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Catalyzing green total factor productivity through digital innovation: mechanisms, evidence, and policy implications from urban China

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Introduction: Digital technological innovation has emerged as a crucial catalyst in balancing economic growth with environmental sustainability. In the context of high-quality development, understanding how digital innovation contributes to green total factor productivity (GTFP) is of growing importance, particularly amid global efforts toward decarbonization and industrial transformation.

Methods: This study investigates the impact and underlying mechanisms of digital technological innovation on green total factor productivity (GTFP) by constructing a panel dataset comprising 278 Chinese prefecture-level cities from 2007 to 2022. To examine both the direct and indirect effects, the analysis applies a range of econometric methods, including fixed effects models, mediation models, and instrumental variable estimation. Robustness of the results is verified through alternative specifications, exclusion of outliers, lagged variables, and policy-based instruments.

Results: The empirical findings demonstrate that digital technological innovation exerts a significant positive impact on GTFP, with each one-unit increase in the digital innovation index leading to an estimated 0.8% improvement in carbon emission efficiency. Further mediation analysis suggests that this enhancement in GTFP is primarily driven by two interrelated mechanisms: the intensification of green technological innovation activities and the advancement of industrial structure toward more sustainable configurations. Additionally, heterogeneity analysis reveals that the strength and direction of this relationship vary notably across cities, depending on their specific resource endowments, the strength of intellectual property protection, and the extent of engagement in green policy pilot initiatives.

Discussion: These findings underscore the importance of integrating digital and green development pathways. To fully harness the potential of digital innovation for promoting green productivity, policymakers should foster a collaborative digital-green innovation ecosystem, improve institutional support for green technology diffusion, and coordinate industrial policies that jointly advance digitalization and environmental goals. City-specific strategies should leverage local strengths to facilitate the emergence of new digital-green industries.

KEYWORDS

digital technological innovation, green total factor productivity, green technological innovation, industrial structure upgrading, digtial economy

1 Introduction

China is currently the world's largest carbon emitter, accounting for approximately 30% of global carbon emissions. Although the share of coal consumption in China's energy mix fell below 55% in 2023, fossil fuels remain the primary source of energy in the short term. Against the backdrop of intensifying climate change and mounting resource constraints, fostering the synergistic development of economic growth and environmental quality has become a global consensus (Wu et al., 2022). The United Nations' 2030 Sustainable Development Goals explicitly call for a clean energy transition and sustainable industrialization, underscoring the unsustainability of traditional, extensive growth models. In response to global environmental challenges, countries have adopted diverse strategies tailored to their national circumstances and developmental stages. For instance, the European Union pledged to achieve carbon neutrality by 2050 in the 2019 European Green Deal; China committed at the 75th session of the United Nations General Assembly in 2020 to peak carbon emissions before 2030 and strive for carbon neutrality by 2060; and the United States allocated USD 369 billion to support clean energy through the Inflation Reduction Act of 2022. Within this context, Green Total Factor Productivity (GTFP) has emerged as a pivotal metric for assessing the quality of economic growth and ecological efficiency. By incorporating undesirable outputs (e.g., carbon emissions, wastewater discharge) and energy consumption (Wang et al., 2021), GTFP captures the green premium of economic growth, enabling the decoupling of economic development from environmental degradation.

Currently, digital technologies (e.g., artificial intelligence, big data, and the Internet of Things) are rapidly permeating all sectors of the economy and society, reshaping production functions and the logic of resource allocation (Wang et al., 2025a; Wang et al., 2025b). Digital technological innovation refers to a systemic innovation process centered on digital technologies that enhances economic and social efficiency, optimizes structural configurations, and promotes sustainable development through technological research and development (R&D), product and service innovation, and business model transformation. Digital innovation contributes to green transformation not only by improving efficiency but also by redefining sustainable development paradigms through innovative models (Li et al., 2025). The "14th Five-Year Plan for Digital Economy Development" explicitly advocates digitalization as a driver of greening. A recent World Bank report suggests that digital technologies could contribute 15%–20% of the global carbon reduction target. China's digital innovation has evolved from a stage of technological catch-up to parallel development and even global leadership in specific domains. As both the largest carbon emitter and a leading digital economy, China offers a unique case for examining the role of digital technological innovation in enhancing GTFP. Exploring the nexus between digital innovation and GTFP is not only a theoretical imperative for addressing the climate crisis and achieving sustainable development, but also a practical urgency for securing technological leadership and mitigating systemic risks. The synergy between the two is poised to reshape the logic of economic growth, shifting from high-carbon development toward a model of digitally driven green prosperity.

Building upon the preceding discussion, it is imperative to further investigate the relationship between digital technological innovation and green total factor productivity, given their intrinsic linkage. Specifically, does digital innovation have a significant influence on GTFP? Through which transmission mechanisms does this influence occur? Moreover, how does the impact of digital technological innovation on GTFP vary across cities with different resource endowments, levels of intellectual property protection, and policy pilot designations? To address these questions, this study employs panel data from 278 prefecture-level cities in China spanning the period from 2007 to 2022, and constructs a series of econometric models to empirically examine both the effects and the underlying mechanisms through which digital technological innovation influences GTFP. By answering these questions, the study aims to inform the formulation of differentiated "digital + green" development policies at the governmental level, support enterprises in reducing environmental compliance costs through digital transformation, and offer practical insights for cities seeking to achieve green growth via technological upgrading.

The main contributions of this study are threefold. First, it enriches the literature on the determinants of GTFP by introducing digital technological innovation as a key explanatory variable and establishing an integrated "technology–economy–environment" analytical framework. Second, it advances the theoretical understanding of the synergistic evolution of the digital and green economies by exploring how digital innovation stimulates GTFP through channels such as green technological progress and industrial structure upgrading, thereby contributing to the emerging theory of dual spiral dynamics between digitalization and greening. Third, the study empirically verifies the effect and mechanism of digital technological innovation on GTFP and conducts heterogeneity analyses based on resource endowments, intellectual property protection levels, and policy pilot city status, offering robust empirical support for the role of digital innovation in fostering green economic transformation.

2 Related work

Recent years have witnessed a surge in scholarly interest in understanding how digital technological innovation influences green development outcomes, particularly in relation to GTFP. As an essential indicator of sustainable economic transformation, the GTFP has drawn increasing attention in discussions on ecological modernization and the integration of the digital economy. Against this backdrop, the existing body of literature can be broadly categorized into two main strands: studies focusing on digital technological innovation and those examining the driving factors of GTFP.

Research on digital technological innovation has primarily focused on several key areas. First, in terms of the concept of digital technological innovation, some scholars view it as a dynamic process aimed at reconfiguring existing digital elements or creating new digital technologies, leading to the development of new products and services (Yoo et al., 2010; George et al., 2021). Other scholars, however, consider digital technological innovation as an outcome, where companies introduce digital technologies to create new products, services, and business models, ultimately resulting in value addition (Hinings et al., 2018). Second, regarding the relationship between digital technologies and the green economy, some studies suggest that digital technologies promote industrial upgrading, optimize resource allocation, and strengthen environmental regulations, which in turn enhance green technological innovation capacity (Fan et al., 2023; Zhao and Qian, 2024), reduce carbon emission intensity (Liu et al., 2023; Shen and Zhang, 2024; Huang et al., 2024), and mitigate air pollution (Shen et al., 2024), thus contributing to the sustainable development of the green economy (Yang et al., 2023). However, other studies argue that the rapid development of digital technologies may exacerbate energy consumption, thereby increasing carbon emissions (Chen et al., 2024). Additionally, digital technologies may have spatial spillover effects, reducing carbon emissions in neighboring cities (Liu et al., 2022; Wang H. et al., 2023). Third, in terms of the environmental governance effects of digital technological innovation, much research has focused on the relationship between digital innovation and carbon emissions, with inconsistent results still being reported. Some scholars argue that digital innovation enables companies to acquire more tacit knowledge, reduce R&D costs, and increase their willingness to engage in technological innovation (Ge et al., 2023). Furthermore, digital technologies can overcome geographical and temporal barriers (Wanof, 2023), accelerate the dissemination of digital knowledge, and improve energy efficiency (Ma and Lin, 2025), thereby reducing carbon emission intensity (Wang X. et al., 2023; Pu et al., 2025). Additionally, some studies propose that the relationship between digital innovation and carbon emissions is nonlinear. One group of studies suggests a U-shaped nonlinear relationship, asserting that digital innovation has a more significant impact on improving carbon emission efficiency than traditional technological innovations (Li and Yue, 2024). Other studies argue for an inverted U-shaped nonlinear relationship, noting that the relationship between digital innovation and carbon emissions varies with the level of technological innovation and economic development (Chen et al., 2022; Li et al., 2024).

