traditional manual control to data-driven automated control. This shift not only reduces labor costs but also enables real-time monitoring and adjustment of production conditions, creating a highly continuous and stable supply chain that differs from the traditional industrial era, thereby boosting automation levels. The automation level of core enterprises can also lead to technological spillovers across the supply chain, significantly improving productivity for companies and industries alike. The data generated in automated production processes can be used for predictive purposes, enhancing the focus of innovation and reducing uncertainties and risks, which in turn promotes green innovation [33]. The adoption of industrial robots increases automation levels [34], and by saving labor costs and adjusting the human capital structure, it has a positive impact on green innovation. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2b: The diffusion of digital technologies within firms can enhance automation levels, thereby promoting green technology innovation.

The deep application of digital technologies across various industries can generate data elements, which not only serve as a new production factor to directly enhance corporate efficiency but also empower other production factors, such as technology, capital, and labor, to improve their efficiency [35-39], thereby boosting a company’s R&D capabilities. Digital technologies enable companies to achieve higher levels of production and data processing, resulting in knowledge spillovers that improve their absorption and learning capabilities, ultimately promoting green technology innovation [30]. The widespread use of digital technologies enhances companies' awareness, sensitivity, and acceptance of cutting-edge technologies, accelerating the formation of learning, R&D, and innovation-oriented production organizations, and strengthening corporate R&D capabilities. Higher R&D capacity facilitates the dissemination of green technologies, processes, equipment, and production models, ensuring efficient economic output while achieving low consumption and pollution, thus driving green innovation. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2c: The diffusion of digital technologies in enterprises can enhance their R&D capabilities, thereby promoting green technology innovation.

The diffusion of digital technologies can foster the development of new management concepts within leadership, enabling the recruitment of high-caliber talent with expertise in digital technologies and green innovation into management roles. The widespread application and diffusion of digital technologies allow management to access production data, including production processes, techniques, products, and user data on the sales side, in the form of data elements. This helps management departments to monitor production conditions in real time, accurately identify production flaws or product defects, and implement corresponding improvement and optimization measures. These actions enhance the stability and scientific rigor of the production process, improve product quality, and increase consumer utility. Therefore, the overall management capabilities of companies in the digital age have significantly improved compared to the era of industrial economics. The diffusion of digital technologies strengthens information exchange between various departments, between physical and virtual spaces, and between companies and consumers, facilitating remote supervision and rapid feedback for managers, enabling timely corrections and faster innovation. Strong management capabilities allow companies to better coordinate resources, improve the efficiency of factor allocation, and achieve environmental protection, low-carbon, and energy-saving goals at minimal cost, thus boosting corporate green innovation levels [40]. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2d: The diffusion of digital technologies within enterprises can enhance management capabilities, thereby promoting green technology innovation.

3. Research design, variable measurement, and data description

3.1. Model construction

To study the impact of digital technology diffusion on green innovation in enterprises, this study establishes the following baseline model:

$$GTI_{it} = \alpha_1 Digital_{it} + \alpha_2 Control_{it} + Stkcd_i + Year_t + \varepsilon_{it} \tag{1}$$

where the subscripts i and t represent the individual enterprise and the year, respectively. GTI_{it} denotes green technology innovation, reflected in the quality ($Invention_{it}$), quantity ($Utility_{it}$) and efficiency ($Efficiency_{it}$) of green innovation,. $Digital_{it}$ represents the level of digital technology diffusion in enterprises, symbolizing the degree of digital transformation. $Control_{it}$ denotes a set of control variables. ε_{it} is the residual term, assumed to be normally distributed. In the empirical analysis, dummy variables for both individuals ($Stkcd_i$) and years ($Year_t$) are controlled, using a two-way fixed effects model.

3.2. Variable definition and description

3.2.1. Enterprise digital transformation (*Digital1*)

Text content from annual reports of all A-share listed companies on the Shanghai and Shenzhen stock exchanges is collected and organized using Python web scraping tools. The text is then extracted using PDFBox (an open-source Java library) and serves as a data pool for subsequent feature term selection. For determining the feature terms related to enterprise digital transformation, a detailed discussion is conducted based on both academic and practical fields. In the academic domain, a series of classic literature on digital transformation is referenced to summarize and organize specific keywords related to digital transformation. Additionally, key policy documents and research reports, such as the "Action Plan for Digital Empowerment of Small and Medium-sized Enterprises," "Implementation Plan for Promoting 'Cloud Adoption and Data Empowerment' Actions to Cultivate New Economic Development," the "2020 Digital Transformation Trend Report," and recent "Government Work Reports," are used as a basis to further expand the digital transformation keyword library. Here is the list of feature terms related to enterprise digital transformation:

4K, 5G, 8K, ADAS, AIoT, Arrhythmia Detection, B2B, B2C, BI, C2B, C2C, Cyber-Physical System, DWS, Fintech, GPU, Hadoop, HCE, IoT, ITSM, LTE, MESH, NBIoT, NFC, NFC Payments, NFV, NLP, NVR, O2O, OTO, RPA, SAAS, SaaS, Spark Streaming, TRS, WEB, web, XR, VR/AR, Codec, Industrial Digitalization, Ultra-HD Video, Vehicle Networking, Storage Technology, Storage Systems, Big Data, Big Data Technology, Third-Party Payments, Computer Networks, E-commerce, Electronic Computers, Electronic Commerce, Electronic Information, E-Government, Ubiquitous Computing, Distributed Computing, Industrial Internet, Industrial Automation, Internet Finance, Internet Healthcare, Mixed Reality, Robotics, Infrastructure, Integration Systems, Computer Networks, Computer Network Engineering, Computer Industry, Computer Hardware, Encryption Technology, Interaction Technology, Interface Design, Financial Technology, Open Banking, Technology Industry, Spatial Data, Brain-Like Computing, Stream Computing, Encryption Keys, Pattern Recognition, In-Memory Computing, Web Crawling, Enterprise Digital Transformation, Blockchain, Blockchain Technology, Artificial Intelligence, Artificial Intelligence Technology, Facial Recognition, Cognitive Computing, Converged Architecture, Software Technology, Software Platforms, Software Systems, Contactless Payment, Business Intelligence, Authentication, Deep Learning, Neural Networks, Biometric Technology, Voiceprint Recognition, Data Warehouse, Data Analysis, Data Analysis Systems, Data Services, Data Management, Data Exchange, Data Visualization, Database Systems, Data Mining, Data Bus, CNC Machine Tools, Digital Industry, Digital Cities, Digitalization, Digital Currency, Digital Education, Digital Finance, Digital Economy, Digital Trade, Digital Culture, Digital Information, Digital Marketing, Algorithms, Communication Engineering, Graph Computing, Image Processing, Image Recognition, Mining, Online Shopping, Network Connectivity, Network Engineering, Network Management, Networking, Network Devices, Network Communication, Network Systems, Network Marketing, Online Transactions, Online Sales, Microbusiness, Text Mining, Drones, Autonomous Driving, Unmanned Retail, IoT, Internet of Things, Signal Processing, Informatization, Information Technology, Information Age, Cyber-Physical Systems, Virtual Reality, Mobile Connectivity, Mobile Internet, Mobile Robotics, Mobile Payments, Heterogeneous Data, Voice Recognition, Domain Controllers, Remote Management, Cloud Computing, Cloud Computing Technology, Online Education, Augmented Reality, Credit Reporting, Smart Cities, Smart Agriculture, Wearable Technology, Smart Grids, Smart Tools, Smart Technology, Smart Environmental Protection, Smart Robots, Smart Homes, Smart Traffic, Smart Customer Service, Smart Energy, Smart Data Analysis, Smart Algorithms, Smart Investment Advisors, Smart Networks, Smart Connected Vehicles, Smart Healthcare, Smart Marketing, Smart Equipment, Intelligent Manufacturing, Automation Control Devices, Autonomous Driving, Natural Language Processing, Computational Software, Smart Digitalization.

