DIGITAL TECHNOLOGY, ENVIRONMENTAL QUALITY AND GREEN FINANCE: THE U-SHAPED RELATIONSHIP AND SPATIAL EFFECT

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Abstract. Green and low-carbon development is the direction of the current technological revolution and industrial transformation. Digital technology innovation and application should aim at green and low-carbon development. Therefore, studying the impact of digital technology innovation on green finance aligns with current development needs. To this end, this paper employs econometric methods to examine the impact of digital technology innovation on green finance, using panel data from 282 prefecture-level cities in China from 2003 to 2022. The study reveals that digital technological innovation exerts a significant U-shaped influence on the development of green finance, initially hindering growth before promoting it. However, the strength of this effect varies depending on factors such as resource endowments and geographical regions. Digital technology innovation can enhance green finance development by improving environmental quality. Furthermore, it can have a U-shaped impact on the green finance development of surrounding areas through spatial spillover effects.
Keywords: *China, technological innovation, green development, nonlinear impact*

Introduction

Amidst intensifying global climate change and deepening sustainable development goals, green finance has become a focal point in policy-making and academic research worldwide, as it offers a key pathway to balancing economic growth with ecological protection. According to the United Nations Environment Programme (UNEP), the aim of green finance is to guide financial resources towards low-carbon, environmentally friendly and sustainable development sectors by allocating financial resources accordingly, thereby supporting the global transition to green development. However, the global implementation of green finance still faces numerous structural challenges, including information asymmetry, inefficient financing, difficulties in carbon emission accounting and insufficient inclusivity. Meanwhile, the rapid advancement of digital technologies, such as big data, blockchain and artificial intelligence, offers innovative solutions to these issues. Digital technology transforms traditional financial operations, enhances transparency, optimises resource allocation and reduces transaction costs, thereby becoming a core driver of financial development (Bhatnagar and Sharma, 2022).

However, the relationship between digital technology and green finance is unclear. Some studies suggest that digital technology can make it easier for financial institution analysts to acquire data, thereby facilitating the tracking of green business activities (Zhong and Jiang, 2021). Leveraging advanced technologies for data collection and storage enables financial institutions to build more extensive databases, overcoming obstacles to the development of green finance (Lu et al., 2022). Furthermore, digital

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technology plays a pivotal role in digital infrastructure by facilitating the flow of technology, materials, capital, and talent via data streams. This promotes the sharing, integration and collaboration of social production factors, as well as their efficient use, thereby stimulating the development of green business models (Zhang and Fan, 2022). These studies have enhanced our understanding of how digital technology might impact the development of green finance. However, few studies have explored this impact, and there is currently no direct evidence that digital technology can effectively promote green finance development. If such an impact does exist, what are its characteristics? What specific mechanisms does it use to operate? Furthermore, does this impact vary based on factors such as geographical location and urban characteristics? Addressing these questions would help China to further optimise its green finance development and provide valuable insights for other emerging countries in their green finance efforts.

In order to address the lack of relevant research, this paper employs econometric methods for empirical analysis, using panel data from 2003 to 2022 and focusing on 282 prefecture-level cities in China. The paper's main contributions are threefold. Firstly, it is the first study to use econometric methods to examine the significant impact of digital technology innovation on green finance development and to verify the specific characteristics and heterogeneity of this impact. Secondly, it examines the specific mechanisms of this impact from an environmental quality perspective. Thirdly, it uses spatial econometrics to test whether digital technology innovation has a spatial spillover effect on green finance development. These three research areas are not covered in existing literature, providing valuable insights that complement existing studies.

Literature review

The environmental impact of digital technology innovation

The new generation of advanced digital technologies, including the Internet of Things, artificial intelligence, blockchain and big data, is at the heart of the Fourth Industrial Revolution and is having a significant impact on human social development (Goldfarb and Tucker, 2019). Studies suggest that digital technology has had a positive influence on economic growth, employment quality, urban renewal and environmental protection (Solomon and Van Klyton, 2020; Berg et al., 2023; Moufid et al., 2023). Notably, the impact of digital technology on environmental quality has been the subject of extensive study. Firstly, digital technological innovation can significantly promote energy conservation and emission reduction, serving as a new driving force for resource conservation and environmental management with notable effects on reducing pollution emissions (Zhu et al., 2024; Ma and Lin, 2025). Secondly, digital technology can significantly reduce carbon emissions. It enhances the efficiency, performance and productivity of carbon reduction (Li and Yue, 2024; Li et al., 2024; Liu and Li, 2025). Digital technology primarily reduces CO_2 emissions by improving production efficiency and resource allocation (Liu et al., 2025). At the same time, digital technology has a threshold effect on carbon emissions, facilitating local reduction and having cross-regional spatial spillover effects (Yang et al., 2024). Furthermore, digital technology is a key driver in the development of more sustainable energy systems (Campana et al., 2025). Innovations in digital technology can significantly enhance urban energy efficiency and reduce regional and corporate energy intensity (Xiao et al., 2025; Gao et al., 2024; Hao et al., 2024). Additionally, digital technology can improve manufacturing energy efficiency and green total factor energy efficiency (Andrei and Johnsson, 2025; Xu et al., 2024).

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Factors influencing the development of green finance

Most studies on the impact of green finance development have examined its effects on the economy and the environment. These effects include its influence on green total factor productivity, carbon emissions and corporate innovation capabilities (Li et al., 2022; Liu and Xiong, 2022; Mamun et al., 2022). However, few studies have explored the specific factors that promote the development of green finance. In addition to information asymmetry, GDP, population size and foreign investment (Stiglitz and Weiss, 1981; Jiang et al., 2020; Nawaz et al., 2021), factors affecting the development of green finance also include resource and environmental conditions, as well as public environmental supervision (Fan et al., 2012; Liang et al., 2024; Zhuang et al., 2025). Research on the relationship between digitalisation and green finance development primarily focuses on two aspects. Firstly, the impact of digital technology on green finance development. Vives (2017) analysed that, from a banking perspective, the application of digital technology can help to optimise the structure of financial institutions, improve their efficiency and enhance their environmental responsibility, thereby promoting the development of green finance. In terms of specific technological applications, blockchain technology can mitigate bank credit risk, enhance information-sharing mechanisms, strengthen regulatory oversight, and encourage innovation in green financial products (Jin and Zhao, 2019). Furthermore, it can significantly increase the volume of green credit issuance, ease green financing constraints effectively, and reduce financing costs (Jiang et al., 2023). Additionally, big data is pivotal in promoting the development of regional green finance (Qin et al., 2024). Secondly, fintech plays a crucial role in the development of green finance. It does this by enhancing banks' risk management, operational capabilities, financial efficiency and green innovation (Wan et al., 2023; Xu et al., 2025). Furthermore, fintech has a spatial spillover effect on green finance development, improving not only local green finance, but also positively impacting green finance development in neighbouring regions (Wang et al., 2023).

