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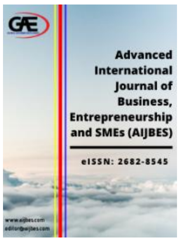

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DIGITAL ECONOMY AND GREEN TOTAL FACTOR PRODUCTIVITY: THE MEDIATING ROLE OF GREEN TECHNOLOGICAL INNOVATION IN CHINESE CITIES

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Abstract:

The paper examines China's progress toward high-quality development, where Green Total Factor Productivity (GTFP) serves as a key measure of economic–environmental coordination. Using panel data from 285 prefecture-level and above cities from 2011 to 2020, it applies the SBM-GML model to measure GTFP and employs two-way fixed effects and mediation models to assess how the digital economy influences urban GTFP and the mediating role of green technological innovation. The results show that: (1) the digital economy significantly improves urban GTFP, and this remains robust after regional fixed effects and multiple tests; (2) green technological innovation partially mediates the digital economy–GTFP relationship, indicating that digitalisation supports green growth through technological progress; and (3) the mediating effect differs across regions. The findings provide theoretical and policy insights for integrating digital economy development with green transformation strategies.

Keywords:

Digital Economy; Green Total Factor Productivity; Green Technological Innovation; Mediation Effect; Regional Heterogeneity

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Introduction

Over the past decade, the rapid development of digital technologies—such as the Internet, big data, artificial intelligence (AI), and blockchain—has profoundly reshaped the global economic landscape. The digital economy, defined as economic activity that takes data as a core production factor, digital technology as the key driver, and information networks as the primary infrastructure, has emerged as a new engine for economic growth and industrial transformation (Carlsson, 2004; G20, 2016). According to the *White Paper on China's Digital Economy (2024)* published by the China Academy of Information and Communications Technology, the size of China's digital economy expanded from RMB 11 trillion in 2012 to RMB 53.9 trillion in 2023, with its share in GDP rising from 21.6% to 42.8%. This dramatic increase highlights the growing importance of the digital economy in driving high-quality development.

At the same time, the Chinese economy is facing mounting challenges stemming from resource depletion, environmental degradation, and population aging. In 2022, China ranked 160th among 180 economies in the Environmental Performance Index (EPI), underscoring the urgent need for a development model that balances economic efficiency with ecological sustainability. Within this context, Green Total Factor Productivity (GTFP) has been widely recognized as a core indicator for green and high-quality economic growth (Feng & Serletis, 2014; Wang et al., 2020).

The interaction between the digital economy and GTFP has attracted growing academic attention (Sun, Jiang, Cui, Xu, & Zhao, 2023). On the one hand, the digital economy may enhance GTFP through technological effects (e.g., promoting green innovation and improving energy efficiency), structural effects (e.g., optimizing industrial structure), and scale effects (e.g., expanding the production frontier via data-driven efficiency gains; Wang & Xue, 2023). Digital platforms help reduce information asymmetries, facilitate the efficient allocation of capital and labor, and enable real-time monitoring and environmental governance (Deng et al., 2022; Sun & Hu, 2021).

On the other hand, the relationship is not unambiguously positive. The ICT industry is itself energy-intensive. In the early stages of digitalization, the construction of infrastructure, data centers, and network facilities may lead to increased carbon emissions and resource consumption (Shi et al., 2018). Moreover, regional disparities in digital development may widen the "digital divide" and exacerbate GTFP gaps, particularly between coastal and inland cities. Some studies have even identified nonlinear or inverted U-shaped relationships between digital economic growth and environmental outcomes, consistent with the Environmental Kuznets Curve hypothesis.

Green technological innovation serves as a crucial mediating mechanism through which the digital economy affects GTFP(Wang & Ren, 2023). By enhancing information flows, facilitating collaborative R&D, and reducing the marginal cost of adopting green technologies, the digital economy fosters an ecosystem conducive to innovation (Hao et al., 2023; Pan et al., 2022). Digital platforms can accelerate the diffusion of clean technologies, improve energy system management, and optimize production processes. However, the extent to which green innovation translates the potential of the digital economy into measurable improvements in GTFP at the urban level remains underexplored.

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Despite a growing body of literature, several research gaps persist. First, most existing studies focus on national or provincial levels, whereas city-level analyses can better capture the local heterogeneity in digital development and environmental performance. Second, although green innovation is widely acknowledged as a driver of GTFP, its mediating role in the digital economy-GTFP nexus has yet to be systematically examined using comprehensive urban datasets.

However, it remains unclear whether and how the rapidly expanding digital economy can effectively translate into green productivity gains at the city level, particularly in the presence of regional disparities, data constraints, and heterogeneous innovation capacities. Accordingly, this study aims to quantify the impact of the digital economy on GTFP, examine the mediating role of green technological innovation, and clarify the conditions under which digital development contributes most significantly to green and high-quality growth. Using panel data for 281 prefecture-level and above cities from 2011 to 2022, the digital economy index is constructed through PCA across infrastructure, industrialization, and innovation dimensions, while GTFP is measured using the SBM-Malmquist-Luenberger index. A mediation analysis framework is then applied to identify both the direct effects of the digital economy on GTFP and the indirect effects transmitted through green innovation.