To refine the feature keyword library, keywords with negations such as "not," "none," or "no," as well as terms related to digital transformation not specifically associated with the company itself (including shareholders, customers, suppliers, and company executives), are excluded. The refined keyword library is then organized into five categories: Artificial Intelligence Technologies, Blockchain Technologies, Cloud

Computing Technologies, Big Data Technologies, and Digital Technology Applications. Using Python, the data extracted from the annual reports of listed companies is utilized to create a data pool. This pool is employed to search, match, and count the frequency of terms. The frequencies of key technological directions are then classified and aggregated to construct an indicator system for enterprise digital transformation. Given the typical "right-skewed" nature of such data, a logarithmic transformation is applied to obtain an overall indicator that characterizes enterprise digital transformation.

3.2.2. Corporate green innovation quality and quantity (*Invention & Utility*)

Considering that corporate green technology patents encompass core content of organizational knowledge in environmental technology and possess advantages in standardization, informatization, and scalability of data, this study adopts the patent indicator construction method referenced from [12] to measure corporate green technology innovation. Further, based on the International Patent Classification (IPC) codes in the "International Patent Classification Green List", the study identifies and matches green technology patents of listed companies. Green technology patents in this study are categorized into two types: green invention patents (*Invention)* and green utility patents (*Utility*). The former are used to measure the quality of corporate green innovation, while the latter are used to measure the quantity of corporate green innovation. To address the issue of right-skewed distribution in data concerning green patent application, the study adds 1 to the patent application numbers and takes the natural logarithm when constructing variables for green invention and utility patents.

3.2.3. Corporate green innovation efficiency (*Efficiency*)

This study follows the approach of Zhao [41] by using the ratio of green innovation output to innovation input to measure corporate green innovation efficiency (*Efficiency*). Specifically, innovation input is measured by corporate annual R&D expenditure, while green innovation output is by the natural logarithm of the total number of green invention, utility, and design patent applications (with 1 added to the total).

3.2.4. Mechanism variables

(i) TFP (*TFPfe*): TFP represents the efficiency with which a firm transforms multiple inputs—typically capital and labor—into outputs. Following Van Beveren [42], we estimate the TFP of Chinese listed companies using the control function method, applying a Cobb–Douglas production function to firm-level panel data. The estimation equation is specified as follows:

$$lnY_{it} = \beta_0 + \beta_k lnK_{it} + \beta_L lnL_{it} + \sum_m \delta_m year_m + \sum_n \gamma_n reg_n + \sum_k \mu_k ind_k + \varepsilon_{it}$$

Let Y_{it} represent the industrial added value of the enterprise i in year t, while K and L denote the enterprise's controlled assets and the scale of employees, respectively. Here, $year$, reg, and ind are dummy variables representing the year, region, and industry, respectively. And ε represents random disturbances and measurement errors that cannot be reflected in the production function. According to the definition of TFP, we have $lnTFP_{it} = \beta_0 + \varepsilon_{it}$, from which the absolute value of TFP can be obtained as follows:

$$TFP_{it} = lnY_{it} - \beta_k lnK_{it} - \beta_L lnL_{it}$$

In the actual TFP estimation process, industry, year, and regional factors are controlled.

This estimation method effectively controls for differences in industry characteristics, macroeconomic trends, and regional development, ensuring that the resulting TFPfe reflects firm-level productivity net of systematic variations.

(ii) Industrial robot penetration rate (*Robot*): This study uses the industrial robot penetration rate to measure the level of automation within enterprises. Acemoglu & Restrepo[42] used a general equilibrium model to examine the impact of robot adoption on regional labor markets in the United States and developed an indicator to measure robot penetration at the regional level based on the model's conclusions, similar to the "Bartik instrument" approach [43,44] . Building on this method and referencing the research of Du & Lin [45] , an enterprise-level robot penetration indicator is constructed as follows:

First, the industrial robot penetration rate indicator at the industry level is calculated, denoted as PR_{it}^{CH}.

$$PR_{it}^{CH} = \frac{MR_{it}^{CH}}{L_{iT}^{CH}}$$

Here, MR_{it}^{CH} represents the stock of industrial robots in the Chinese industry i in year t, L_{it}^{CH} indicates the employment in the Chinese industry i in the base year t, and PR_{it}^{CH} shows the industrial robot penetration rate of the Chinese industry i in year t.

The industrial robot penetration rate indicator at the enterprise level is constructed as follows:

$$CHFexposure\ to\ robots_{jit} = \frac{PWP_{jit=T}}{ManuPWP_{t=T}} * \frac{MR_{it}^{CH}}{L_{iT}^{CH}}$$

This indicator measures the industrial robot penetration rate of enterprise j in industry i in a given year t. $\frac{PWP_{jit=T}}{ManuPWP_{t=T}}$ refers to the ratio of the proportion of production department employees in enterprise *j*, industry i in year T (base year) to the median proportion of production department employees across all manufacturing enterprises in the same year. This ratio is used as a weight to decompose the industry-level industrial robot penetration rate to the enterprise level, allowing the examination of industrial robot penetration at the enterprise level. For enterprise *j*, changes in the robot penetration rate primarily reflect changes in the technological characteristics of the domestic industry, independent of the unique characteristics of the enterprise itself.

(iii) R&D input (*RD*): This study uses the logarithmic value of corporate annual R&D expenditure to measure the level of corporate R&D.

While R&D expenditure is widely used as a proxy for innovation input, it may not fully capture the multidimensional nature of corporate innovation activities. Innovation inputs such as capital investment in green infrastructure, human resource development, and inter-organizational collaborations also play critical roles, especially in the context of green innovation. However, due to data availability constraints, particularly at the firm level, these elements are often difficult to quantify consistently across large samples. Acknowledging these limitations, this study interprets R&D input as a key—albeit partial—component of innovation efforts, and complements it with output-based indicators such as green patent applications to provide a more comprehensive assessment of green innovation performance.

(iv) Executives' green awareness (*Gmanage*): In traditional management, the focus is primarily on financial drivers, reflected in management expenses and cost inputs. However, new management emphasizes innovation in management structures, which largely depends on the transformation of managerial concepts, reflecting the overall management capability of the enterprise. In this study, executives with green awareness are defined as managers possessing modern management skills and higher management capabilities. The proportion of executives with green awareness among the board and senior management is selected as a variable to measure corporate management capability. A text analysis method is used to assess executive awareness, selecting a series of keywords from three dimensions: green competitive advantage awareness, corporate social responsibility awareness, and perception of external environmental pressure. The frequency of these terms in the annual reports of listed companies is counted, and the natural logarithm of this frequency plus one is taken to obtain the green awareness indicator for executives.

(v) Control variables: This study further introduces firm-level and macroeconomic control variables. Specifically, they include: firm size (*Size*), measured by the natural logarithm of the firm's total assets for the year; leverage ratio (*Lev*), derived from dividing year-end total liabilities by year-end total assets; cash flow ratio (*Cashflow*), represented by net cash flow from operating activities divided by total assets; accounts receivable ratio (*REC*), obtained by dividing net accounts receivable by total assets; inventory ratio (*INV*), expressed as net inventory divided by total assets; fixed asset ratio (*Fixed*), derived from net fixed assets divided by total assets; board size (*Board*), measured by the natural logarithm of the number of board members; proportion of independent directors (*Indep*), calculated by dividing the number of independent directors by the total number of directors; book-to-market ratio (*BM*), represented by book value divided by total market value; price-to-book ratio (*PB*), expressed as share price divided by net assets per share; Tobin's Q (TobinQ), formulated as (market value of floating shares + number of non-floating shares × net assets per share + book value of liabilities) divided by total assets; management shareholding ratio (*Mshare*), determined by dividing the number of shares held by executives by total share capital; operating expenses ratio (*Ofee*), represented by (management expenses + selling expenses) divided by operating revenue; management expenses ratio (*Mfee*), obtained by dividing management expenses by operating revenue; and large shareholder fund appropriation (*Occupy*), calculated as net other receivables divided by total assets.