Another major strand of literature focuses on the determinants of GTFP. As an extension of traditional total factor productivity, GTFP incorporates environmental constraints and pollution factors into the productivity framework, providing a more accurate assessment of sustainable economic development and serving as an essential indicator for evaluating the transition toward green and high-quality growth. Existing studies have explored the driving forces of GTFP from multiple perspectives. At the macro level, scholars have emphasized the role of green technological innovation, green finance, and the digital economy in reducing information asymmetries and improving resource allocation efficiency, ultimately enhancing regional GTFP (Fan et al., 2022; Lee and Lee, 2022; Lyu et al., 2023). From a microeconomic perspective, research has shown that firms' digital transformation and government subsidies can alleviate financing constraints and improve production efficiency, thereby contributing to improvements in firm-level green productivity (Wang J. et al., 2023; Qian and Zhou, 2024). In addition, from a policy perspective, various public initiatives (e.g., smart city pilot programs, clean air actions, and low-carbon city policies) have been found to stimulate technological upgrading, foster innovation, and optimize industrial structures, all of which are conducive to enhancing GTFP (Wang et al., 2022; Zhou et al., 2024; Liu et al., 2024).

In summary, existing literature primarily focuses on the definition of digital technological innovation, the relationship between digital technologies and the green economy, the environmental governance effects of digital technological innovation, and the factors driving GTFP at the macro, micro, and policy levels. These studies provide theoretical support and empirical foundations for exploring the relationship between digital technological innovation and GTFP. However, gaps remain in this area: Firstly, most studies focus on the impact of digital technological innovation on carbon emissions, treating carbon reduction and green economy development as separate entities. This paper adopts a holistic approach, considering both economic growth and environmental quality, to examine the green economic effects of digital technological innovation. Secondly, while most research focuses on the effects of digital technologies on the green economy, few studies address digital technological innovation from the perspective of patent elements to explore its green economic effects. This study investigates the environmental economic benefits of digital technologies from a patent perspective. Thirdly, there is a lack of research exploring the mechanisms through which digital technological innovation influences GTFP. We systematically examine the impact mechanisms of digital technological innovation on GTFP, integrating green technological innovation and industrial upgrading into the analysis framework, thus providing new insights into the black box of how digital technological innovation affects GTFP.

3 Theoretical analysis and research hypotheses

3.1 Direct impact of digital technological innovation on green total factor productivity

Digital technological innovation can directly enhance GTFP through several mechanisms. First, it promotes efficiency improvement. On the one hand, digital innovation facilitates the restructuring of smart manufacturing systems. The integration of industrial internet platforms enables real-time monitoring of energy consumption throughout production processes, thereby increasing efficiency and reducing energy use on the production line. On the other hand, digital technologies also support the transformation of intelligent energy systems by enhancing monitoring and optimization capabilities in energy generation, making production more flexible and efficient while curbing energy consumption. Second, digital innovation enables business model innovation. The rise of the sharing economy—supported by Internet of Things (IoT) and 5G-enabled shared manufacturing platforms—enhances equipment utilization and fosters the transition to greener business models. Moreover, digital technologies support the development of circular economies by improving material recovery rates, establishing closed-loop recycling systems, and reducing raw material consumption. Third, it facilitates data factor reconstruction. Digital innovation enables the integration of urban data resources and the efficient flow of data among firms, governments, and the public, thus breaking data monopolies and optimizing urban governance. At the same time, it promotes the construction of data governance frameworks that address issues such as data security and privacy, leading to innovation in urban governance models and facilitating the transition to green urban economies. Fourth, digital innovation drives governance upgrades. It strengthens government digital oversight by establishing continuous environmental monitoring networks, which in turn compel firms to reduce emissions and improve their green productivity. Furthermore, the development of digital infrastructure for carbon markets, including tamper-proof carbon accounts and automatically executed smart contracts for emissions trading, enhances urban management efficiency and contributes to improvements in green productivity. Based on this, we propose the following research hypothesis.

H1: Digital technological innovation significantly promotes green total factor productivity.

3.2 Mechanisms of digital technological Innovation's impact on GTFP

3.2.1 Green innovation mechanism

Digital innovation contributes to the enhancement of green innovation capabilities by unlocking digital dividends. First, it provides firms with accurate tools for resource and cost management, allowing for precise tracking of green innovation investments and returns. Through real-time environmental data collection, AI algorithms can analyze pollution sources, energy consumption distribution, and other key metrics, providing targeted insights for green technology research and development. It reduces resource waste and production costs, thereby encouraging firms to engage in green technological innovation. Second, unlike traditional innovation, digital innovation overcomes geographical and temporal constraints, possesses strong spillover effects and information retrieval capabilities, and enables the aggregation and sharing of fragmented knowledge on green innovation. Such capabilities break down traditional barriers and limitations, fostering collaboration and coordinated responses among firms and advancing their green innovation capabilities (Luo et al., 2023). Third, digital technology innovation is highly versatile, allowing it to blur the boundaries of economic activities across different firms and industries. It can transcend traditional industry barriers, enabling cross-domain collaboration in data, equipment, and supply chains, promoting the recombination of production factors, fostering the emergence of green business models, and advancing the intelligent transformation of the economy.

Additionally, green innovation serves as a crucial pathway for achieving sustainable development while fostering economic growth. On the one hand, companies can enhance their energy efficiency through green processes and technologies, thereby significantly reducing energy consumption per unit of output, minimizing resource waste, and mitigating the negative environmental impacts associated with traditional production methods. It helps lower the costs of environmental governance and boosts regional GTFP (Hao et al., 2023). On the other hand, green innovation products can influence consumer preferences. Through differentiated design and functionality, they gradually change consumer behavior, guiding consumers toward more sustainable consumption patterns and increasing public environmental awareness (Zhang et al., 2018). Consumer preference for green products can create a favorable competitive environment for businesses, forming a market-driven selection mechanism. It encourages firms to improve their technologies and reduce emissions to remain competitive, fostering a "demand-driven supply" cycle that improves production efficiency and reduces pollution emissions. Based on this, we propose the following research hypothesis.

H2: Digital technological innovation can enhance green innovation capabilities, which in turn contributes to the improvement of GTFP.

3.2.2 Industrial structure upgrading mechanism

Digital technological innovation has the potential to unlock the digital dividend and drive industrial structural upgrading. First, digital technological innovation is highly permeative and deeply integrated into traditional production and management processes. Technologies such as the IoT, big data, and artificial intelligence (AI) optimize traditional production workflows, enabling disruptive innovations in traditional industries and transforming the original industrial division of labor. As specialization and division of labor within industries increase, the production segments of traditional industries gradually shift towards service-oriented functions. Correspondingly, the secondary sector exhibits a trend of transitioning towards the tertiary sector, leading to an economy characterized by "servicification" and, ultimately, industrial structural upgrading. Second, with the development of digital technological innovation, companies, pressured by competition, must adopt technologies such as cloud computing, AI, and IoT to optimize production processes and improve efficiency. In turn, it fosters the emergence of new technological service industries. Traditional manufacturing industries are transforming into a "manufacturing + services" model (e.g., industrial internet platforms), giving rise to high-value-added services such as technical consulting and data analysis. As a result, the share of the tertiary sector continues to grow. Additionally, traditional service industries are undergoing digital upgrades and, through deep integration with technological services, are forming synergistic effects. These industries are rapidly

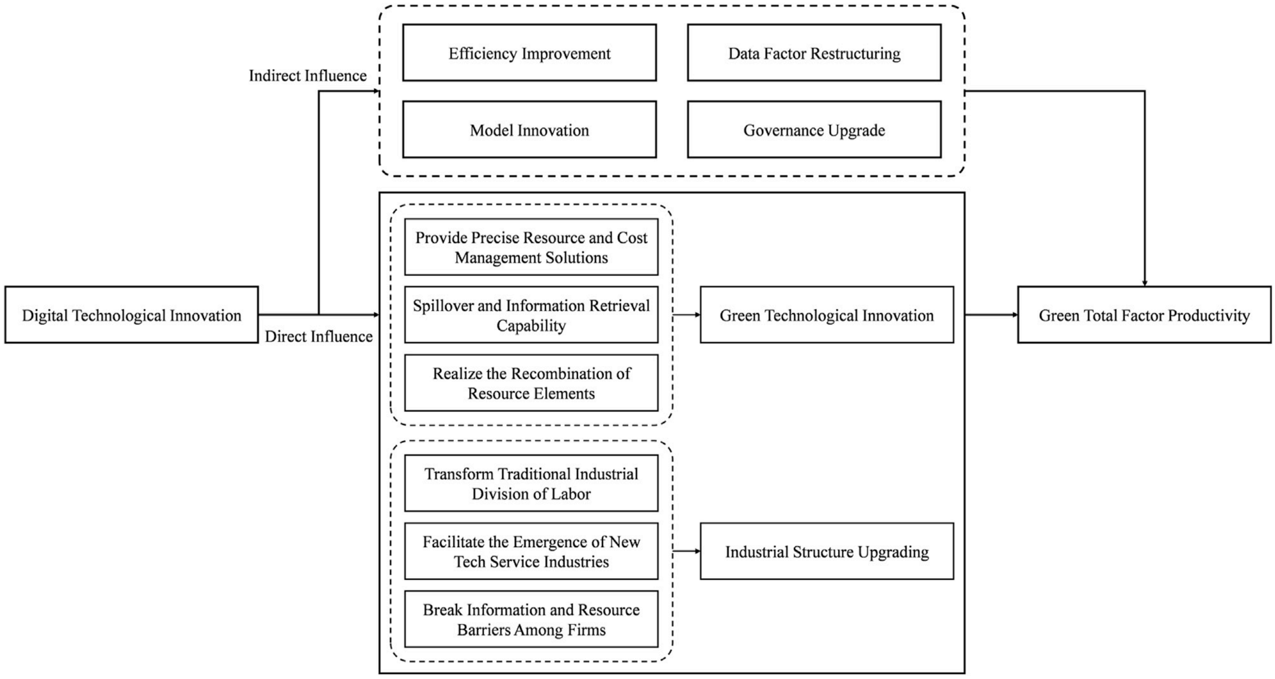

FIGURE 1
Theoretical framework for examining the impact of digital technological innovation on green total factor productivity.