A review of the literature on the development of digital technology and green finance provided valuable references for this article. However, the existing literature also has several limitations. Firstly, no direct research has been conducted using econometric methods to examine the impact of digital technology innovation on green finance. Secondly, when discussing the influence of big data, blockchain and other digital technologies on green finance, normative analysis is the primary method used rather than more objective quantitative analysis and econometric methods. Thirdly, although econometric methods have been employed to examine the impact of fintech on green finance, fintech alone cannot fully replace digital technology. Fintech and digital technology are distinct concepts. Therefore, in the era of digital intelligence, using econometric methods to empirically test the relationship between digital technology innovation and the development of green finance holds significant theoretical and practical importance.

Theoretical analysis and research hypothesis

The non-linear relationship between digital technology innovation and the development of green finance

The non-linear impact of digital technology innovation and its application on green finance development can be analysed in two stages.

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In the early stages, the development of green finance was challenged by the innovation and application of digital technology. Firstly, the transition between and integration of new and old technologies must be considered. Financial institutions, enterprises and regulatory bodies require time to familiarise themselves with these new technologies. Secondly, when digital technology is incompatible with existing business processes and management models, it can temporarily reduce operational efficiency, thereby hindering the growth of green finance. Secondly, data quality issues are significant. Digital technology relies heavily on large volumes of data, but in the early stages, data quality cannot be fully guaranteed. Inaccurate, incomplete or inconsistent data can affect the accuracy of green finance decision-making. Thirdly, there is a shortage of specialised talent. Integrating digital technology with green finance requires professionals who are proficient in both digital technology and the financial and green industries. In the early stages, the scarcity of such individuals has posed significant challenges for financial institutions and enterprises looking to apply digital technology to green finance. Lastly, high costs are a significant barrier. The application of digital technology requires substantial investment in equipment, research and development (R&D), and talent development. For many small and medium-sized financial institutions and enterprises, these costs may exceed their capacity, thereby limiting the use of digital technology in green finance.

In its mature stage, digital technology plays a positive role in the development of green finance across multiple fronts. Firstly, it improves the transparency and efficiency of information. As digital technology matures and becomes more widely adopted, the efficiency of information collection, processing and transmission improves significantly. In the green finance sector, big data technology can integrate various sources of information, including environmental, financial and operational data from enterprises. This helps financial institutions to more accurately identify green projects and companies, thereby reducing information asymmetry. Secondly, digital technology improves risk assessment and management capabilities. Digital technology provides powerful tools for risk assessment and management in green finance. AI technology can analyse large datasets to create risk assessment models, predict the potential risks of green projects and help financial institutions formulate more effective risk management strategies. Thirdly, it strengthens product innovation and service expansion. Financial institutions can use digital technology to develop a range of green finance products that meet the needs of different customers. Furthermore, digital technology can broaden the scope of green financial services by offering convenient services via online platforms. Fourthly, it optimises market scale and synergistic effects. Digital technology can stimulate growth in the green finance market, attracting more participants and expanding its size. As more financial institutions, enterprises and investors join the green finance market, they create synergistic effects that promote green finance development. For this reason, this paper proposes the following research hypothesis.

H1: Digital technology innovation has a U-shaped impact on the development of green finance.

The influence of digital technology innovation on the development of green finance

Digital technological innovation creates a transmission chain of “technology empowerment - efficiency improvement - environmental improvement - financial response” by reconstructing the economic development paradigm and environmental

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governance model. Digital technology promotes green finance development through two core processes: improving carbon productivity and reducing (SO_2) emissions.

Digital technology drives the development of green finance by increasing carbon productivity. Firstly, digital technology enables improvements in carbon productivity. It mainly achieves this through three key processes. It enhances energy efficiency. It can realise real-time monitoring of energy consumption and combine this with big data analysis to build an energy consumption model. This promotes precise energy conservation in industry, construction, transportation and other fields. Secondly, it upgrades industrial structure. Digital technology accelerates the digital transformation of traditional industries, creating digital economy industries with low energy consumption and high added value. It can also guide the flow of resources to low-carbon industries and promote the transformation of 'carbon-intensive industries' into 'knowledge- and technology-intensive industries'. Improve factor allocation efficiency. Digital technology can overcome information asymmetry and enable the cross-regional optimisation of technology, capital, talent and other resources via data-sharing platforms. Secondly, carbon productivity has a transmission effect. Improving carbon productivity can enhance the efficiency of the green financial market by signalling and reducing risk. High carbon productivity means that enterprises with mature low-carbon technologies and controllable environmental risks are more likely to obtain financing through green bonds, green credit, and other channels. Improving carbon productivity through digital technology can mitigate the impact of climate policy changes on businesses and reduce the risk of default in green finance.

Innovations in digital technology empower the development of green finance by reducing sulphur dioxide emissions. Firstly, it involves the technical management of these emissions. SO_2, a common atmospheric pollutant, requires the monitoring of pollution sources, the upgrading of treatment technologies and the coordination of industrial processes to reduce emissions. Digital technology can provide comprehensive solutions that enhance the accuracy of monitoring and regulation. It promotes continuous improvement in monitoring technologies and systems, enabling real-time capture of SO_2 emission data from key sources of pollution such as industrial boilers and coal-fired power stations. It accelerates the adoption of clean energy sources, facilitating the dynamic adjustment of energy consumption structures and the transition from a coal-dominated to a diversified, clean energy landscape. Furthermore, it supports the circular economy by integrating waste processing data via industrial internet platforms and promoting the recycling and utilisation of sulphur resources. Digital twin technology simulates production processes, identifies stages with high pollution levels and optimises processes to achieve the dual goals of reducing emissions and enhancing efficiency. Secondly, reducing SO_2 emissions encourages green finance. A decline in SO_2 emissions stimulates demand for green finance by improving environmental quality and providing policy incentives. Improved air quality raises public environmental awareness and encourages green investment. Financial institutions incorporate environmental indicators, such as SO_2 concentration, into their ESG scoring systems, thereby guiding funds towards low-pollution enterprises. Achievements in reducing emissions supported by digital technology help cities secure policy benefits such as low-carbon pilot projects and environmental protection special funds, driving innovation in green financial tools. Based on the above analysis, this paper proposes the following research hypothesis.