3.3. Data description

The firm-level data used in this study are primarily derived from the annual reports of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges. These reports provide standardized and regulated disclosures covering financial indicators, innovation inputs, governance characteristics, and managerial narratives. However, we acknowledge that such data sources are not without limitations. Specifically, there may be selective disclosure practices or strategic exaggeration of digital transformation efforts, driven by reputational concerns or policy pressures.

To address these potential issues, we adopt a multi-pronged strategy. First, the key variables used in our analysis—such as R&D expenditure and green patent applications—are based on quantifiable data that are subject to financial auditing and regulatory review, thus limiting manipulation. Second, for indicators involving qualitative assessment (e.g., executive awareness of green innovation), we apply longitudinal textual analysis techniques that reduce the influence of isolated or superficial statements. Third, we perform robustness tests and exclude firms with abnormal reporting patterns or incomplete data.

These steps help mitigate the risks of misreporting and ensure the validity of our findings based on publicly disclosed data:

Table 1. Descriptive statistics.

Variables	Variable symbol	Sample	Mean	Median	Standard deviation	Minimum	Maximum
Explanatory variable	*Digital1*	30,741	1.387	1.099	1.424	0	6.301
Dependent variables	*Invention*	30,740	0.312	0	0.727	0	6.744
	Utility	30,740	0.269	0	0.640	0	6.080
	Efficiency	30,741	0.0260	0	0.0470	0	0.406
Mechanism	*TFPfe*	26,048	11.38	11.23	1.327	6.208	15.79

Variables	Variable symbol	Sample	Mean	Median	Standard deviation	Minimum	Maximum
variables	*Robot*	27,759	6.639	6.496	3.964	0.00200	15.49
	RD	26,948	17.66	17.68	1.611	5.094	25.02
	Gmanage	28,105	0.800	0.693	0.890	0	6.033
Control variables	*Size*	29,183	22.07	21.87	1.273	19.32	26.45
	Lev	29,183	0.397	0.386	0.200	0.0270	0.908
	Cashflow	29,183	0.0480	0.0470	0.0670	-0.223	0.283
	Rec	29,135	0.134	0.115	0.101	0	0.506
	Inv	28,979	0.133	0.112	0.103	0	0.772
	Fixed	29,183	0.203	0.175	0.145	0.00200	0.769
	Board	29,147	2.120	2.197	0.196	1.609	2.708
	Indep	29,147	37.59	36.36	5.361	25	60
	Bm	28,731	0.606	0.603	0.239	0.0640	1.246
	Pb	28,731	3.787	2.893	3.143	0.413	44.50
	Tobinq	28,731	2.066	1.658	1.308	0.802	15.61
	Mshare	28,441	16.54	3.698	20.92	0	70.60
	Ofee	29,007	0.167	0.131	0.128	0.0110	0.791
	Mfee	29,183	0.0890	0.0730	0.0670	0.00700	0.641
	Occupy	29,169	0.0140	0.00700	0.0210	0	0.212

Table 1. (*Continued*)

4. Empirical results and analysis

4.1. Trend analysis

This study first conducts linear and nonlinear fittings to analyze the trend of changes in green innovation quality, quantity, and efficiency as they correlate with the extent of digital technology diffusion in enterprises, aiming to explore the causal configuration between green innovation and digital technology diffusion. **Figures 2, 3, and4** present the linear (solid black line) and nonlinear (dashed blue line) effects of digital technology diffusion on green innovation. From **Figures 2 and 4**, it can be seen that digital technology diffusion (*Digital1*) has a clear positive impact on both the quality of green innovation (*Invention*) and the efficiency of green innovation (*Efficiency*). However, as shown in **Figure 3**, while digital technology diffusion (*Digital1*) promotes green innovation quantity (*Utility*) in the linear model, it exhibits an overall inverted U-shaped influence in the nonlinear model. This suggests that the effect of digital technology diffusion on green innovation quantity varies at different stages of digital transformation, with the turning point determined by the degree of digital transformation within the enterprise.

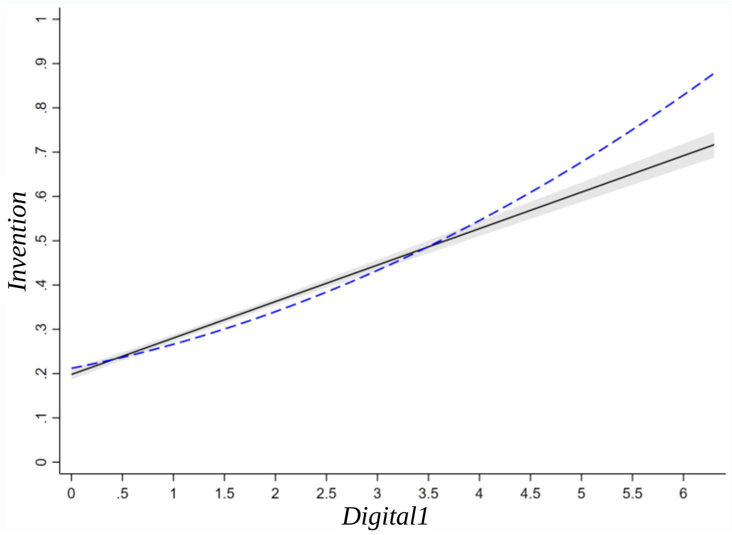

Figure 2. Corporate digital technology diffusion and green innovation quality.

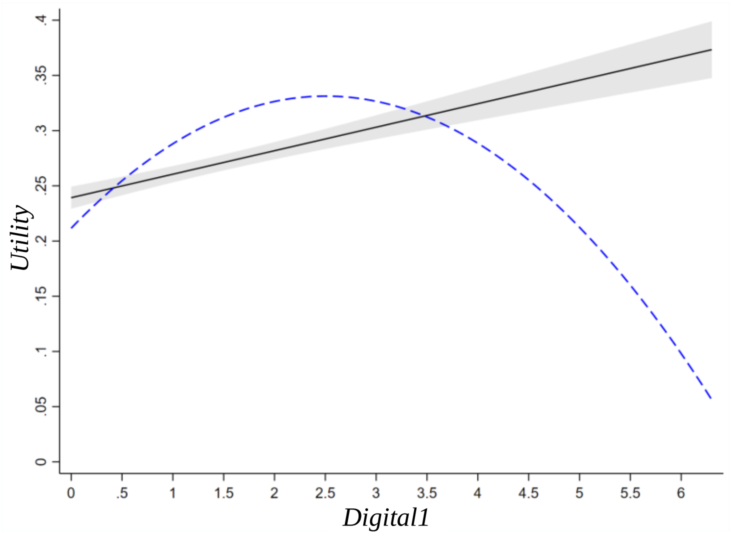

Figure 3. Corporate digital technology diffusion and green innovation quantity.