becoming a driving force within the broader industrial structure, contributing significantly to the overall upgrading of the economy. Third, the application of digital technologies can break down information and resource barriers between firms (Niu et al., 2023). Technologies such as blockchain and cloud computing enable real-time cross-enterprise data sharing, eliminating information silos. This promotes the interconnectedness of information, knowledge, and resources across the entire industrial chain, effectively reducing information, knowledge, and resource biases. Furthermore, through the use of electronic contracts and smart contracts, automated transaction processes are realized, shortening settlement cycles, reducing manual verification costs, and lowering transaction fees. These innovations enhance communication and coordination efficiency across the industrial chain, collectively driving the optimization and upgrading of the entire industrial structure.

In addition, the transfer of production factors (e.g., capital, labor, and technology) from high-energy-consuming, low-efficiency traditional industries (e.g., steel and chemicals) to low-energy-consuming, high-value-added emerging industries (e.g., renewable energy and advanced manufacturing) leads to a more efficient industrial structure. The shift fosters the substitution of high-energy-consuming industries with high-value-added ones. Through digitalization, intelligent technologies, and green processes, emerging industries are reducing energy intensity, gradually replacing traditional industries that are high-pollution and high-carbon-emission. It promotes the low-carbon transformation of the economy and significantly reduces energy consumption per unit of GDP, enhancing both production and environmental efficiency, thereby driving the improvement of GTFP (Lin et al., 2024). Furthermore, industrial structure upgrading is often accompanied by technological progress, and the dissemination, diffusion, and transfer of technology help enhance the green production efficiency of firms, further promoting regional GTFP. Based on the above, we propose the following research hypothesis.

H3: Digital technological innovation can promote industrial structure upgrading, which in turn contributes to the improvement of GTFP.

Based on the above hypotheses, this study constructs the theoretical framework as illustrated in Figure 1.

4 Data and model description

4.1 Model design

4.1.1 Baseline regression model

To comprehensively examine the relationship between digital technological innovation and green total factor productivity, we construct the following fixed effects model to estimate the impact of digital innovation on GTFP, as specified in Equation 1.

$$GTFP_{i,t} = \beta_0 + \beta_1 \times DTI_{i,t} + \theta_1 \times X_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $GTFP_{i,t}$ denotes green total factor productivity in city i and year t, $DTI_{i,t}$ represents digital technological innovation, $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the random error term. The coefficients β_0, β_1, and θ_1 represent the intercept, the coefficient of interest (i.e., the effect of digital innovation on GTFP), and the vector of coefficients for the control variables, respectively.

4.1.2 Transmission path model

To test the mechanisms through which digital technological innovation affects GTFP (e.g., green innovation capacity and industrial structure upgrading), we establish the following mediation models in conjunction with the baseline regression, as specified in Equations 2, 3.

$$M_{i,t} = \alpha_0 + \alpha_1 \times DTI_{i,t} + \theta_2 \times X_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$GTFP_{i,t} = \gamma_0 + \gamma_1 \times DTI_{i,t} + \gamma_2 \times M_{i,t} + \theta_3 \times X_{i,t} + \varepsilon_{i,t} \tag{3}$$

where, $M_{i,t}$ denotes the mediator variable (e.g., green innovation capacity or industrial structure upgrading). The coefficient α_1 captures the effect of digital innovation on the mediator, while γ_1 and γ_2 indicate the direct and indirect (mediated) effects of digital innovation on GTFP.

4.2 Variable descriptions

4.2.1 Dependent Variable

Green Total Factor Productivity (GTFP) is calculated using a super-efficiency Slack-Based Measure (SBM) model with undesirable outputs, combined with the Global Malmquist Luenberger (GML) index. The SBM model is an enhanced version of data envelopment analysis that simultaneously accounts for slack variables in both inputs and outputs, while incorporating both ideal and non-ideal outputs. GTFP emphasizes the inclusion of environmental costs in economic growth, treating pollution as an undesirable output and directly incorporating it into the efficiency evaluation framework. Compared to the Stochastic Frontier Analysis (SFA) model, the SBM model enables the inclusion of both expected and undesirable outputs, facilitating multi-objective optimization to calculate efficiency losses directly. It mitigates the bias that might arise if negative factors, such as pollution emissions, are ignored, which is often a limitation in SFA models that must use dummy variables or modify model structures to indirectly address undesirable outputs, potentially introducing estimation errors or bias in assumptions. Therefore, the SBM model, which accommodates undesirable outputs, provides a more comprehensive and precise measurement of GTFP. By incorporating the Malmquist index or a time-series analysis framework, the GML-SBM model decomposes changes in GTFP into two components: technological progress and efficiency change effects, quantifying the dynamic evolution of environmental efficiency over time. The GML index is a green productivity index, which can be further decomposed into the Green Efficiency Change (GEC) and Green Technical Change (GTC) indices. The measurement criterion for all three indices is whether they exceed 1. When all three indices are greater than 1, it indicates an improvement in green productivity, technological efficiency, and progress. Conversely, when all indices are less than 1, it suggests a decline in these areas.

The calculation process of the undesirable output super-efficiency SBM model combined with the GML index requires input (e.g., labor, capital, and energy), expected outputs, and undesirable output indicators. Labor input is represented by the number of employed persons in each city, capital input is represented by the fixed capital stock in each city, and the total electricity consumption of each city represents energy input. The actual GDP of each city measures expected output, while undesirable output is measured by industrial SO_2 emissions, smoke (dust) emissions, and wastewater discharges. Additionally, fixed capital stock is calculated using the perpetual inventory method, with 2007 as the base year.

4.2.2 Core independent variable

Digital Technological Innovation (DTI). This study measures digital technological innovation at the prefecture-level city level using the number of authorized digital technology patents. Patent authorizations reflect the efficiency of technological output, with a higher number indicating greater regional activity in digital technology research, application, and intellectual property protection. The specific measurement process is as follows: (1) Based on the Classification System of Key Digital Technology Patents, relevant International Patent Classification codes are used to extract digital patent data from the China National Intellectual Property Administration database; (2) Patent publication numbers filter the dataset to retain only authorized digital technology patents; (3) Authorized patent counts are aggregated annually for each city based on the geographic location of the patents; (4) The total number of authorized patents is incremented by one and then log-transformed to serve as a proxy indicator for each city's digital technological innovation capability.

4.2.3 Mediating variables

Green Innovation Capacity (GIC). Patents serve as a key carrier of knowledge and a direct output of innovation activities. Green patents encompass a diverse range of domains, including renewable energy, pollution control, and the circular economy. Thus, the number of green patent applications can comprehensively reflect a city's green technology portfolio and industrial diversification rather than merely representing a single technological breakthrough. Moreover, green patent application data sourced from official or authoritative databases offer an objective and quantifiable measure of innovation input in environmental protection, clean energy, and energy conservation. It helps reduce subjectivity and allows for consistent cross-city comparisons. Accordingly, this study uses the number of green patent applications, incremented by one and log-transformed, as a proxy for green innovation capability.

Industrial Structure Upgrading (ISU). An increase in the share of the tertiary industry often signifies progress in industrial structure optimization and upgrading. Therefore, this study uses the ratio of tertiary industry output to secondary industry output as a proxy for industrial structure upgrading. A higher ratio indicates a growing share of services in the economic structure, reflecting a shift toward high-value-added and technology-intensive sectors.

4.2.4 Control variables

The control variables included in this study are as follows:

Financial Development Level (FDL). Measured by the ratio of year-end financial deposits and loans to GDP for each city. On one hand, a more developed financial sector can ease financing constraints for green and low-carbon projects, thereby supporting green economic development. On the other hand, increased financial activity may also channel capital into high-pollution,

TABLE 1 Descriptive statistics for variables.