H2: Digital technology innovation has a U-shaped impact on the development of green finance by improving environmental quality.

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The spatial spillover effect of digital technology on green finance

The spatial spillover effects of digital technology innovation on green finance development primarily manifest through three pathways. Firstly, knowledge spillovers and technology diffusion. Cities with high levels of digital technology innovation attract a large number of high-tech enterprises, research institutions and talented individuals. These entities accumulate extensive knowledge in the research and application of digital technologies. Through academic exchanges, industrial collaborations and personnel mobility, this knowledge gradually spreads to surrounding cities, enhancing their precision marketing, risk identification and management efficiency in green finance. Secondly, the outcomes of digital technology innovation can spread across regions through technology transfer and cooperation. This can drive the upgrading of the green finance industry in surrounding cities, particularly with regard to infrastructure construction and business process optimisation. Secondly, there is economic agglomeration and industrial synergy. Cities that are at the forefront of digital technology innovation have stronger economic agglomeration capabilities, attracting a large number of green finance-related enterprises, funds and talent. The scale and demonstration effects of this economic agglomeration can spread to surrounding cities. This attracts enterprises and investors from surrounding cities, strengthening their cooperation with agglomerated cities in the field of green finance and promoting its development in these areas. Furthermore, digital technological innovation facilitates the green transformation of local industrial structures and enhances industrial synergy with neighbouring cities. This optimises the regional green finance ecosystem, promoting the effective allocation of green finance resources over a wider area. Thirdly, there is market competition and exemplary leadership. Local financial institutions are actively leveraging new technologies to enhance the competitiveness of their green finance business, driven by innovation in digital technology. This competitive pressure will gradually spread to surrounding cities through market connections. In order to avoid being phased out, financial institutions in these surrounding cities will also increase their use of digital technology and adopt advanced green financial service models. Cities that lead in digital technology innovation often lead in green finance practices too. The successful experience of these cities in innovating green financial products and building policy support systems will serve as a model for other cities. Based on this, this paper proposes the following research hypothesis.

H3: Digital technology innovation has a significant spatial spillover effect on the development of green finance.

Study design

Model construction

Baseline regression test model

According to theoretical analysis, digital technological innovation will impact the development of urban green finance. To accurately explore the specific impact of digital technology on urban green finance development, this paper sets up a double fixed effects model.

$$GF_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 DT_{it}^2 + \alpha_3 X_{it} + \mu_t + \lambda_i + \varepsilon_{it} \tag{Eq.1}$$

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In *Equation 1*, *i* denotes the city, *t* represents the year. The *GF* represents the level of green finance development, and *DT* and DT^2 represent the first and second powers, respectively, of the level of digital technology innovation. The *X* represents the control variables. The a_0 is the constant term. The *a* is the estimated coefficient. The μ is the time fixed effect. The λ is the city fixed effect, and ε is the random error term.

Test model of the mechanism of action

To test whether digital technological innovation can promote the development of urban green finance by improving carbon productivity and reducing sulphur dioxide emissions, this paper proposes the following test model of the mechanism.

$$M_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 DT_{it}^2 + \beta_3 X_{it} + \mu_t + \lambda_i + \varepsilon_{it} \quad \text{(Eq.2)}$$

In *Equation 2*, *M* is the mediating variable, which includes urban carbon productivity (*CP*) and sulphur dioxide emissions (SO_2). The β is the estimated coefficient. The other variables have the same meaning as in *Equation 1*.

Spatial effect test model

To test the spatial spillover effect of digital technology innovation on green finance development, this paper presents the following spatial econometric model.

$$GF_{it} = \eta_0 + \eta_1 DT_{it} + \eta_2 DT_{it}^2 + \eta_3 X_{it} + W_{it}(\rho_1 GF_{it} + \rho_2 DT_{it} + \rho_3 DT_{it}^2 + \rho_n Z_{it}) + \mu_t + \lambda_i + \varepsilon_{it} \quad \text{(Eq.3)}$$

In *Equation 3*, the coefficient to be estimated is represented by η. The spatial autoregressive coefficient is represented by ρ_1. The coefficients of the spatial interaction terms for the first and second powers of digital technology innovation levels are represented by ρ_2 and ρ_3, respectively. The coefficient of the spatial interaction term for control variables is represented by ρ_n, with *W* representing the spatial weight matrix. The meanings of the other variables are consistent with those in *Equation 1*.

Variable selection

Dependent variable

The dependent variable is the level of green finance development (*GF*). Current literature primarily measures green finance development in two ways. The first method uses representative green finance policies, such as green finance innovation and reform pilot zones, and green credit policies (Han and Li, 2025; Zhang et al., 2025a). The second method involves constructing a comprehensive indicator system to measure the level of green finance development. For example, Liu et al. (2024) developed a measurement index system from five perspectives: green credit, green bonds, green insurance, green investment and carbon finance. Additionally, some studies suggest that green finance should include government institutional arrangements, as well as green financial tools provided by financial institutions and markets (Liu et al., 2023a). This paper synthesises the existing literature on the essence and development of green finance (Liu et al., 2023b; Zhang et al., 2025b) to create a multidimensional evaluation system comprising seven indicators: green credit, green investment, green support, green insurance, green bonds, green funds and green equity (including carbon finance). The entropy value method was

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used to measure the level of green finance development in Chinese prefecture-level cities from 2003 to 2022.

The seven specific indicators of green finance are measured as follows, in reference to existing research: Green credit is measured by the ratio of loans for energy-saving and environmental protection projects to total loans. The ratio of investment in regional environmental pollution control to GDP is used to measure green investment. The proportion of environmental protection expenditure to total fiscal expenditure is used to measure green support. Environmental pollution liability insurance, a form of green insurance with ‘proxy supervision’ functions, helps to reduce corporate pollution. Therefore, the ratio of income from environmental pollution liability insurance to total insurance income is used to measure green insurance. The ratio of the total market value of regional green funds to the total market value of all funds is used to measure green funds. Green bonds, an important component of the green financial system, are measured by dividing the total amount of local green bond issuance by the total amount of all bond issuances, thus eliminating the impact of regional bond market size. Green rights are measured by the ratio of the total amount of carbon trading, energy use rights trading and emission trading that reduce environmental pollutant emissions, divided by the total amount of rights market transactions. For detailed explanations of these indicators, see *Figure 1*.