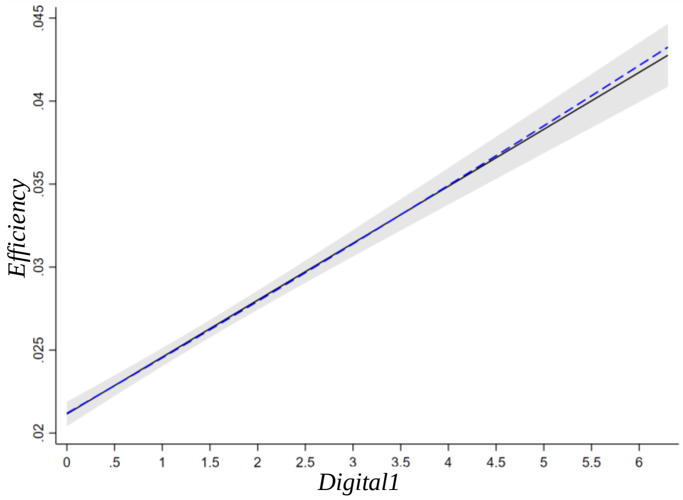

Figure 4. Corporate digital technology diffusion and green innovation efficiency.

4.2. Baseline Regression Analysis

Table 2 reports the baseline regression results for how digital technology diffusion drives green innovation in enterprises. Given that a nonlinear model is used in the trend analysis to fit the causal relationship between variables, *Digital1^2* is also included as one of the key explanatory variables in the baseline regression analysis. Columns (2) to (4) present the regression analysis results of digital technology diffusion on green innovation quality (*Invention*), columns (5) to (7) show the results for its effect on green innovation quantity (*Utility*), and columns (8) to (10) cover the impact on green innovation efficiency *(Efficiency*). Columns (2), (3), (5), (6), (8), and (9) present simplified regression results without control variables and controlling effects, while columns (4), (7), and (10) provide the baseline regression results with control variables and bidirectional controlling effects included. For robustness, subsequent analysis focuses on the empirical results from columns (4), (7), and (10). The data show that the estimated coefficients for digital technology diffusion (*Digital1*) are all positively significant at the 1% level, indicating that digital technology diffusion has a significant positive driving effect on green innovation quality, quantity, and efficiency. The higher the degree of digital technology diffusion in enterprises, the more conducive it is to achieving high-quality, efficient green technology innovation. Thus, Hypothesis 1 is confirmed. Moreover, the effect of digital technology diffusion is strongest in improving green innovation quality (0.046), followed by green innovation quantity (0.017), and weakest for green innovation efficiency (0.001).

Table 2. Baseline regression analysis results.

Variables	**Green innovation quality** ***Invention***			**Green innovation quantity** ***Utility***			**Green innovation efficiency** ***Efficiency***		
Digital1	0.082***		0.046***	0.021***		0.017***	0.003***		0.001***
	(0.003)		(0.004)	(0.003)		(0.004)	(0.000)		(0.000)
Digital1^2		0.020***			0.002***			0.001***	
		(0.001)			(0.001)			(0.000)	
Size			0.121***			0.079***			0.004***
			(0.007)			(0.007)			(0.000)
Lev			-0.058			-0.015			-0.008***
			(0.033)			(0.031)			(0.002)
Cashflow			-0.064			-0.005			0.001
			(0.053)			(0.050)			(0.004)
Rec			0.187**			0.135*			0.035***
			(0.064)			(0.060)			(0.004)
Inv			-0.050			-0.076			0.003
			(0.060)			(0.056)			(0.004)
Fixed			0.119**			0.094*			0.006*
			(0.044)			(0.041)			(0.003)
Board			-0.081*			-0.061*			-0.001
			(0.032)			(0.030)			(0.002)
Indep			-0.001			-0.001			-0.000
			(0.001)			(0.001)			(0.000)
Bm			0.043			0.040			0.006**
			(0.027)			(0.025)			(0.002)

Variables	Green innovation quality *Invention*			Green innovation quantity *Utility*			Green innovation efficiency *Efficiency*		
Pb			-0.004			-0.005**			-0.000
			(0.002)			(0.002)			(0.000)
Tobinq			0.014**			0.015**			0.000
			(0.005)			(0.005)			(0.000)
Mshare			0.000			-0.000			0.000
			(0.000)			(0.000)			(0.000)
Ofee			-0.108			-0.064			0.007
			(0.078)			(0.074)			(0.005)
Mfee			-0.114			0.009			0.015
			(0.116)			(0.109)			(0.008)
Occupy			-0.341			0.207			-0.007
			(0.179)			(0.169)			(0.012)
Constant	0.198***	0.234***	-2.232***	0.239***	0.259***	-1.372***	0.021***	0.023***	-0.070***
	(0.006)	(0.005)	(0.177)	(0.005)	(0.004)	(0.166)	(0.000)	(0.000)	(0.012)
Individual	No	No	Yes	No	No	Yes	No	No	Yes
Time	No	No	Yes	No	No	Yes	No	No	Yes
Sample	30,740	30,740	27,585	30,740	30,740	27,585	30,740	30,740	27,585

Table 2. (*Continued*)

Note: ****, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses. The same applies to the tables below.*

4.3. Robustness checks

To ensure the reliability of the research findings, a series of robustness checks are conducted. At the level of the explanatory variables, first, the diffusion of digital technology in enterprises requires a certain number of years, and the impact of new technology on productivity may exhibit a lag effect. Therefore, the digital technology diffusion variable is lagged by one period and reintroduced into the regression analysis for estimation. Second, the digital technology diffusion variable *Digital1* is constructed based on the approach of Zhuo & Chen[40] , Guo et al.[46], which characterizes the degree of transformation from the perspective of word frequency statistics related to “enterprise digital transformation” in annual reports. The corresponding keyword frequency measures from the annual reports published by enterprises are used as a proxy indicator for the degree of digital transformation. This study further constructs the digital technology diffusion variable *Digital2* to replace *Digital1* in the regression analysis for robustness checks. Specifically, relevant national policy statements related to the digital economy are selected to establish a comprehensive digital vocabulary. Using machine learning-based text analysis, a more comprehensive indicator reflecting the digital transformation of China’s listed enterprises is constructed. Considering the differences in the length of the Management Discussion and Analysis (MD&A) text in annual reports, after extracting the frequency of various keywords from each listed company’s annual report, the total frequency of digital-related vocabulary is divided by the length of the MD&A segments to measure the micro-level degree of digital transformation within enterprises. In terms of the dependent variables, both green innovation quality (*Invention*) and green innovation quantity (*Utility*) are constructed using the logarithm of the number of green patent applications plus one. To test the robustness of the research results, this study further uses the number of green invention patents and the number of green utility patents to construct green innovation quality (*Ninvention*) and green innovation quantity (*Nutility*), respectively. Given that the explained variables are discrete numerical variables, the general linear regression model is replaced with a nonlinear Poisson regression model to examine the driving effect of digital technology diffusion on green innovation.

Table 3 presents the results of the robustness checks. Analysis of rows (2) and (3) shows that even after lagging and substituting the explanatory variables, the estimated coefficient of enterprise digital technology diffusion remains significantly positive, indicating that enterprise digital technology diffusion continues to have a significant positive driving effect on the quality, quantity and efficiency of green innovation. Furthermore, analysis of columns (4) and (7) reveals that after changing the explained variables and the regression model, the estimated coefficient of enterprise digital technology diffusion *(Digital1*) remains significantly positive at the 1% level. This suggests that the conclusion regarding the positive impact of enterprise digital technology diffusion is robust on improving the quality and quantity of green innovation. Thus, Hypothesis 1 is again confirmed.

Table 3. Robustness check results.