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
GTFP	4,448	1.004	0.075	0.488	2.828
DTI	4,448	2.906	2.166	0.000	10.809
GIC	4,448	1.504	3.613	0.000	49.982
ISU	4,448	1.011	0.582	0.094	5.650
FDL	4,448	2.653	1.833	0.560	38.237
IDL	4,448	10.409	9.023	0.000	108.370
GID	4,448	0.067	0.120	0.000	1.266
UL	4,448	1.734	0.185	0.452	2.128

GTFP: green total factor productivity; DTI: digital technological innovation; GIC: green innovation capacity; ISU: industrial structure upgrading; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level.

energy-intensive industries, thereby hindering the growth of green initiatives.

Infrastructure Development Level (IDL). Proxied by *per capita* urban road area. While improved infrastructure can enhance the synergy between economic growth and environmental quality, it may also rely heavily on energy-intensive and polluting industries, potentially stimulating demand in those sectors and undermining green development.

Government Intervention Degree (GID). Measured by the ratio of government fiscal expenditure to GDP. A higher degree of government intervention can direct resources toward clean energy and circular economy sectors, thereby promoting green development. However, excessive intervention may create path dependence among firms and weaken their capacity for independent innovation, which could be detrimental to green development.

Urbanization Level (UL). Proxied by the logarithm of population density in each city. Urbanization can enhance resource allocation efficiency by concentrating population and industries, thereby reducing energy consumption and emissions per unit of output. However, rapid urban expansion also increases demand for construction materials and energy, exacerbating resource scarcity and potentially impeding green development.

4.3 Data sources

This study examines data from 278 prefecture-level cities in China for the period 2007–2022. The selection of this time window is based on several factors. First, regarding key time points, the year 2007 marks the onset of the global financial crisis, which prompted countries worldwide to adopt technological innovation as a strategy for economic recovery. During this period, China launched the “Digital China” strategy, and digital technologies entered a phase of accelerated development. From 2020 to 2022, the global spread of the COVID-19 pandemic triggered a surge in demand for digital transformation, with remote work and green energy technologies becoming focal points. This period allows us to observe both the short-term shocks and long-term adaptability of digital technologies on green productivity. Second, regarding data completeness and policy continuity, China initiated the “National Medium- and Long-Term Plan for Science and Technology Development (2006–2020)” in 2008, followed by the “14th Five-Year Plan (2021–2025)” in 2021. These documents provide a comprehensive policy framework that covers the full implementation cycle, facilitating the analysis of policy effects. Additionally, public data from institutions such as the National Bureau of Statistics of China and the World Bank has become more robust after 2007, ensuring the availability of high-quality data for the study. Finally, the technological evolution and green transformation align well within the selected timeframe. From 2007 to 2022, cloud computing, artificial intelligence, and renewable energy technologies experienced rapid growth, coinciding with the early stages of China’s “dual carbon” goals. This period effectively captures the dynamic impact of digital technological innovation on green total factor productivity.

The research data is sourced from the National Intellectual Property Database and the China City Statistical Yearbook. To ensure data consistency and diversity, the following data processing steps were applied: 1) Data consistency: Data was standardized to ensure comparability across different datasets; 2) Missing data: Missing data points were filled using linear interpolation methods; 3) Price-adjusted indicators: For indicators containing price factors, the base year of 2000 was used, and corresponding price indices were applied to deflate the data; 4) Diversity of data: The study covers 278 cities to ensure data diversity, with selected variables spanning economic, social, and environmental dimensions. In summary, descriptive statistics for the key variables used in this study are presented in Table 1.

5 Empirical results and analysis

To empirically examine the effect and underlying mechanisms of digital technological innovation on green total factor productivity, this study adopts the following methodological approach. The research design is illustrated in Figure 2.

5.1 Empirical results of the baseline regression

Table 2 presents the estimation results of Model (2). Column (1) reports the baseline regression without the inclusion of control variables. The coefficient of digital technological innovation is significantly positive at the 1% level, indicating that digital

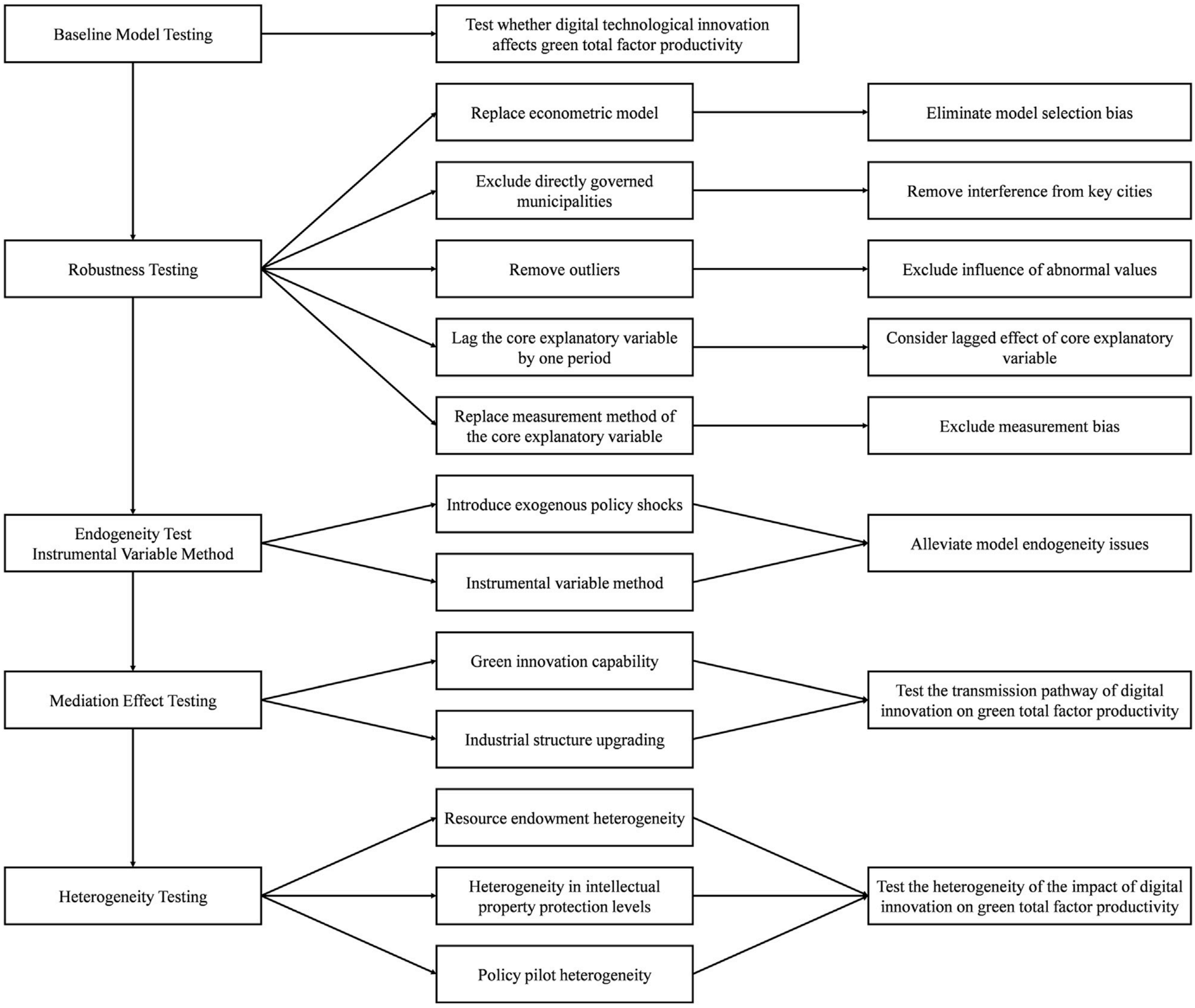

FIGURE 2
Analytical framework and empirical strategy.

TABLE 2 Empirical results of baseline regression.

Variable	(1)	(2)	(3)	(4)	(5)
DTI	0.008*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
FDL		0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
IDL			0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
GID				0.023** (0.010)	0.023** (0.010)
UL					0.030 (0.082)
CFE	YES	YES	YES	YES	YES
YFE	YES	YES	YES	YES	YES
Constant	0.980*** (0.003)	0.976*** (0.003)	0.970*** (0.004)	0.968*** (0.004)	0.916*** (0.143)
Observations	4,448	4,448	4,448	4,448	4,448

DTI: digital technological innovation; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

TABLE 3 Empirical results of endogeneity check.