Figure 1. *Evaluation index system for the development level of green finance in Chinese cities*

Core explanatory variables

The core explanatory variable is the level of digital technology (*DT*) innovation. Most existing literature measures technological innovation from two perspectives: R&D investment and output. As it is difficult to accurately measure R&D investment in digital technology-related industries, this paper uses Luo and Wang’s (2024) method to evaluate digital technological innovation based on R&D output. Since the number of patent applications in the digital technology sector usually reflects the industry’s technological trends, this paper uses the logarithm of the sum plus one of the number of patent

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applications in digital economy-related industries to measure the level of digital technological innovation. The process of selecting digital technology patents is divided into three steps. First, the specific scope of the digital economy and its core industries is determined based on the 'Statistical Classification of the Digital Economy and its Core Industries (2021)', identifying 156 subcategories across five major categories: computer and communication equipment manufacturing; telecommunications; radio, television and satellite transmission services; and internet and related services. Secondly, the 'International Patent Classification and National Economic Industry Classification Reference Relationship Table (2018)' is used to determine the international patent classification numbers for each industry. Thirdly, the number of digital economy-related patent applications in 282 cities nationwide from 2003 to 2022 is obtained from the national intellectual property patent database based on these classification numbers.

Mechanism variables

The mechanism variables are carbon productivity (*CP*) and sulphur dioxide emissions (SO_2). The concept of carbon productivity was first introduced by Yokobori and Kaya (1999). This indicator directly affects the efficiency of resource utilisation and the environmental burden, making it a more accurate measure of the performance of economic growth. Carbon productivity is measured by the ratio of gross domestic product to CO_2 emissions. The CO_2 emissions of each city are calculated using the emission factor method published by the Intergovernmental Panel on Climate Change (IPCC). Air pollution from transportation and industrial development in urban areas has become increasingly severe, with China currently having the highest SO_2 emissions. Sulfur dioxide is a major component of atmospheric pollutants. Therefore, this paper uses carbon productivity and sulphur dioxide emissions as the mechanism variables.

Control variables

To avoid unreliable estimated coefficients due to omitted variables, this paper selects the following control variables: economic development level (*PGDP*), population density (*PD*), government intervention (*GI*), deposit balance (*DB*) and industrial structure upgrading (*LA*). Economic development level is measured by per capita GDP. Population density is defined as the number of people per square kilometre in urban areas. Government intervention is measured by the ratio of government fiscal expenditure to regional GDP. The level of development of the deposit business is measured by the ratio of various deposit balances at the end of the year to regional GDP. Industrial structure upgrading is measured by the ratio of the output value of the tertiary industry to that of the secondary industry.

Table 1 shows the names, symbols and descriptions of the variables.

Data sources and descriptive statistics

This study uses balanced panel data from 282 prefecture-level cities in China, covering the period from 2003 to 2022. The original digital technology patent data are sourced from the China National Intellectual Property Administration. Socioeconomic data are derived from the annual China Statistical Yearbook and China City Statistical Yearbook. Any missing data is supplemented by consulting the relevant provinces' and prefecture-level cities' statistical yearbooks. A small amount of missing data was interpolated using linear interpolation.

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Table 1. *Variable definitions and descriptions*

Variable type	Variable name	Variable symbol	Variable declaration
Explained variable	The level of green finance development	*GF*	The index is calculated using the entropy method
Explanatory variable	Digital technology innovation capability	*DT*	Ln (number of patents)
Metavariable	Carbon productivity	*CP*	GDP per unit of carbon dioxide emitted
	Sulphur dioxide emissions	SO_2	Ln (sulphur dioxide emissions)
Controlled variable	Level of economic development	*PGDP*	Ln (per capita GDP)
	Population density	*PD*	Ln (population per km^2)
	Government intervention	*GI*	The ratio of fiscal expenditure to GDP
	Development level of deposit business	*DB*	The ratio of commercial bank deposits to GDP at the end of the year
	The industrial structure is more sophisticated	*IA*	The ratio of output value of the tertiary industry to that of the secondary industry

The descriptive statistics for all the variables are presented in *Table 2*. The capabilities of digital technology innovation, sulphur dioxide emissions, levels of economic development, and population density are expressed using absolute values and were therefore transformed into logarithmic values for the regression analysis. Levels of green finance development, carbon productivity, government intervention, deposit business development and industrial structure upgrading are all relative indicators and were not altered in the regression analysis.

Table 2. *Descriptive statistics of variables*

Stats	N	Min	Mean	P50	Max	Sd
GF	5640	0.0468	0.299	0.298	0.657	0.106
DT	5640	0	4.736	4.771	11.670	2.192
CP	5640	0.036	0.811	0.546	13.530	0.886
SO_2	5640	0.693	9.979	10.180	13.660	1.356
PGDP	5640	4.595	10.320	10.410	13.060	0.851
PD	5640	3.296	7.897	7.886	9.908	0.840
GI	5640	0	0.175	0.149	1.485	0.102
DB	5640	0.245	1.339	1.202	20.100	0.617
IA	5640	0.094	0.966	0.847	5.650	0.521

Empirical test results

Benchmark regression results

In order to examine the impact of digital technology innovation on the development of green finance, this paper conducts a regression analysis of *Equation 1*. The results are presented in *Table 3*. Column (1) in *Table 3* uses only the first power of digital technology innovation as an explanatory variable, without including control variables. The results

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show that the coefficient of digital technology innovation on green finance development is significantly negative. Column (2), which includes control variables, also shows a significant negative coefficient. Column (3) uses both the first and second powers of digital technology innovation as explanatory variables without including control variables. The results indicate that the first power has a significant negative effect, while the second power has a significant positive effect. After adding control variables in column (4), the direction and significance of the coefficients for both explanatory variables remain consistent with those in column (3). The estimated coefficients for digital technology innovation are -0.0115 and 0.0010 respectively, both of which are significant at the 1% level. These findings suggest that digital technology innovation has a U-shaped impact on green finance development: initially inhibiting growth, but subsequently promoting it. This supports Hypothesis H1.