Variables	**Green innovation quality**			**Green innovation quantity**			**Green innovation efficiency**	
	Invention		***Ninvention***	***Utility***		***Nutility***	***Efficiency***	
L.Digital1	0.035***			0.015***			0.001***	
	(0.005)			(0.004)			(0.000)	
Digital2		0.045***			0.013**			0.001**
		(0.006)			(0.005)			(0.000)
Digital1			0.140***			0.057***		
			(0.007)			(0.009)		
Constant	-1.280***	-1.411***		-0.801***	-1.803***		-0.037*	-0.047***
	(0.227)	(0.204)		(0.215)	(0.123)		(0.015)	(0.014)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sample	23,122	26,900	14,666	23,122	26,900	13,558	23,122	26,900

4.4. Endogeneity discussion

To address the endogeneity issue caused by omitted variables, this study has already included a series of control variables in the baseline regression analysis. However, it may still face endogeneity challenges. Enterprises with high levels of green technology innovation often possess stronger innovation capabilities, as they have superior and stable conditions for innovation. Consequently, they have greater motivation and intention to diffuse digital technologies. This reverse causality may lead to endogeneity issues in the baseline regression results. To further mitigate the endogeneity problem in the model, this study follows the approach of Luo et al.[47]and uses the total number of post offices per million people and the number of telephones per million people in various cities across the country in 1984 as instrumental variables for enterprise digital technology diffusion. Since this study utilizes panel data from listed companies, the two types of variables mentioned above are multiplied by the internet penetration rates of enterprises in various provinces and cities across the country from 2007 to 2021, resulting in *IVpost* and *IVphone*. These are used as instrumental variables in the two-stage least squares regression. On one hand, the total number of post offices and telephones in 1984 reflects the state of communication infrastructure in different regions during the early stages of China's reform and opening-up, while the internet penetration rate indicates the level of information technology development among enterprises in each province and city. These provide external support for enterprise digital technology diffusion, satisfying the relevance requirement. On the other hand, the 1984 postal and telecommunication data are historical and reflect local communication infrastructure and information technology levels, without directly affecting enterprise green technology innovation, thus meeting the exogeneity requirement.

Tables 4 and 5 present the results of the two-stage least squares regression using *IVpost* and *IVphone* as instrumental variables. Analysis of the results from both tables indicates that the Kleibergen-Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis of insufficient identification of the instrumental variables. The Cragg-Donald Wald F statistic also rejects the null hypothesis of weak instruments, confirming the reasonableness of the selected instrumental variables. Column (2) in both tables shows the first-stage regression results, where the coefficient of enterprise digital technology diffusion is significantly positive at the 1% level in relation to the instrumental variables. Columns (3) to (5) display the second-stage regression results; after addressing potential endogeneity issues, the coefficient for enterprise digital technology diffusion remains significantly positive. This indicates that enterprise digital technology diffusion has a robust driving effect on green innovation, significantly enhancing its quality, quantity, and efficiency, thus supporting the main conclusions of this study.

Table 4. Endogeneity test results (I).

Variables	*IV1 Digital1*	*IV2 Invention*	*IV2 Utility*	*IV2 Efficiency*
IVpost	0.034***			
	(0.001)			
Digital1		0.179***	0.101***	0.005***
		(0.022)	(0.020)	(0.001)
Control variables	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes
Time	No	No	No	No
Anderson canon corr LM value	245.511***			
Kleibergen-Paap rk LM value	268.305***			
Cragg-Donald Wald F value	247.563			
Sample	27,585	27,585	27,585	27,585

Table 5. Endogeneity test results (II).

Variables	*IV1 Digital1*	*IV2 Invention*	*IV2 Utility*	*IV2 Efficiency*
IVphone	2.659***			
	(0.112)			
Digital1		0.204***	0.116***	0.004***
		(0.027)	(0.025)	(0.001)
Control variables	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes
Time	No	No	No	No

Variables	*IV1 Digital1*	*IV2 Invention*	*IV2 Utility*	*IV2 Efficiency*
Anderson canon corr LM value		174.063***		
Kleibergen-Paap rk LM value		143.218***		
Cragg-Donald Wald F value		175.060		
Sample	27,585	27,585	27,585	27,585

Table 5. (*Continued*)

4.5. Heterogeneity analysis

4.5.1. Heterogeneity test of regions

This study references the research method of Zhou et al.[48] and divides the 30 sample provinces into three groups based on their geographical location: Eastern, Central, and Western regions (the Eastern group includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; the Central group includes Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, Jiangxi; the Western group includes Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang). The enterprises are then grouped regionally based on the geographical location of the listed companies, and regression analysis is conducted for each group. Additionally, the Fisher combination test is employed to examine differences between groups. Columns (2) to (4) in **Tables 6, 7**, and **8** provide the results of the regional heterogeneity analysis regarding the impact of enterprise digital technology diffusion on green innovation. Overall, it can be seen that enterprise digital technology diffusion has a significant positive effect on the quality, quantity, and efficiency of green innovation in enterprises located in the Eastern, Central, and Western regions. However, in more specific terms, the positive driving effect of digital technology diffusion on green innovation is strongest for enterprises in the Central region, while the effect is weaker for those in the Eastern and Western regions. The reasons for this can be summarized as follows: first, the Central region lags behind the Eastern region in terms of economic development level, utilization of advanced technology, rational allocation of labor resources, and innovation environment. This creates significant room for innovation, making the momentum for digital technology diffusion to promote green innovation strong. Additionally, the proximity of the Central region to the Eastern region facilitates the spread of innovative technologies and development models from the East, thereby promoting high-quality and efficient development in the Central region. Second, the driving effect of digital technology diffusion on green innovation in the Eastern region is relatively weak. This may be due to the concentration of new manufacturing and service industries in the East, leading to a developed economy and advanced technology. This enables a more rational allocation of production factors, accelerates the elimination of outdated capacity, promotes a favorable industrial structure, and improves TFP. The existing development model in the Eastern region already supports high-quality growth for enterprises, resulting in limited innovation space and development levels close to the upper limit, making the impact of digital technology diffusion on green innovation somewhat lackluster. Finally, the development of the Western region is primarily based on traditional industries, with emerging industries still in their infancy. The investment in digital technology R&D is insufficient, and green innovation requires significant technological and human resources to create the necessary environment and conditions. As a result, the driving effect of digital technology diffusion is relatively low on green innovation in this region.

4.5.2. Heterogeneity test of technological development levels

The differences in the level of technological development among enterprises are reflected in aspects such as the reserve of innovative talent, the use of innovative technologies, and the dissemination of innovative models. These factors significantly influence the degree of technology diffusion and innovation capacity, directly affecting the level of digital technology diffusion in enterprises and indirectly impacting the upper limit of corporate green innovation. This study focuses on high-tech enterprises among all A-share listed companies in China. By referencing the Directory of Strategic Emerging Industries, Classification of Strategic Emerging Industries (2012) (Trial), and relevant documents from the Organization for Economic Cooperation and Development (OECD, which defines the high-tech industries as the following five sectors: computer-related industries, electronics industry, information technology industry, biopharmaceutical industry, and telecommunications industry), the high-tech listed company industry codes are determined in accordance with the Guidelines for the Industry Classification of Listed Companies (2012 Revision). The enterprises are then matched to the panel data and categorized into high-tech and non-high-tech groups. Regression tests and heterogeneity analyses are then conducted based on this classification, and Fisher's combination test is used for inter-group difference testing. The results are shown in columns (5) to (6) of **Tables 6, 7, and 8**. From an overall perspective, both high-tech and non-high-tech enterprises can positively promote the quality, quantity, and efficiency of green innovation through the diffusion of digital technology, with statistically significant coefficients. However, in terms of the magnitude of the coefficients, the impact of digital technology diffusion on the efficiency of green innovation seems to be similar for both high-tech and non-high-tech enterprises. Specifically, the positive effect of digital technology diffusion on the quality of green innovation in high-tech enterprises is significantly greater than that in non-high-tech enterprises. However, the positive impact of digital technology diffusion on the quantity of green innovation in non-high-tech enterprises is higher than in high-tech enterprises. The reason for this may be that the quality of green innovation is determined by the number of invention patents. High-tech enterprises generally possess better innovation capabilities, environments, and conditions compared to non-high-tech enterprises, allowing them to engage in green innovation aimed at inventing new things. This fundamentally involves creating entirely new elements that can influence production activities. In contrast, non-high-tech enterprises have weaker overall innovation capabilities and tend to focus on improving existing tools based on their actual production conditions. Their green innovation efforts primarily aim to enhance and optimize traditional elements, bringing their production levels closer to theoretical limits.