Variable	Exogenous policy shock		Instrumental variable approach	
	Smart city pilot policy	Broadband China pilot policy	DTI	GTFP
DTI				0.028*** (0.002)
SCPP	0.014*** (0.004)			
BCPP		0.029*** (0.004)		
NPO			0.000*** (0.000)	
FDL	0.004*** (0.001)	0.003*** (0.001)	0.376*** (0.015)	−0.008*** (0.001)
IDL	0.001*** (0.000)	0.001*** (0.000)	0.048*** (0.004)	−0.001*** (0.000)
GID	0.008 (0.010)	0.011 (0.010)	−2.068*** (0.250)	0.075*** (0.014)
UL	0.132 (0.081)	0.071 (0.081)	5.726*** (0.180)	−0.162*** (0.017)
CFE	YES	YES	YES	YES
YFE	YES	YES	YES	YES
Constant	0.755*** (0.141)	0.859*** (0.141)	−8.599*** (0.321)	1.228*** (0.028)
LM Statistic				560.141*** (0.000)
Wald F Statistic				663.922 [16.38]
Observations	4,448	4,448	3,551	3,551

DTI: digital technological innovation; SCPP: smart city pilot policy; BCPP: broadband china pilot policy; NPO: number of post offices; GTFP: green total factor productivity; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

innovation plays a significant role in enhancing GTFP. Columns (2) through (5) sequentially incorporate control variables into the model. The coefficient for digital technological innovation remains significantly positive at the 1% level across all specifications, reaffirming its critical role as a key driver in promoting GTFP.

Regarding the control variables, the coefficient for financial development is significantly positive, suggesting that improvements in financial development can help alleviate financing constraints faced by green investment projects, thereby facilitating their implementation and contributing to the enhancement of GTFP. The coefficient for infrastructure development is also significantly positive, implying that improved infrastructure can markedly enhance urban environmental quality and residents' living standards, which in turn supports the advancement of GTFP. Government intervention is likewise positively associated with GTFP at a statistically significant level, highlighting the role of proactive environmental legislation and increased governmental emphasis on pollution control in fostering green productivity growth. In contrast, the coefficient for the level of urbanization is statistically insignificant, indicating no robust effect on GTFP in this context.

5.2 Empirical results of the endogeneity check

To mitigate potential endogeneity issues (e.g., reverse causality) may bias the baseline regression results, we employ three empirical strategies to address possible endogeneity concerns.

5.2.1 Exogenous policy shocks

We exploit two exogenous policy shocks related to digital technology development to instrument for digital innovation in cities.

(1) Smart City Pilot Policy: Recognizing that the Smart City initiative substantially promotes the adoption of digital technologies such as the IoT, cloud computing, and Information and Communication Technology, we use China's Smart City pilot program, which was launched in three phases in 2012, 2013, and 2015, as an exogenous source of variation. A policy dummy is constructed by assigning a value of one to pilot cities from the pilot year onward and 0 to all other cities. Column (2) of Table 3 reports the regression results. The estimated coefficient on the Smart City policy is significantly positive, suggesting that the implementation of the policy leads to a marked improvement in cities' GTFP.

(2) Broadband China Pilot Policy: To further validate our findings, we incorporate the Broadband China pilot policy, implemented in three batches during 2014, 2015, and 2016, as an alternative exogenous shock. This policy aimed to accelerate broadband infrastructure and facilitate digital transformation, thereby encouraging enterprise-level innovation in digital technologies. Similarly, a dummy variable is constructed to equal one for pilot cities from the implementation year onward. As shown in Column (3) of Table 3, the estimated coefficient remains significantly positive, indicating a robust positive impact of the policy on GTFP.

TABLE 4 Empirical results of the robustness.

Variable	Model replacement	Municipality exclusion	Outlier removal	One-period lag	Alternative GTFP measure	Alternative DTI measure
	(1)	(2)	(3)	(4)	(5)	(6)
DTI	0.014*** (0.003)	0.006*** (0.001)	0.005*** (0.001)		0.029*** (0.001)	0.006*** (0.001)
L.GTFP	0.524*** (0.118)					
L.DTI				0.007*** (0.001)		
FDL	−0.002 (0.001)	0.002*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	−0.001 (0.001)	0.003*** (0.001)
IDL	0.003*** (0.001)	0.001*** (0.000)	−0.000* (0.000)	0.001*** (0.000)	0.000** (0.000)	0.001*** (0.000)
GID	0.057*** (0.021)	0.022*** (0.008)	0.023*** (0.008)	0.019* (0.010)	0.018 (0.012)	0.031*** (0.011)
UL	0.172 (0.154)	−0.025 (0.065)	0.047 (0.061)	0.008 (0.087)	0.074 (0.098)	0.052 (0.082)
AR statistics (1)	−4.399					
AR statistics (2)	3.554					
Sargan	245.428					
CFE	YES	YES	YES	YES	YES	YES
YFE	YES	YES	YES	YES	YES	YES
Constant	0.113 (0.346)	1.015*** (0.113)	0.899*** (0.106)	0.955*** (0.151)	0.118 (0.170)	0.872*** (0.142)
Observations	4,170	4,384	4,016	4,170	4,448	4,448

DTI: digital technological innovation; GTFP: green total factor productivity; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; AR, statistics: Arellano-Bond test for autocorrelation; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

5.2.2 Instrumental variable approach

We further employ an instrumental variable strategy using the number of post offices in each city in 1984 as the instrument for digital innovation. This variable satisfies both relevance and exogeneity criteria: historically determined postal infrastructure is plausibly exogenous to current GTFP levels, while also serving as a proxy for early-stage communication infrastructure that may influence the foundation for contemporary digital technology development.

The two-stage least squares regression results are presented in Columns (4) and (5) of Table 3. In the first stage, the instrument is significantly and positively associated with digital innovation, confirming its relevance. In the second stage, digital innovation remains significantly and positively correlated with GTFP, consistent with the baseline results. Moreover, the Kleibergen–Paap LM test yields a p-value of 0.000, indicating no under-identification issue. The Wald F-statistic for weak instruments is 663.922, which far exceeds the 10% critical value of 16.38, ruling out concerns of weak instrumentation. These results support the validity and robustness of the chosen instrument.

5.3 Empirical results of the robustness analysis

To ensure the reliability of the baseline regression results, this study conducts a series of robustness checks using five alternative approaches.

(1) Alternative Estimation Method. To rule out the possibility that the observed improvement in GTFP is driven by model specification, the Generalized Method of Moments (GMM) is employed for re-estimation. As shown in Column (1) of Table 4, the coefficient of digital technological innovation remains significantly positive, confirming that the observed relationship is robust to model changes. Moreover, the Arellano-Bond test for autocorrelation (AR statistics) and the Sargan test for over-identifying restrictions both reject the null hypotheses, indicating no evidence of serial correlation or over-identification issues in the GMM model.
(2) Excluding Municipalities. Given the distinctive economic scale and development patterns of the four centrally administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing), their inclusion may overestimate the effect of digital innovation on GTFP. Thus, a robustness check is conducted by excluding these municipalities from the sample. Column (2) of Table 4 shows that the coefficient of digital innovation remains significantly positive, indicating that the baseline findings are not driven by sample selection bias related to municipalities.
(3) Excluding Outliers. To account for the potential influence of extreme values on regression results, all continuous variables are winsorized at the 1st and 99th percentiles. As presented in Column (3) of Table 4, the coefficient of digital innovation remains significantly positive and consistent with the baseline estimates, supporting the robustness of the findings.
(4) Lagged Core Explanatory Variable. Considering the potential time-lagged effect of digital innovation on GTFP, a one-period lag of the core explanatory variable is introduced.

TABLE 5 Empirical results of mechanism check.

Variable	Model (1)	Model (2)	Model (3)	Model (2)	Model (3)
	GTFP	gpa	GTFP	Ind	GTFP
DTI	0.008*** (0.001)	0.820*** (0.030)	0.004*** (0.001)	0.144*** (0.004)	0.006*** (0.001)
GIC			0.004*** (0.001)		
ISU					0.013*** (0.004)
FDL	0.003*** (0.001)	−0.030 (0.024)	0.003*** (0.001)	0.034*** (0.003)	0.002*** (0.001)
IDL	0.001*** (0.000)	−0.020*** (0.005)	0.001*** (0.000)	−0.001 (0.001)	0.001*** (0.000)
GID	0.023** (0.010)	1.207*** (0.312)	0.018* (0.010)	−0.028 (0.042)	0.023** (0.010)
UL	0.030 (0.082)	28.670*** (2.473)	−0.089 (0.084)	−0.116 (0.344)	0.032 (0.082)
CFE	YES	YES	YES	YES	YES
YFE	YES	YES	YES	YES	YES
Constant	0.916*** (0.143)	−50.497*** (4.288)	1.125*** (0.145)	0.716 (0.595)	0.907*** (0.142)
Observations	4,448	4,448	4,448	4,448	4,448

DTI: digital technological innovation; GIC: green innovation capacity; ISU: industrial structure upgrading; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

The results in Column (4) of Table 4 show that the lagged variable of digital innovation still yields a significantly positive coefficient, suggesting a persistent and sustained impact of digital innovation on the enhancement of GTFP.

(5) Alternative Measurement of the Dependent Variable. To account for the possibility that the measurement method for GTFP may affect the regression results, we adopt an alternative approach by recalculating GTFP using the undesirable output super-efficiency SBM model combined with the Malmquist–Luenberger index. As presented in Column (5) of Table 4, the coefficient of digital technological innovation remains significantly positive, consistent with the baseline findings, thereby confirming the robustness of the results.