Table 3. *Baseline regression results*

Variable	(1)	(2)	(3)	(4)
DT	-0.0052*** (0.0012)	-0.0044*** (0.012)	-0.0116*** (0.0020)	-0.0115*** (0.0020)
DT^2			0.0009*** (0.0002)	0.0010*** (0.0002)
PGDP		-0.0069* (0.0040)		-0.0005 (0.0038)
PD		-0.0037*** (0.0012)		-0.0035*** (0.0011)
GI		-0.0105 (0.0105)		0.0241 (0.0164)
DB		0.0029 (0.0021)		0.0032 (0.0022)
IA		0.0050 (0.0030)		0.0051* (0.0031)
Time fixed	Yes	Yes	Yes	Yes
Urban fixed	Yes	Yes	Yes	Yes
R^2	0.8278	0.8305	0.8327	0.8352
Sample capacity	5640	5640	5640	5640

*** and * indicate significance at the 1% and 10% levels, respectively. The bracket shows the robust standard error. 'Yes' indicates whether the model controls for relevant variables

Endogeneity and robustness tests

Endogeneity test

Digital technology innovation may be bidirectionally causally related to the development of green finance. This means that digital technology innovation can promote the development of green finance and be driven by it. Due to the potential time lag in the impact of digital technology innovation on green finance, this paper uses the lagged explanatory variable method and the instrumental variable method to test for endogeneity.

First, the explanatory variables are lagged by one period, then by two, before regression estimation is used to test the impact of the level of digital technological innovation in the previous period on current green finance development. As shown in

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columns (1) and (2) of *Table 4,* the regression coefficients for the one- and two-period lags of digital technology innovation are both significant at the 1% level of significance, similar to the results of the benchmark regression. These results suggest that the U-shaped impact of digital technology innovation on green finance development is robust.

On the other hand, the instrumental variable (IV) method is used to address potential issues of endogeneity. While the prevalence of fixed telephones has historically been linked to levels of innovation in digital technology, technological advancements have led to a significant decrease in the use of fixed telephones, which now have a minimal impact on current economic activities (Nunn and Qian, 2014). Since China began officially tracking the number of telephones in 1985, this study uses the number of telephones per 100 people in each province in 1984 as the basis for constructing the IV. As this variable is based on cross-sectional data, we refer to existing literature to construct panel data and select the interaction term between the number of internet users in cities the previous year and the number of fixed telephones per 100 people in each province in 1984 as the instrumental variable for digital technology innovation. The results are estimated using two-stage least squares (2SLS), as shown in columns (3) to (5). The test results indicate that the selected instrumental variables are free from issues such as identification deficiency, weak instruments or over-identification. The regression coefficients of the first-stage variables are also significant and consistent with economic reality. Second-stage estimation results show that the digital technology innovation coefficient on green finance development remains significantly positive, effectively mitigating the impact of endogeneity and ensuring the reliability of research conclusions.

Table 4. *Results of endogenous tests*

Variable	Lag phase I	Lag phase II	Stage I		Stage II
	(1)	(2)	(3)	(4)	(5)
DT	-0.0104*** (0.0019)	-0.0093*** (0.0019)			0.0267*** (0.0041)
DT^2	0.0010*** (0.0002)	0.0009*** (0.0002)			0.0012*** (0.0004)
IV			-0.7932*** (0.1012)	-33.3282*** (1.0888)	
IV^2			0.0706*** (0.0046)	1.8366*** (0.0495)	
LM			1583.194		
F			1095.254		
Time fixed	Yes	Yes	Yes	Yes	Yes
Urban fixed	Yes	Yes	Yes	Yes	Yes
R^2	0.8231	0.8305			0.3112
Sample capacity	5358	5640	5640	5640	5640

*** indicates significance at the 1% level. The bracket shows the robust standard error. ‘Yes’ indicates whether the model controls for relevant variables

Robustness test

Test for a U-shaped relationship. Hans et al. (2016) noted that the significance of the squared coefficient alone is insufficient to confirm the existence of a U-shaped

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relationship; thus, a test for the U-shaped relationship is necessary. This paper tests for a U-shaped relationship between digital technology innovation and green finance development, as shown in *Table 5*. The results indicate that the level of digital technology innovation ranges from 0.000 to 11.671, with a turning point at 6.318. The slope on the left side is -0.012, which is significant at the 1% level. The right-hand slope is 0.010, which is also significant at the 1% level. These findings suggest an inverted U-shaped relationship between digital technology innovation and green finance development, providing further support for Hypothesis H1.

Table 5. *Test results of U-shaped relationship between digital technology innovation and green finance development*

Variable	Lower bound	Upper bound
Interval	0.000	11.67073
Slope	-0.012	0.010
t-value	-5.756	2.888
$P > \|t\|$	0.000	0.002

Further verification of the U-shaped relationship was achieved using the cubic test. According to Hans et al. (2016), the cubic term for digital technology was added to the baseline model. After the quadratic regression model became significant, the cubic term of the explanatory variable was added to observe whether a cubic relationship exists between the explanatory and dependent variables — in other words, whether an N-shaped or horizontal S-shaped relationship exists. This paper further adds the cubic term of digital technology innovation (DT^3) to the model to examine whether a cubic relationship exists between digital technology innovation and green finance development. *Table 6,* column (1), shows that, after adding the cubic term of the explanatory variable, the coefficient of the DT^3 term is not significant. This indicates that no such relationship exists, suggesting that the U-shaped relationship between digital technology innovation and green finance development is robust.

Replacement of explanatory variables. Although the number of patent applications avoids bias to some extent, caused by issues such as time lag, it can effectively examine the impact of digital technological innovation on green financial development (Xu and Cui, 2020). However, the number of authorised patent applications is of great significance in measuring the scientific and technological strength of a city, as it is one of the important outputs of science and technology innovation activities. In order to evaluate the impact of digital technology innovation on the development of green finance in a comprehensive manner, this paper uses the number of digital technology patents granted in cities as an explanatory variable and conducts a regression analysis. As shown in *Table 6,* column (2), the results obtained by using the number of digital technology patents granted as an explanatory variable are highly similar to those from the benchmark regression.