4.5.3. Heterogeneity test of pollution levels

Heavy pollution enterprises, characterized by extensive development, are key responsibility entities in current environmental governance. This study posits that the differences in endowment characteristics between heavy pollution and non-heavy pollution enterprises can influence the driving effects of digital technology diffusion on green innovation. Therefore, based on the Classified Management Directory of Listed Companies in the Environmental Protection Verification Industries published by the Ministry of Ecology and Environment, the enterprise samples are divided into heavy pollution and non-heavy pollution categories. Group regression tests are conducted for heterogeneity identification, and Fisher's combination test is used for examining inter-group difference, as shown in columns (7) to (8) of **Tables 6, 7, and 8**. Overall, both heavy pollution and non-heavy pollution enterprises show that digital technology diffusion significantly drives green innovation. The difference lies in the estimated coefficients of digital technology diffusion and the values from Fisher's combination test; the driving effect of digital technology diffusion on green innovation appears to be stronger for heavy pollution enterprises compared to non-heavy pollution enterprises, particularly in terms of green innovation quality and quantity. This may be due to the fact under a series of regulatory measures imposed by relevant authorities, heavy pollution enterprises are compelled to innovate in green technology. Additionally, as the green finance system gradually improves, heavy pollution enterprises face greater financing challenges than their non-polluting counterparts. This regulatory pressure enhances their motivation for green technology innovation. Furthermore, heavy pollution enterprises experience substantial innovation space, and the effects of their innovations can be immediate, creating a positive feedback mechanism. Consequently, the driving effect of digital technology diffusion on green innovation in these enterprises is particularly pronounced. Thus, Hypothesis 1 remains confirmed.

Table 6. Heterogeneity test (I).

Variables	***Group1 Invention***			***Group2 Invention***		***Group3 Invention***	
	Eastern region	**Western region**	**Central region**	**High-tech**	**Non-high-tech**	**Heavy pollution**	**Non-heavy pollution**
Digital1	0.045^{***}	0.028^{**}	0.079^{***}	0.053^{***}	0.028^{***}	0.037^{***}	0.026^{***}
	(0.005)	(0.011)	(0.011)	(0.005)	(0.006)	(0.010)	(0.005)
Constant	-2.479^{***}	-3.171^{***}	-0.310	-2.846^{***}	-1.515^{***}	-1.401^{**}	-1.395^{***}
	(0.213)	(0.440)	(0.488)	(0.225)	(0.298)	(0.448)	(0.235)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fisher's test	0.005^{*}	0.022^{*}	-0.037^{*}	-0.026^{*}		-0.001^{*}	
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	No	No	No	No	No	Yes	Yes
Sample	20,043	4,265	3,277	19,059	8,526	6,296	21,289

Table 7. Heterogeneity test (II).

Variables	***Group1 Utility***			***Group2 Utility***		***Group3 Utility***	
	Eastern region	**Western region**	**Central region**	**High-tech**	**Non-high-tech**	**Heavy pollution**	**Non-heavy pollution**
Digital1	0.017^{***}	0.023^{**}	0.045^{***}	0.017^{***}	0.031^{***}	0.051^{***}	0.037^{***}
	(0.004)	(0.009)	(0.011)	(0.005)	(0.006)	(0.009)	(0.004)
Constant	-1.348^{***}	0.121	-1.651^{***}	-1.665^{***}	0.390^{*}	-0.042	0.417^{***}
	(0.201)	(0.219)	(0.466)	(0.207)	(0.156)	(0.203)	(0.105)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fisher's test	0.000^{*}	0.020^{*}	-0.031^{*}	-0.007^{*}		-0.023^{*}	
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	No	No	No	No	No	No	No
Sample	20,043	4,265	3,277	19,059	8,526	6,296	21,289

Table 8. Heterogeneity test (III).

Variables	***Group1 Efficiency***			***Group2 Efficiency***		***Group3 Efficiency***	
	Eastern region	**Western region**	**Central region**	**High-tech**	**Non-high-tech**	**Heavy pollution**	**Non-heavy pollution**
Digital1	0.002^{***}	0.002^{**}	0.003^{***}	0.002^{***}	0.002^{***}	0.003^{***}	0.002^{***}
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Constant	-0.076^{***}	0.012	-0.016	-0.091^{***}	0.015	0.014	0.016^{*}
	(0.015)	(0.016)	(0.034)	(0.015)	(0.011)	(0.015)	(0.008)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Variables	Group1 Efficiency			Group2 Efficiency		Group3 Efficiency	
	Eastern region	Western region	Central region	High-tech	Non-high-tech	Heavy pollution	Non-heavy pollution
variables							
Fisher's test	0.000	0.001	-0.002	0.000		0.000	
Individual	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	No	No	No	No	No	No	No
Sample	20,043	4,265	3,277	19,059	8,526	6,296	21,289

Table 8. (*Continued*)

4.6. Mechanism analysis

Based on the previous theoretical analysis, this section focuses on analyzing the internal capability building of enterprises from four aspects: production level, automation level, R&D level, and management level, to explore the mechanism by which digital technology diffusion affects green innovation. In the empirical research design, production level (*TFPfe*) is measured using TFP under fixed effects (FE) estimation; automation level (*Robot*) is assessed through the penetration rate of industrial robots; R&D level (*RD*) is measured by the amount of corporate R&D investment; and management level (*Gmanage*) is gauged by the proportion of senior executives with green awareness. **Tables 9, 10, and 11** report the internal capability building of enterprises and the specific mechanisms by which digital technology diffusion influences green innovation. As shown in **Table 9**, the estimated coefficients of digital technology diffusion (*Digital1*) are all positively significant at the 1% level, indicating that digital technology diffusion has a significant positive driving effect on production level, automation level, R&D level, and management level within enterprises. This demonstrates that digital technology diffusion strengthens the internal capability building of enterprises. Therefore, Hypotheses 2a, 2b, 2c, and 2d are all validated.

Table 9. Test of internal capacity building mechanism in firms.

Variables	Production level *TFPfe*	Automation level *Robot*	R&D level *RD*	Management level *Gmanage*
Digital1	0.012***	0.266***	0.035***	0.028***
	(0.002)	(0.038)	(0.006)	(0.006)
Constant	-6.483***	-12.641***	-2.022***	-0.084
	(0.111)	(1.684)	(0.314)	(0.281)
Control variables	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes
Time	Yes	No	Yes	No
Sample	23,779	24,806	24,093	25,450

Tables 10 and 11 specifically illustrate how enterprises enhance their internal capability building to promote green innovation. **Table 10** primarily reveals the mechanisms through which firms strengthen their production and automation levels to drive green innovation. Columns (2) to (4) show that digital technology diffusion significantly enhances TFP, which in turn drives improvements in the quality, quantity, and efficiency of green innovation. Columns (5) and (6) indicate that digital technology diffusion boosts the adoption of industrial robots, increasing the automation level within firms, thereby enhancing the quality and quantity of green innovation. However, column (7) reveals that an increase in automation level may lead to a decline in green innovation efficiency. This could be due to the close relationship between automation and industrial production, where highly automated production modes generate higher output and economic returns, potentially crowding out green innovation outputs. As a result, the share of green innovation in total output decreases, leading to reduced efficiency in green innovation. **Table 11** primarily illustrates the mechanisms by which enterprises promote green innovation by enhancing their R&D and management levels. Columns (2) to (4) demonstrate that digital technology diffusion significantly improves R&D levels, which in turn drives substantial increases in the quality, quantity, and efficiency of green innovation. Columns (5) to (7) show that digital technology diffusion enhances management levels, which positively influences green innovation. Moreover, the coefficients for digital technology diffusion indicate that the effect of management level on improving the quality, quantity, and efficiency of green innovation is generally greater than that of R&D level. From the combined analysis of **Tables 10 and 11**, it is evident that production and management levels have the largest impact on the quality of green innovation, with marginal effects of 0.043 and 0.042, respectively. Management level also has the greatest influence on the quantity of green innovation, with a marginal effect of 0.057. The impact of internal capability building on green innovation efficiency is generally smaller, with management level showing the highest marginal effect at 0.007. Therefore, digital technology diffusion primarily promotes green innovation by strengthening production and management levels.