(6) Alternative Measurement of the Core Explanatory Variable. To assess whether the measurement of digital technological innovation (DTI) affects the results, we substitute the original indicator with industrial robot density, a proxy for the intensity of digital and automation technology integration in production processes. The increasing installation density of industrial robots across cities reflects the depth of digital technology application in industrial production. Column (6) of Table 4 demonstrates that the coefficient of digital innovation remains significantly positive, consistent with the baseline results, thus confirming the robustness of the empirical conclusions.

5.4 Empirical results of the mechanism check

The preceding regression analysis supports the hypothesis that digital technological innovation contributes to the improvement of GTFP. To further examine the underlying transmission mechanisms, we conduct a mediation effect analysis based on Models (1)–(3), with the regression results presented in Table 5.

5.4.1 Effect via green innovation capability

Column (3) of Table 5 reports the impact of digital technological innovation on GTFP. The regression coefficient of digital innovation is significantly positive, indicating that digital technological innovation enhances green innovation capability. Furthermore, in Model (3) shown in Column (4), the coefficient of digital innovation remains significantly positive at 0.004, which is smaller than the coefficient reported in Model (1) (0.008, shown in Column (2)). This suggests that green innovation capability acts as a partial mediator in the relationship between digital innovation and GTFP. In other words, digital technological innovation promotes GTFP in part by improving green innovation capacity.

5.4.2 Effect via industrial structure upgrading

Column (5) of Table 5 presents the effect of industrial structure upgrading on GTFP. The regression coefficient of digital innovation is significantly positive, indicating that digital innovation facilitates the upgrading of the industrial structure. In Model (3), shown in Column (6), the coefficient of digital innovation remains significantly positive at 0.006, which is again lower than the coefficient in Model (1) (0.008). This implies that industrial structure upgrading also serves as a partial mediator in the pathway from digital innovation to GTFP. That is, digital innovation contributes to the enhancement of GTFP by driving the transformation and upgrading of the industrial structure.

5.5 Empirical results of the heterogeneity test

The baseline regression results provide empirical support for the hypothesis that digital technological innovation promotes improvements in GTFP. However, the magnitude and significance of this impact may vary across cities due to

TABLE 6 Empirical results of heterogeneity check.

Variable	Resource endowment heterogeneity		Intellectual property protection heterogeneity	
	Resource-scarce cities	Resource-abundant cities	Cities with weaker intellectual property protection	Cities with stronger intellectual property protection
DTI	0.007*** (0.001)	0.009*** (0.001)	0.005*** (0.001)	0.008*** (0.002)
FDL	0.003** (0.001)	0.002** (0.001)	0.002*** (0.001)	0.004** (0.002)
IDL	0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.001*** (0.000)
GID	0.017 (0.017)	0.025* (0.013)	0.016* (0.010)	0.032 (0.024)
UL	0.083 (0.175)	0.040 (0.091)	−0.014 (0.074)	0.223 (0.234)
CFE	YES	YES	YES	YES
YFE	YES	YES	YES	YES
Constant	0.814*** (0.312)	0.910*** (0.153)	1.004*** (0.122)	0.548 (0.424)
Observations	2,222	2,216	2,214	2,224

DTI: digital technological innovation; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

differences in resource endowments, the level of intellectual property protection, and policy designation status. To account for this, we conduct a series of heterogeneity tests as follows.

5.5.1 Heterogeneity by resource endowment

On the one hand, cities with lower resource endowments exhibit higher levels of industrial development and more substantial marginal returns to digital innovation, potentially leading to more pronounced improvements in GTFP. On the other hand, such cities often exhibit more diversified industrial structures and lower levels of environmental pollution, thereby facing less pressure for environmental governance. As a result, digital innovations specifically targeting environmental protection may be less prevalent, limiting their contribution to GTFP enhancement.

In this study, the ratio of employment in the mining sector to total employment is used as a proxy for the level of resource endowment. By calculating the average of this ratio over the period 2007–2022, we classify cities with values above the median as resource-abundant and those below as resource-scarce. As shown in Table 6, digital innovation exhibits a significantly positive coefficient in both groups. Notably, the effect is stronger in resource-abundant cities, with a coefficient of 0.009 compared to 0.007 in resource-scarce cities. It is attributed to the prevalence of natural resource extraction and processing industries in resource-abundant cities, where the adoption of digital technologies can substantially enhance resource utilization efficiency, reduce pollutant emissions, and improve waste treatment, thereby fostering GTFP growth.

5.5.2 Heterogeneity by intellectual property protection

On the one hand, stronger intellectual property (IP) protection ensures the exclusivity of digital innovations, thereby stimulating firms' motivation and incentives to innovate, ultimately promoting GTFP. On the other hand, excessively stringent IP protection may hinder inter-firm knowledge spillovers, suppressing the diffusion of digital innovation and impeding its contribution to productivity growth.

We proxy the level of IP protection using the number of IP-related court case closures in each city. By calculating the average number of such cases from 2007 to 2022, cities above the median are classified as having strong IP protection, while those below the median are considered to have weaker IP protection. According to Table 6, digital innovation maintains a significantly positive effect on GTFP across both categories. However, the effect is more pronounced in cities with strong IP protection, where the estimated coefficient is 0.008, compared to 0.005 in the weaker-IP group. This finding aligns with the argument that a well-established IP protection regime can reduce firms' risk of infringement (Sweet and Maggio, 2015), enhance innovation incentives, and play a critical role in enabling digital technologies to contribute effectively to green productivity improvements.

5.5.3 Heterogeneity by policy pilot status

5.5.3.1 Low-carbon city pilot policy

The low-carbon city initiative seeks to reduce carbon emissions and promote green development through institutional and technological innovation. Cities are classified as either pilot or non-pilot cities based on their inclusion in the national low-carbon pilot program. Table 7 shows that digital innovation has a positive effect on GTFP in both groups, with a stronger effect observed in pilot cities (coefficient = 0.008) compared to non-pilot cities (coefficient = 0.007). This suggests that pilot cities, which prioritize industrial upgrading and digital-industrial integration, are more effective in leveraging digital innovation for green productivity growth.

5.5.3.2 Smart City Pilot Policy

Smart city policies aim to enhance urban innovation capabilities via advancements in technology, products, markets, resource allocation, and organizational structures. Cities are categorized as pilot or non-pilot cities based on their official designation as smart city pilots. As shown in Table 7, the impact of digital innovation on GTFP remains significantly positive in both groups. Interestingly, the effect is stronger in non-pilot cities (coefficient = 0.009) than in

TABLE 7 Empirical results of heterogeneity check (Policy Pilot Heterogeneity).

Variable	Policy pilot heterogeneity			
	Low-carbon city pilot	Non-low-carbon city pilot	Smart city pilot	Non-smart city pilot
DTI	0.008*** (0.002)	0.007*** (0.001)	0.006*** (0.001)	0.009*** (0.001)
FDL	0.005*** (0.002)	0.001** (0.001)	0.003*** (0.001)	0.002** (0.001)
IDL	0.001*** (0.000)	0.000 (0.000)	−0.000 (0.000)	0.001*** (0.000)
GID	0.005 (0.022)	0.029*** (0.009)	−0.014 (0.012)	0.041*** (0.014)
UL	0.111 (0.229)	0.040 (0.069)	−0.057 (0.139)	0.058 (0.101)
CFE	YES	YES	YES	YES
YFE	YES	YES	YES	YES
Constant	0.760* (0.401)	0.910*** (0.118)	1.078*** (0.239)	0.860*** (0.175)
Observations	1904	2,544	1,440	3,008

DTI: digital technological innovation; FDL: financial development level; IDL: infrastructure development level; GID: government intervention degree; UL: urbanization level; CFE: city fixed effects; YFE: Year Fixed Effects. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, while the values in parentheses indicate standard errors.

pilot cities (coefficient = 0.006). One possible explanation is that smart city pilots already possess well-established digital infrastructure (e.g., IoT, AI), reducing the marginal benefits of further innovation. In contrast, non-pilot cities may exhibit stronger latecomer advantages, allowing digital innovation to yield greater returns in terms of GTFP enhancement (Caragliu and Del Bo, 2019).

6 Research conclusions and policy implications

The synergistic development of digital technological innovation and green total factor productivity constitutes a crucial pathway toward achieving China's dual carbon goals and fostering high-quality economic growth. Using panel data from 278 prefecture-level cities in China from 2007 to 2022, this study employs a fixed effects model and a mediation analysis framework to empirically investigate both the impact and mechanisms through which digital innovation influences GTFP. The main findings are as follows: First, digital technological innovation significantly promotes the improvement of GTFP. Second, this effect is primarily mediated by two channels: enhancement in green technological innovation and the upgrading of industrial structure. Third, the impact of digital innovation on GTFP exhibits notable heterogeneity across cities with different resource endowments, levels of intellectual property protection, and policy pilot statuses. Specifically, the positive effect is slightly more pronounced in cities with higher resource endowments, stronger intellectual property protection, participation in low-carbon city pilot programs, and designation as smart city pilots. These findings underscore the importance of tailoring digital innovation strategies to local contextual factors to maximize their contribution to green and sustainable development. The conclusions of the study are shown in Figure 3.