Quantile regression. Unlike the mean regression estimation used in benchmark regression estimation, quantile regression does not require any distribution assumptions for the model. This method uses different quantiles to perform regression analysis on the model, based on the information contained in the sample. Using the quantile regression method not only alleviates the bias caused by outliers, but also better captures the structural characteristics of the impact of digital technology innovation on the development of green finance. The regression results are shown in columns (3) to (5) of

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Table 6. At the 25%, 50% and 75% percentiles, the regression coefficients for the first power of digital technology innovation are significantly negative, whereas the coefficients for the second power are significantly positive. This is consistent with the baseline regression results.

Table 6. *Robustness test results*

Variable	(1)	(2)	(3)25%	(4)50%	(5)75%
DT	-0.0090** (0.0037)	-0.0101*** (0.0019)	-0.0103*** (0.0005)	-0.0099*** (0.0008)	-0.0097*** (0.0007)
DT^2	0.0003 (0.0008)	0.0010*** (0.0002)	0.0008*** (0.0001)	0.0009*** (0.0001)	0.0009*** (0.0001)
DT^3	0.00004 (0.00004)				
Time fixed	Yes	Yes	Yes	Yes	Yes
Urban fixed	Yes	Yes	Yes	Yes	Yes
R^2	0.8354	0.8349	0.7945	0.7815	0.7817
Sample capacity	5460	5640	5640	5640	5640

*** indicates significance at the 1% level. The bracket shows the robust standard error. 'Yes' indicates whether the model controls for relevant variables

Heterogeneity analysis

Heterogeneity of resource endowment

Resource-based cities rely on specific natural resources for development and production. The enthusiasm and initiative of these cities in terms of digital technological innovation and green financial development are more likely to be affected by factors such as fluctuations in resource prices, industrial restructuring, and changes in market demand. Cities that are not resource-based, and therefore do not depend on a single natural resource, have a more diversified industrial structure and often require digital technology innovation and green finance more urgently. This paper therefore refers to the classification standards outlined in the 'Notice on the National Sustainable Development Plan for Resource-Based Cities (2013–2020)' in order to distinguish between resource-based and non-resource-based cities, and to conduct an analysis of resource endowment heterogeneity. As shown in columns (1) and (2) of *Table 7,* the regression results indicate that digital technology innovation has a U-shaped impact on green finance development in both types of cities. However, there are significant differences between the two types of city. In non-resource-based cities, the square of digital technology has a significantly positive effect on green finance at the 1% level. In contrast, in resource-based cities, the square of digital technology only has a significant positive effect on green finance at the 5% level. This suggests that the promotion effect of digital technology innovation on green finance development is more pronounced in non-resource-based cities. This is primarily because non-resource-based cities are typically dominated by emerging industries or services, resulting in a more flexible economic structure and less path dependence in green transformation. Digital technology can more effectively match the demand and supply of green finance. These cities are more proactive in innovating green financial products and establishing standard systems, and the marginal benefits of digital technology are greater. However, resource-based cities tend to have a high proportion of

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traditional, high-carbon industries and face a greater technological lock-in effect and sunk costs when it comes to transformation. Consequently, the application of digital technology may be limited to the partial optimisation of existing industries rather than the systematic restructuring required for green finance development.

Heterogeneity of economic development

In order to explore whether the impact of digital technology innovation on green finance development is influenced by regional economic development, this paper calculates the average per capita GDP for 282 prefecture-level cities over the sample period. By comparing each city's total per capita GDP with the average value, the sample is divided into groups with high and low economic development. Ultimately, 106 prefecture-level cities are classified as being in the high economic development group and 176 as being in the low economic development group. The results are shown in columns (3) and (4) of *Table 7*. By comparing the magnitude and significance of the estimation coefficients, it can be seen that in areas with high economic development, the first-order estimation coefficient of digital technology is smaller. This indicates a lesser inhibitory effect on the development of green finance in the early stages. However, there is no significant difference in the second power of the digital technology coefficient between the two regions. This may be because regions with high economic development generally have more advanced digital infrastructure and a more mature financial ecosystem. This allows digital technology to be quickly integrated into existing green finance processes, reducing the friction costs associated with introducing the technology. Additionally, enterprises in high-economic regions undergo digital transformation at a significantly higher rate than those in low-economic regions, thereby lowering the marginal cost of applying digital technology. As the level of digital technology innovation improves, however, the gap in innovation levels gradually narrows and the technology's impact on green finance development becomes more consistent.

Table 7. *Heterogeneity test results*

Variable	(1) Resource-based cities	(2) Non-resource-based cities	(3) High economic development group	(4) Low economic development group
DT	-0.0103*** (0.0034)	-0.0117*** (0.0029)	-0.0136*** (0.0043)	-0.0117*** (0.0029)
DT^2	0.0010** (0.0004)	0.0007*** (0.0003)	0.0011*** (0.0003)	0.0011*** (0.0004)
Time fixed	Yes	Yes	Yes	Yes
Urban fixed	Yes	Yes	Yes	Yes
R^2	0.8183	0.8483	0.8417	0.8334
Sample capacity	2260	3380	2120	3520

*** and ** indicate significance at the 1% and 5% levels, respectively. The bracket shows the robust standard error. 'Yes' indicates whether the model controls for relevant variables

Heterogeneity of geographical regions

Due to China's vast territory, different regions have significantly different natural conditions and development foundations, exhibiting strong regional characteristics. Based on standard regional classifications and the locations of the cities, this paper

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divides the sample cities into three groups: eastern, central and western. The group regression results are shown in columns (1) to (3) of *Table 8*. The findings indicate the following. Firstly, in the eastern region, digital technology innovation has a significant U-shaped impact on the development of green finance, with all impact coefficients being significant at the 1% level. Secondly, in the central region, the positive effect of digital technology on green finance is only significant at the 10% level, which is lower than in the eastern region. Finally, in the western region, digital technology innovation does not significantly affect the development of green finance. These regional differences stem from the fact that the eastern coastal areas account for over 50% of the national economy, boast a comprehensive industrial infrastructure, and are home to world-leading digital economy clusters, providing a robust foundation for the integration of digital technology and green finance. High-tech industries, green industries and financial services are highly concentrated in these regions, where digital technology can directly empower green project financing through tools such as supply chain finance and carbon accounting platforms. This creates a positive cycle of ‘technology-industry-finance’. In contrast, the central and western regions are still dominated by traditional energy and heavy industry. They have limited green industries and lack application scenarios for digital technology. This results in weaker spillover effects.