Table 10. Test of corporate green innovation mechanism (I).

Variable	*Invention*	*Utility*	*Efficiency*	*Invention*	*Utility*	*Efficiency*
TFPfe	0.043^{***}	0.035^{***}	0.001^{*}			
	(0.009)	(0.008)	(0.001)			
Robot				0.003^{***}	0.002^{**}	-0.001^{*}
				(0.001)	(0.001)	(0.000)
Constant	-0.534^{***}	-0.242	-0.012	0.457^{***}	0.436^{***}	-0.044^{**}
	(0.140)	(0.132)	(0.010)	(0.105)	(0.097)	(0.014)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	No	No	Yes
Sample	23,779	23,779	23,779	24,806	24,806	24,806

Table 11. Test of corporate green innovation mechanism (II).

Variable	*Invention*	*Utility*	*Efficiency*	*Invention*	*Utility*	*Efficiency*
RD	0.033^{***}	0.023^{***}	0.001^{***}			
	(0.005)	(0.005)	(0.000)			
Gmanage				0.042^{***}	0.057^{***}	0.007^{***}
				(0.005)	(0.005)	(0.000)
Constant	-1.410^{***}	-0.606^{**}	-0.019^{*}	-4.761^{***}	-3.142^{***}	-0.240^{***}
	(0.217)	(0.204)	(0.009)	(0.129)	(0.116)	(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual	Yes	Yes	Yes	No	No	No
Time	Yes	Yes	Yes	No	No	No
Sample	24,093	24,093	24,093	25,450	25,450	25,450

5. Expansion study

In Section 3.1., this study uses linear and nonlinear trend analysis to fit an inverted U-shaped relationship between digital technology diffusion (*Digital1*) and green innovation quantity (*Utility*). Specifically, in the early stages of digital technology diffusion, it significantly increases green innovation quantity, benefiting green innovation. However, in the later stages, digital technology diffusion reduces green innovation quantity, which hinders green innovation. Based on this, the study further investigates the inflection point of the inverted U-shaped trend to identify the dividing line between the early and later stages of digital technology diffusion. Considering the robustness of the results and the validity of the sample data, both *Digital1* and *Digital2* are used as the main independent variables to numerically simulate their effects on *Utility*. Samples where either or both *Digital1* and *Utility* are zero are excluded, and a quadratic polynomial model is applied for numerical fitting. **Table 12** presents the specific parameter values obtained from the polynomial fitting of the nonlinear impact of digital technology diffusion on the green innovation quantity of enterprises. In this context, the condition $\alpha_i(i = 1,2) < 0$ determines the inverted "U" shape of the nonlinear effect, with both $\beta_i(i = 1,2)$ and $\alpha_i(i = 1,2)$ jointly defining the inflection point x_0 of this trend. **Figures 5 and 6** display the results of quadratic polynomial fitting of *Utility* using *Digital1* and *Digital2* as independent variables, respectively. In Fig. B, the horizontal axis is expanded tenfold compared to Fig. A to better observe the inverted "U" effect of digital technology diffusion on green innovation quantity. It can be seen that when *Digital1* is the independent variable, the inflection point for changes in *Utility* is 2.319, while for *Digital2*, the inflection point is 1.638. Taking the average, it is reasonable to infer that the inflection point for the nonlinear effect of digital technology diffusion on green innovation quantity for most enterprises occurs around $Digital = 2$. Therefore, $Digital = 2$ can be considered as the boundary point for dividing the early and later stages of digital technology diffusion.

Table 12. Polynomial fitting parameters.

Variable & Coefficient	*Digital1*	*Digital2*
α_1	-0.0248（-0.0388，-0.0109）	
β_1	0.115（0.0427，0.188）	
α_2		-0.0149（-0.0254，-0.0046）
β_2		0.0488（0.0031，0.0945）
Constant	1.173（1.091，1.255）	1.221（1.186，1.255）
RMSE	0.705	0.674
R^2	0.223	0.234
x_0	2.319	1.638
Number	4,307	5,987

Note: *The results in this table are obtained from polynomial fitting using Matlab, with the values in parentheses indicating the range of the variable coefficients.*

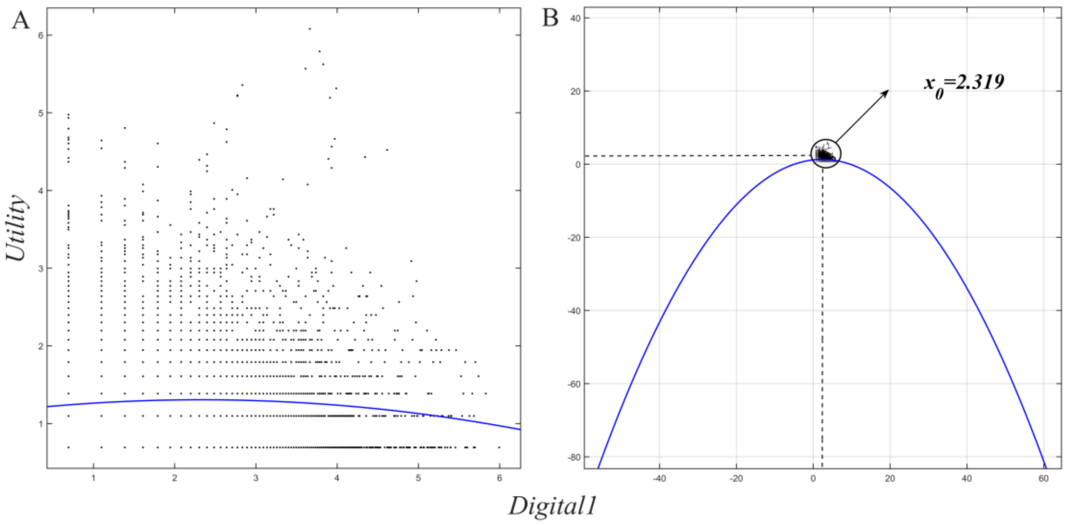

Figure 5. The inverted "U" shape impact of *Digital1* on *Utility*.

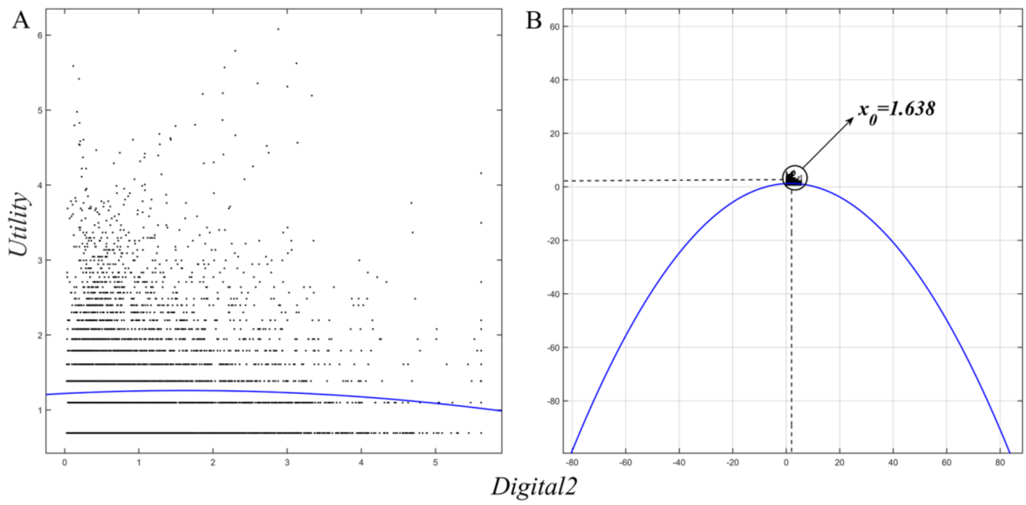

Figure 6. The inverted "U" shape impact of *Digital2* on *Utility*.