Based on empirical findings, this study proposes the following policy implications: (1) Governments should reinforce the green orientation of digital technological innovation by prioritizing breakthroughs in core technologies, establishing dedicated funds for green digital R&D, and promoting key innovations such as AI-driven energy optimization, blockchain-based carbon footprint tracking, and industrial internet applications for energy conservation. Policy support should also facilitate scenario-based applications through the development of digital-green demonstration zones and the implementation of carbon efficiency standards for digital infrastructures, including data centers and cloud computing. Moreover, green technical standards should be enhanced by establishing a carbon efficiency evaluation system for digital technologies, such as implementing carbon emission limits per unit of computing power for digital infrastructure (e.g., data centers and cloud computing platforms). At the same time, attention must be paid to the potential negative externalities of digital technological innovation on green total factor productivity. For example, technologies such as cloud computing and AI are highly dependent on energy-intensive infrastructure; rapid hardware iteration generates increasing volumes of electronic waste; and small- and medium-sized enterprises (SMEs) may struggle to participate in green digital upgrades due to technological and financial barriers. Therefore, the government should strike a balance between the deployment of digital technology and green productivity goals by developing energy-efficient chips, establishing green digital technology standards, and promoting international cooperation. (2) A synergistic innovation system integrating digital and green technologies should be developed by enhancing the institutional environment for green technology transfer, establishing cross-sector R&D funds (e.g., AI + clean energy, blockchain + carbon accounting), and fostering open-source platforms for environmental algorithms and databases. It will lower innovation barriers for SMEs. Moreover, evaluation metrics in academic institutions should include indicators such as green patent commercialization rates and emissions reductions enabled by digital technologies. Financial instruments, such as digital green insurance products and preferential green loans, should be further developed and refined to enhance their effectiveness. (3) Industrial policy should be guided by dual priorities of digitalization and decarbonization, with support for emerging digital-green industries. Sector-specific benchmarks

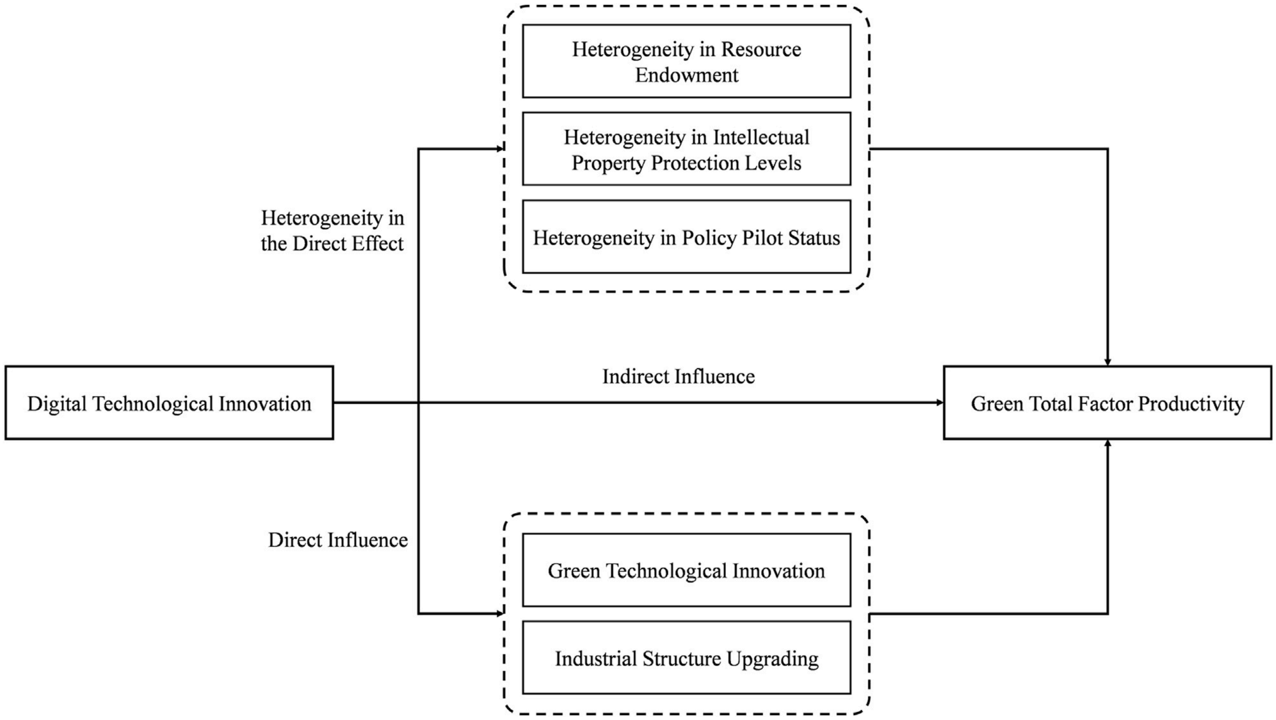

FIGURE 3
Synthesized conclusions and policy implications.

(e.g., digital transformation rates and carbon intensity per unit output) should be established, particularly for high-emission sectors, with incentives for compliance. Emerging business models like virtual power plants and carbon asset management platforms should be promoted. Real-time environmental assessments using digital tools can facilitate the phased exit of inefficient capacities. (4) A differentiated, place-based digital innovation strategy should be adopted to advance local green development. In resource-rich cities, policies should encourage enterprises to adopt intelligent digital upgrades that promote cleaner resource use, supported by fiscal incentives for green outcomes. In contrast, resource-scarce cities should focus on developing high-end green manufacturing through digital innovation. Cities with weaker IP protection should enhance regulatory enforcement and integrate environmental credit systems, while those with stronger IP regimes should be encouraged to build advanced digital R&D labs. Additionally, pilot and non-pilot cities should be treated with differentiated strategies: digital technologies should be leveraged for real-time policy adjustment in pilot cities, and cost-effective lightweight digital upgrades should be promoted in non-pilot cities. A coordinated optimization mechanism between pilot and non-pilot cities should also be established to foster regional digital-green alliances and promote data sharing for integrated regional development.

Despite its contributions, this study has several limitations that warrant further consideration: (1) Data Selection and Measurement Issues. The calculation of green total factor productivity relies heavily on environmental data. However, China's environmental data collection systems remain incomplete, which may lead to measurement errors and an underestimation of the actual impact of digital innovation on GTFP. In addition, using only patent counts to measure digital technological innovation overlooks the influence of intangible factors such as technology diffusion, digital skills, and data quality. (2) Model Construction Constraints. The empirical model may overlook key variables, such as industry-specific differences and policy interventions (e.g., carbon taxes, subsidies), which could compromise the explanatory power of the findings. Furthermore, the model assumes a linear relationship, whereas the link between digital innovation and GTFP may be nonlinear. For instance, the productivity benefits of innovation may be limited in the early stages but could accelerate after reaching a critical threshold due to diffusion or scale effects. A linear model may fail to capture such threshold or S-curve dynamics, resulting in biased estimates. (3) Limited Insight into Long-Term Effects. The study does not fully capture the dynamic and lagged impacts of digital innovation, which may unfold over longer technological cycles. Given the time required for innovation diffusion and industrial upgrading, short-term observation windows may miss the extended pathways through which digital innovation affects GTFP via green innovation or structural transformation. (4) Insufficient Discussion of Potential Risks. The study lacks an in-depth examination of potential risks, including the increased energy consumption associated with digital technologies. This dependency on complex technologies may hinder the transformation of traditional industries and pose significant ethical risks, including data privacy breaches and algorithmic bias. These factors should be integrated into future policy design and research frameworks to inform effective decision-making.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The authors will provide the raw data supporting the conclusions of this paper without reservation. Data could obtained directly from the corresponding author or the first author. Requests to access these datasets should be directed to yaolu0901@163.com.

Author contributions

LY: Methodology, Validation, Supervision, Investigation, Writing – review and editing, Resources, Project administration, Funding acquisition, Writing – original draft, Software, Visualization. CL: Investigation, Writing – review and editing, Resources, Writing – original draft, Software, Supervision, Data curation, Visualization.