Table 8. *Results of heterogeneity test and mechanism of action test*

Variable	(1) Eastern region	(2) Central region	(3) Western region	(4) Carbon productivity	(5) Sulfur dioxide
DT	-0.0062*** (0.0022)	-0.0112*** (0.0029)	-0.0003 (0.0034)	-0.1723** (0.0714)	0.2311*** (0.0470)
DT^2	0.0006*** (0.0002)	0.0006* (0.0003)	0.0001 (0.0005)	0.0226*** (0.0069)	-0.0205*** (0.0045)
Time fixed	Yes	Yes	Yes	Yes	Yes
Urban fixed	Yes	Yes	Yes	Yes	Yes
R^2	0.9111	0.8411	0.7403	0.4328	0.7372
Sample capacity	2340	1600	1700	5640	5640

***, ** and * indicate significance at the 1%,5% and 10% levels, respectively. The bracket shows the robust standard error. ‘Yes’ indicates whether the model controls for relevant variables

Mechanism of action test

Based on the earlier theoretical analysis, this paper proposes that digital technology innovation may influence the development of urban green finance through two pathways: enhancing carbon productivity and reducing sulphur dioxide emissions. As shown in *Table 8,* column (4), digital technology innovation has a significant U-shaped impact on carbon productivity, meaning that it initially inhibits carbon production before promoting it. This finding is consistent with existing literature (Xu and Dong, 2024) and real-world observations. Column (5) shows that digital technology innovation also has a significant inverted U-shaped impact on sulphur dioxide emissions, meaning it first promotes carbon production before inhibiting it. These findings demonstrate that digital technology innovation has a significant effect on improving environmental quality. Digital technology innovation enhances corporate environmental governance capabilities, thereby improving environmental performance. This improvement in environmental

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performance helps companies obtain environmental qualification certifications, enabling them to secure green financial support (Xie, 2021). Environmental degradation can raise public awareness of environmental issues, increasing public concern and promoting government and corporate green preferences and environmental responsibility. This improves environmental quality and drives investment decisions towards green assets (Agliardi and Agliardi, 2019; El Ouadghiri et al., 2021). For instance, enhanced environmental quality can boost demand for green bonds (He and Shi, 2023). The empirical results confirm the validity of Hypothesis H2.

Further analysis: spatial effect

Spatial correlation test

The spatial correlation of the core variables is essential for conducting spatial econometric analysis. In order to verify the spatial spillover effect between digital technology innovation and green finance development, this paper uses Moran's I to conduct a global spatial autocorrelation test on the core variables in the model. The results show that, using a geographical adjacency spatial weight matrix, Moran's I for both digital technology and green finance is significantly positive at the 1% level each year, indicating a clear positive spatial correlation between digital technology innovation and green finance development. *Figure 2* illustrates the Moran's I and Z values for digital technology and green finance.

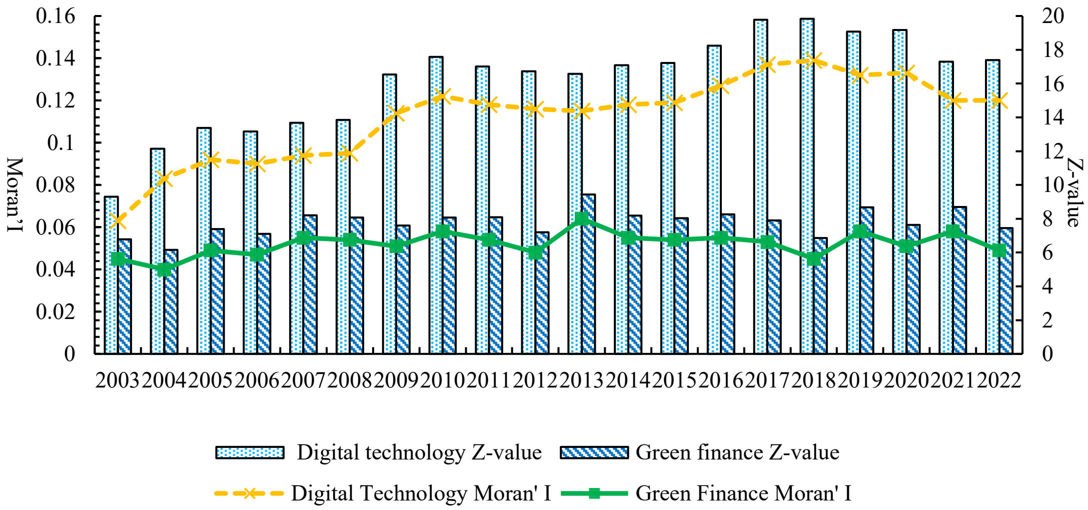

Figure 2. *Moran's I for digital technology and green finance*

While the global Moran's I index reveals the overall spatial correlation between digital technology and green finance, it does not capture atypical local spatial relationships. To address this issue, this paper employs local spatial autocorrelation analysis to examine the correlation and spatial clustering distribution of variables within a local area and its neighbouring regions. The Moran's index scatter plot provides a clearer representation of the spatial clustering characteristics of digital technology and green finance. This paper therefore presents local Moran's index scatter plots for digital technology and green

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finance in 2003 and 2022 (see *Figs. 3* and *4*). These plots demonstrate that the Moran's Index for digital technology and green finance is predominantly concentrated in the first and third quadrants, indicating a 'high-high' and 'low-low' clustering pattern. This indicates that areas with higher levels of digital technology and green finance tend to be adjacent to other areas with similarly high levels of these technologies.