6. Research conclusions and countermeasures

6.1. Research conclusions

China is currently in a new development stage focused on fostering new types of productivity. This study constructs a theoretical framework for the model in which the diffusion of digital technologies drives green innovation to achieve coordinated and sustainable economic and environmental development. Using A-share listed companies from 2007 to 2021 as the research sample, the empirical study finds that the diffusion of digital technologies has a significant positive impact on the quality, quantity, and efficiency of green innovation. Therefore, the diffusion of digital technologies can effectively drive comprehensive green innovation, helping enterprises achieve a high-quality and efficient transition from traditional productivity to new types of productivity.

The differences in regions, technological development, and pollution levels in which enterprises operate can lead to varying impacts on the process of digital technology diffusion driving green innovation. On the one hand, the existing development model in the eastern region has already enabled high-quality development for companies there, resulting in limited innovation space and weaker motivation for innovation. Thus, the driving effect of digital technology diffusion on green innovation is somewhat weaker. In contrast, the central region has greater potential for innovation and is geographically closer to the eastern region, which facilitates the diffusion of innovation technologies and development models from the east to the central area. Therefore, the potential for digital technology diffusion to promote green innovation in the central region is stronger and broader. In the western region, development is still based on traditional industries, and emerging industries are in the early stages of growth, with insufficient digital technology R&D efforts. Green innovation in this region still requires a substantial amount of technology, talent, and other production factors to create the necessary environment and conditions, resulting in a lower driving effect of digital technology diffusion on green innovation for companies there. On the other hand, the diffusion of digital technologies drives green innovation in high-tech enterprises primarily by improving the quality of green innovation, while in non-high-tech enterprises, it mainly increases the quantity of green innovation. Heavily polluting enterprises, compared to non-polluting ones, face greater regulatory pressure and stronger financing constraints, which gives them a stronger internal motivation for green innovation, thereby increasing their demand for digital technology diffusion to a certain extent. Mechanism analysis shows that the diffusion of digital technologies can promote green innovation by enhancing internal capacity building, primarily by improving production and management levels to boost the quality, quantity, and efficiency of green innovation. Additionally, the expanded research quantitatively analyzes the inverted "U"-shaped inflection point of the impact of digital technology diffusion on the quantity of green innovation, offering a new perspective for distinguishing between the early and late stages of digital technology diffusion.

This study contributes both theoretically and practically to the understanding of how digital technology diffusion drives corporate green innovation, particularly in the context of China's transition toward high-quality, sustainable development. Existing literature has largely focused on the linear effects of digitalization on firm innovation or environmental performance, often emphasizing either macro-level policy effects or general resource allocation mechanisms. However, few studies have systematically unpacked the internal capability pathways through which digital technologies influence the quality, quantity, and efficiency of green innovation at the firm level. By integrating Dynamic Capability Theory with the Technology–Organization–Environment (TOE) framework, this research constructs a novel and testable mechanism-based model that explains how digital diffusion reshapes firms' production, automation, R&D, and management capacities to achieve sustainable innovation outcomes.

Theoretically, the study extends the literature in three key ways. First, it introduces a multi-dimensional mediation framework that clarifies how digital technologies drive green innovation through specific internal capabilities, moving beyond the oversimplified view of technology as an exogenous input. Second, it highlights heterogeneous effects across industries, regions, and firm types—providing evidence that digital transformation does not produce uniform innovation outcomes and must be evaluated contextually. Third, the identification of a nonlinear (inverted U-shaped) relationship between digital diffusion and green innovation quantity contributes a new explanatory dimension to existing models, offering insight into the diminishing returns and threshold effects often overlooked in prior research.

Practically, this study offers several actionable insights for enterprise managers, especially in the Chinese context. While digital transformation is often treated as a strategic imperative, many firms lack clarity on the concrete pathways through which digital tools can lead to green outcomes. This study demonstrates that digital investment alone is insufficient; only when combined with the development of internal capabilities—particularly in production processes and managerial systems—can digitalization truly unlock green innovation potential. This provides Chinese enterprise leaders with new, empirically grounded knowledge on:Why high-tech and non-high-tech firms experience different innovation outcomes under digital diffusion;How to align digitalization efforts with sustainability goals based on firm type and development stage;When digital transformation is most effective, especially in light of the diminishing marginal effects captured by the inverted U-shaped pattern.

Moreover, the findings suggest that digital transformation strategies should be staged and differentiated: high-tech firms should deepen quality-focused innovation through smart R&D integration, while non-high-tech and heavily polluting firms should prioritize early-stage diffusion to accelerate basic innovation output. These insights are particularly valuable for managers in state-owned enterprises, traditional industries, and resource-constrained firms, many of whom may overestimate the role of technology while underestimating the need for organizational capability restructuring.

In sum, this research contributes a more comprehensive, context-sensitive, and actionable framework for understanding and applying digital technologies in the pursuit of green innovation. It bridges the gap between strategic vision and operational transformation and provides both scholars and practitioners with new tools to rethink the role of digital diffusion in sustainability transitions.

6.2. Countermeasures

To strengthen the driving effect of digital technology diffusion on corporate green innovation, companies should enhance their internal management capabilities, including production level, automation level, R&D level, and management level. Among these, production level and management level play a key role. Specifically, the production level reflects the company’s overall production capacity and can comprehensively demonstrate its abilities in various areas, resulting in the production of high-quality, efficient, and environmentally friendly products, as evidenced by an improvement in TFP. Continuous optimization of production management is crucial, as companies with strong production management capabilities have an advantage in using digital technologies to promote green development. Management level, represented by leadership with new management concepts, plays an important role in harnessing digital technology diffusion to enhance green innovation. Therefore, companies should recruit talent with green innovation concepts into management positions, replacing leaders with traditional management mindsets. For high-tech enterprises, which have an advantage in driving green innovation quality through digital technology diffusion, it is necessary to reinforce pilot projects for the application of digital technologies. For non-high-tech enterprises, guidance should be strengthened to promote the enhancement of green innovation quality, building upon the increase in green innovation quantity driven by digital technology diffusion. Heavily polluting enterprises, constrained by regulatory pressure, have stronger intrinsic motivations for green innovation, driving a greater need for accelerated digital technology application and diffusion to promote green innovation. Regarding the inverted “U” shaped inflection point of digital technology diffusion’s impact on green innovation quantity, during the early stages of diffusion, the effect on green innovation is accelerated. In this period, both the government and enterprises should take active measures to expedite the application and diffusion of digital technologies, which will help rapidly enhance green innovation levels.

Resource Availability

Lead Contact

Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Ni Xiong (7531751@qq.com).

Data and Code Availability

This article includes all datasets generated or analyzed during this study.

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Author contributions

N.X. and X.Z. conceived the concept of this study. Y.H., and B.G. collected and analyzed the data. N.X. and W.Z.. directed the project. N.X., Y.H., Z. W.. wrote and revised the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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