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Conflict of interest

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

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References

Caragliu, A., and Del Bo, C. F. (2019). Smart innovative cities: the impact of smart city policies on urban innovation. *Technol. Forecast. Soc. Change* 142, 373–383. doi:10.1016/j.techfore.2018.07.022

Chen, X., Mao, S., Lv, S., and Fang, Z. (2022). A study on the non-linear impact of digital technology innovation on carbon emissions in the transportation industry. *Int. J. Environ. Res. Public Health* 19 (19), 12432. doi:10.3390/ijerph191912432

Chen, Y., Subhan, M., Ahmad, G., Adil, M., and Zamir, M. (2024). Unveiling the linkages among digital technology, economic growth, and carbon emissions: a resource management perspective. *Resour. Policy* 91, 104868. doi:10.1016/j.resourpol.2024.104868

Fan, M., Yang, P., and Li, Q. (2022). Impact of environmental regulation on green total factor productivity: a new perspective of green technological innovation. *Environ. Sci. Pollut. Res.* 29 (35), 53785–53800. doi:10.1007/s11356-022-19576-2

Fan, M., Liu, J., Tajeddini, K., and Khaskheli, M. B. (2023). Digital technology application and enterprise competitiveness: the mediating role of ESG performance and green technology innovation. *Environ. Dev. Sustain.*, 1–31. doi:10.1007/s10668-023-03979-3

Ge, C., Lv, W., and Wang, J. (2023). The impact of digital technology innovation network embedding on firms' innovation performance: the role of knowledge acquisition and digital transformation. *Sustainability* 15 (8), 6938. doi:10.3390/su15086938

George, G., Merrill, R. K., and Schillebeeckx, S. J. D. (2021). Digital sustainability and entrepreneurship: how digital innovations are helping tackle climate change and sustainable development. *Entrepreneursh. theory Pract.* 45 (5), 999–1027. doi:10.1177/1042258719899425

Hao, X., Li, Y., Ren, S., Wu, H., and Hao, Y. (2023). The role of digitalization on green economic growth: does industrial structure optimization and green innovation matter? *J. Environ. Manag.* 325, 116504. doi:10.1016/j.jenvman.2022.116504

Hinings, B., Gegenhuber, T., and Greenwood, R. (2018). Digital innovation and transformation: an institutional perspective. *Inf. Organ.* 28 (1), 52–61. doi:10.1016/j.infoandorg.2018.02.004

Huang, J., Chen, X., and Zhao, X. (2024). How digital technology reduces carbon emissions: from the perspective of green innovation, industry upgrading, and energy transition. *J. Knowl. Econ.* 15, 19294–19326. doi:10.1007/s13132-024-01895-z

Lee, C. C., and Lee, C. C. (2022). How does green finance affect green total factor productivity? Evidence from China. *Energy Econ.* 107, 105863. doi:10.1016/j.eneco.2022.105863

Li, X., and Yue, S. (2024). Blessing or curse? The role of digital technology innovation in carbon emission efficiency. *J. Environ. Manag.* 365, 121579. doi:10.1016/j.jenvman.2024.121579

Li, H., Xie, S., and Su, M. (2024). Does digital technology innovation promote low-carbon development in agriculture? a spatial econometric analysis based on 31 provinces in China. *Environ. Sci. Pollut. Res.* 31 (3), 4478–4499. doi:10.1007/s11356-023-31369-9

Li, S., Zhang, Z., and Lee, C. C. (2025). The spillover effects of digital technology innovation on carbon emissions in urban agglomerations: a perspective based on manufacturing investment networks and geospatial spillovers. *Sustain. Cities Soc.* 124, 106321. doi:10.1016/j.scs.2025.106321

Lin, S., Zhou, Z., Hu, X., Chen, S., and Huang, J. (2024). How can urban economic complexity promote green economic growth in China? The perspective of green technology innovation and industrial structure upgrading. *J. Clean. Prod.* 450, 141807. doi:10.1016/j.jclepro.2024.141807

Liu, J., Yu, Q., Chen, Y., Liu, J., et al. (2022). The impact of digital technology development on carbon emissions: a spatial effect analysis for China. *Resour. Conservation Recycl.* 185, 106445. doi:10.1016/j.resconrec.2022.106445

Liu, H., Wang, L., and Shen, Y. (2023). Can digital technology reduce carbon emissions? Evidence from Chinese cities. *Front. Ecol. Evol.* 11, 1205634. doi:10.3389/fevo.2023.1205634

Liu, Y., Wu, K., and Liang, X. (2024). Does low-carbon pilot policy promote corporate green total factor productivity? *Econ. Analysis Policy* 84, 1–24. doi:10.1016/j.eap.2024.08.015

Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., and Hao, Y. (2023). Digitalization and sustainable development: how could digital economy development improve green innovation in China? *Bus. strategy Environ.* 32 (4), 1847–1871. doi:10.1002/bse.3223

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

Ma, R., and Lin, B. (2025). The impact of digital technology innovation on energy-saving and emission reduction based on the urban innovation environment. *J. Environ. Manag.* 375, 124176. doi:10.1016/j.jenvman.2025.124176

Niu, Y., Wen, W., Wang, S., and Li, S. (2023). Breaking barriers to innovation: the power of digital transformation. *Finance Res. Lett.* 51, 103457. doi:10.1016/j.frl.2022.103457

Pu, Z., Qian, Y., and Liu, R. (2025). Is digital technology innovation a panacea for carbon reduction? *Technol. Econ. Dev. Econ.* 31 (2), 496–524-496–524. doi:10.3846/tede.2024.22208

Qian, J., and Zhou, Y. (2024). The effect and mechanism of subsidies on green total factor productivity of enterprises. *J. Water Clim. Change*, 2024069. doi:10.2166/wcc.2024.069

Shen, Y., and Zhang, X. (2024). Towards a low-carbon and beautiful world: assessing the impact of digital technology on the common benefits of pollution reduction and carbon reduction. *Environ. Monit. Assess.* 196 (8), 695. doi:10.1007/s10661-024-12860-3

Shen, Y., and Zhang, X. (2024). Blue sky protection campaign: assessing the role of digital technology in reducing air pollution. *Systems* 12 (2), 55. doi:10.3390/systems12020055

Sweet, C. M., and Maggio, D. S. E. (2015). Do stronger intellectual property rights increase innovation? *World Dev.* 66, 665–677. doi:10.1016/j.worlddev.2014.08.025

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

Wang, K. L., Pang, S. Q., Zhang, F. Q., Miao, Z., and Sun, H. P. (2022). The impact assessment of smart city policy on urban green total-factor productivity: evidence from China. *Environ. Impact Assess. Rev.* 94, 106756. doi:10.1016/j.eiar.2022.106756

Wang, H., Li, Y., Lin, W., and Wei, W. (2023a). How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China. *J. Environ. Manag.* 325, 116524. doi:10.1016/j.jenvman.2022.116524

Wang, X., Qin, C., Liu, Y., Tanasescu, C., and Bao, J. (2023b). Emerging enablers of green low-carbon development: do digital economy and open innovation matter? *Energy Econ.* 127, 107065. doi:10.1016/j.eneco.2023.107065

Wang, J., Liu, Y., Wang, W., and Wu, H. (2023c). How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. *J. Clean. Prod.* 406, 136954. doi:10.1016/j.jclepro.2023.136954

Wang, X., Safi, A., and Ge, F. (2025a). Towards carbon neutrality: will artificial intelligence and green bond become catalysts? *Energy Econ.* 148, 108711. doi:10.1016/j.eneco.2025.108711

Wang, X., Wang, K., Xu, B., and Jin, W. (2025b). Digitalisation and technological innovation: panaceas for sustainability? *Int. J. Prod. Res.*, 1–18. doi:10.1080/00207543.2025.2468883

Wanof, M. I. (2023). Digital technology innovation in improving financial access for low-income communities. *Technol. Soc. Perspect. (TACIT)* 1 (1), 26–34. doi:10.61100/tacit.v1i1.35

Wu, J., Xia, Q., and Li, Z. (2022). Green innovation and enterprise green total factor productivity at a micro level: a perspective of technical distance. *J. Clean. Prod.* 344, 131070. doi:10.1016/j.jclepro.2022.131070

Yang, Y., Gu, R., Ma, S., and Chen, W. (2023). How does digital technology empower urban green development efficiency in the beijing-tianjin-hebei Region—Mechanism analysis and spatial effects. *Environ. Sci. Pollut. Res.* 30 (11), 31471–31488. doi:10.1007/s11356-022-24368-9

Yoo, Y., Henfridsson, O., and Lyytinen, K. (2010). Research Commentary—The new organizing logic of digital innovation: an agenda for information systems research. *Inf. Syst. Res.* 21 (4), 724–735. doi:10.1287/isre.1100.0322

Zhang, Y., Wang, J., Xue, Y., and Yang, J. (2018). Impact of environmental regulations on green technological innovative behavior: an empirical study in China. *J. Clean. Prod.* 188, 763–773. doi:10.1016/j.jclepro.2018.04.013

Zhao, X., and Qian, Y. (2024). Does digital technology promote green innovation performance? *J. Knowl. Econ.* 15 (2), 7568–7587. doi:10.1007/s13132-023-01410-w

Zhou, L., Fan, J., Hu, M., and Yu, X. (2024). Clean air policy and green total factor productivity: evidence from Chinese prefecture-level cities. *Energy Econ.* 133, 107512. doi:10.1016/j.eneco.2024.107512