Figure 3. *Moran's index scatterplot for digital technology in 2003 and 2022*

Figure 4. *Moran's index scatterplot for green finance in 2003 and 2022*

Selection of spatial econometric models

The LM and LR tests are commonly used to select spatial econometric regression models. The LM test is primarily used to select between spatial error and spatial lag models. Following the LM test, the LR test is used to re-evaluate and select from three models, including the spatial Durbin model. The results of the LM and LR tests are presented in *Table 9*. The LM (lag), robust LM (error) and LM (error) tests for digital technology and green finance are all significant at the 1% level. The Robust LM (lag) test also shows significance at the 1% level, indicating that the spatial lag model (SAR) is more suitable than the spatial error model (SEM). In the LR test, the LR (lag) and LR (error) tests both reject the null hypothesis at the 1% significance level. This suggests that the spatial Durbin model differs significantly from the spatial error or spatial lag models and is therefore more appropriate for this study. Finally, the Wald test was used to confirm the robustness of the SDM model. The results show that the Wald (lag) and Wald (error) tests are significant at the 1% level, thus rejecting the null hypothesis that the SDM model would degrade into the SEM or SLM models. Additionally, choosing between fixed and

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random effects is crucial for achieving accurate results. Therefore, the Hausman test provides important guidance for model specification. As can be seen in *Table 9,* the Hausman statistic is significant at the 1% level, indicating that the fixed effects model provides a better analysis than the random effects model.

Table 9. *Test results for the spatial econometric model*

Inspect	Statistic	P-value	Inspect	Statistic	P-value
LM test no spatial lag	22000	0.000	Wald test spatial lag	232.68	0.000
Robust LM test no spatial lag	176.70	0.000	LR test spatial lag	101.31	0.000
LM test no spatial error	57000	0.000	Wald test spatial error	285.67	0.000
Robust LM test no spatial error	35000	0.000	LR test spatial error	120.45	0.000
Hausman test	65.56	0.000			

Spatial effect analysis

The maximum likelihood estimation (ML) method is one of the most commonly used methods in spatial panel regression models. Drawing on Elhorst's (2010) research, this paper employs the ML method for regression analysis. To ensure the reliability of the results, both an adjacency matrix and an inverse distance matrix are employed. The results of the regression analysis investigating the spatial impact of digital technology on green finance are presented in *Table 10*. Columns (1) to (4) show the estimates using the adjacency matrix and columns (5) to (8) show the estimates using the inverse distance matrix. Columns (1) and (5) show that the coefficients of the spatial interaction terms $W\times DT$ and $W\times DT^2$ are significantly positive, indicating that digital technology innovation clearly promotes the development of green finance in surrounding areas. However, simple point estimation results can lead to biased estimates when analysing inter- and intra-regional spillover effects. To accurately describe the spatial relationship between digital technology innovation and green finance development, the comprehensive impact is decomposed into direct and indirect effects using a partial differential method, with a focus on the spatial spillover effect. Indirect effect estimates from columns (3) and (7) show that the spatial spillover effect of digital technology innovation on green finance development exhibits a significant U-shaped pattern. The results show that improving the level of local digital technology innovation not only enhances local green finance development, but also has a positive impact on the green finance development of neighbouring cities, thus verifying Hypothesis H3.

Research conclusions and policy implications

In the context of digitalisation, China, the world's largest carbon emitter and energy consumer, offers a valuable opportunity to study the impact of digital technology innovation on green finance development. This study examines this relationship and the underlying mechanisms by analysing data from 282 prefecture-level cities in China from 2003 to 2022. Through empirical testing, the study provides detailed insights into this relationship. The findings suggest that digital technology innovation has a significant U-shaped impact on green finance development: initially inhibiting growth, then promoting it. However, the strength of this effect varies depending on factors such as resource endowment, economic development and geographical location. The U-shaped impact of

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digital technology innovation on green finance is more pronounced in non-resource-based cities and eastern regions. Digital technology innovation can influence green finance by improving environmental quality, specifically by enhancing carbon productivity and reducing sulphur dioxide emissions. Digital technology innovation not only has a U-shaped impact on local green finance development, but also exerts a U-shaped influence on surrounding areas through spatial spillover effects.

Table 10. *Results of the spatial effects test*

Variable	Adjacency matrix				Anti-distance matrix			
	(1)	**Direct effects (2)**	**Indirect effects (3)**	**Total utility (4)**	**(5)**	**Direct effects (6)**	**Indirect effects (7)**	**Total utility (8)**
DT	-0.0088*** (0.0009)	-0.0088*** (0.0009)	-0.0498*** (0.0069)	-0.0586*** (0.0069)	-0.0075*** (0.0009)	-0.0085*** (0.0010)	-0.2645*** (0.0696)	-0.2730*** (0.0697)
DT^2	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0052*** (0.0006)	0.0058*** (0.0006)	0.0005*** (0.0001)	0.0006*** (0.0001)	0.0212*** (0.0052)	0.0218*** (0.0052)
$W \times DT$	-0.0356*** (0.0051)				-0.0392*** (0.0068)			
$W \times DT^2$	0.0037*** (0.0004)				0.0032*** (0.0005)			
ρ	0.2371*** (0.0726)				0.8226*** (0.0367)			
Log-likelihood	13147.5353				13239.7652			
Time fixed	Yes							
Urban fixed	Yes							
R^2	0.7825							
Sample capacity	5640							

*** indicates significance at the 1% level. The bracket shows the robust standard error. ‘Yes’ indicates whether the model controls for relevant variables

This study reveals that the impact of digital technological innovation on the development of green finance follows a U-shaped pattern: initial suppression is followed by a significant boost. It also exhibits significant spatial spillover effects. To accelerate the deep integration of digital technology and green finance, the following policy recommendations are proposed: Firstly, the strategic deployment of digital technology should be strengthened. Increase investment in core technologies such as artificial intelligence, blockchain and big data, in order to shorten the initial suppression phase. Second, establish regional incubation funds for digital green technology, focusing on non-resource-based cities and pilot projects in eastern regions to leverage their leading role in the U-shaped effect. Secondly, a differentiated regional promotion mechanism should be established. Eastern regions should further develop the application of digital technology in green finance scenarios. Meanwhile, central and western regions, as well as resource-based cities, must upgrade their infrastructure and implement policy compensation mechanisms to avoid a transformation gap. The ‘digital fly land’ model should be explored to guide the spillover effect of technological advancements to less developed areas. Thirdly, establish a channel for converting environmental benefits. Incorporate carbon productivity and digital monitoring of pollutants into green finance standards. Encourage financial institutions to develop products that link environmental improvement with financing costs, thus enhancing the financial application of environmental data through digital technology. Fourth, improve cross-regional collaborative governance. Establish a regional alliance of digital green finance platforms

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to break down data barriers. Provide fiscal and tax incentives for technology diffusion projects that generate positive spatial spillovers to promote the cross-domain sharing of green technology and joint risk prevention and control.

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