This study contributes to the literature in several key ways. First, it provides micro-level evidence on the digital economy–GTFP relationship based on city-level data, addressing the limitations of previous research focused on national or provincial levels. Second, it explicitly incorporates green innovation into the analytical framework, revealing the transmission mechanism through which the digital economy fosters sustainable growth. Third, by employing unified measurement methods and robust empirical strategies, this study enhances the comparability and policy relevance of its findings.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and theoretical framework. Section 3 outlines the methodology, variable definitions, and data sources. Section 4 presents the empirical results and mediation analysis. Section 5 discusses policy implications, research limitations, and directions for future research.

Theoretical Framework and Hypotheses

The Linear Effect of the Digital Economy on Green Total Factor Productivity (GTFP)

Driven by the rapid development of technologies such as big data, artificial intelligence (AI), cloud computing, and blockchain, the digital economy has emerged as a transformative force for economic growth and industrial restructuring. According to endogenous growth theory, technological progress is a fundamental driver of total factor productivity (TFP), while ecological modernization theory posits that both technological and institutional innovations can reconcile economic growth with environmental protection. Within this context, the digital economy is expected to exert a direct and measurable influence on green total factor productivity (GTFP) through multiple channels.

First, the technological effect is central to the linear relationship between the digital economy and GTFP. Digital infrastructure enables the generation, transmission, and application of massive volumes of data, supporting real-time monitoring, predictive maintenance, and precise environmental governance. By reducing information asymmetry and transaction costs, digital

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technologies facilitate cleaner production processes and the adoption of energy-efficient equipment, thereby improving environmental efficiency (Zhang, Zhang, & Guo, 2014; Deng et al., 2022).

Second, the structural effect operates through industrial upgrading and the transition towards low-carbon, high value-added sectors. The expansion of digital platforms has accelerated the decline of energy-intensive industries and fostered the development of modern services and advanced manufacturing, which have a lower environmental footprint per unit of output. Empirical studies have shown that the positive impact of digitalization on GTFP is stronger in regions with more advanced industrial structures (Sun & Hu, 2021; Wang et al., 2020).

Third, the scale and agglomeration effects enhance GTFP by leveraging economies of scale in digital infrastructure and stimulating innovation clusters. The concentration of digital resources in urban centers not only promotes local innovation but also facilitates the diffusion of clean technologies and managerial practices across enterprises (Hao et al., 2023; Pan et al., 2022).

Based on the above, it is hypothesized that the digital economy has a significant and positive linear impact on urban-level GTFP.

H1: The development of the digital economy has a significantly positive effect on GTFP at the city level.

The Mediating Role of Green Technological Innovation

While the digital economy may directly enhance GTFP, its full potential is often realized through the mediation of green technological innovation. As a subset of technological innovation, green innovation aims to reduce environmental impact by improving energy efficiency, reducing emissions, and promoting resource recycling. Both the resource-based view and innovation diffusion theory suggest that a region's or firm's ability to adopt and commercialize green technologies depends on its absorptive capacity, collaborative networks, and knowledge infrastructure.

The digital economy supports green innovation through multiple mechanisms. First, enhanced information flows and digital collaboration platforms lower the marginal costs of R&D, enabling firms to experiment with and deploy cleaner technologies more efficiently (Hao et al., 2023). Second, data-driven optimization allows for better resource allocation during production and helps identify inefficiencies and emission reduction opportunities. Third, the open innovation ecosystems fostered by digital platforms improve cross-sectoral collaboration and accelerate the diffusion of green technologies across industries and regions (Pan et al., 2022).

Empirical evidence shows that regions with higher levels of digitalization often exhibit stronger performance in green patents, eco-innovation activities, and low-carbon technology adoption (Feng & Serletis, 2014; Shi et al., 2018). This suggests that green innovation serves as a crucial transmission channel through which the digital economy fosters sustainable productivity growth.

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Accordingly, the following mediating hypothesis is proposed:

H2: Green technological innovation mediates the relationship between the digital economy and GTFP; thus, higher levels of digital development lead to more green innovation, which in turn improves GTFP.

Mechanism Heterogeneity from a Structural Perspective: Institutional Boundaries of Green Innovation Effects

Although green technological innovation theoretically mediates the impact of the digital economy on GTFP, this mechanism exhibits significant heterogeneity across regions and institutional settings. Institutional nesting theory posits that the institutional environment selectively shapes how new technologies are embedded, thereby influencing the efficiency with which digital technologies translate into green outcomes (Mahoney & Thelen, 2010).

In cities with strong technological capacity and well-established institutional foundations, digital platforms and green innovation tend to form synergies that enhance resource allocation efficiency and ecological productivity (Sun & Hu, 2021). In contrast, in central-western or resource-based cities, where infrastructure and green finance capabilities are relatively weak, a "technology-institution mismatch" may occur, and digitalization may not necessarily yield green dividends (Zhou et al., 2023).

Moreover, policy orientation and the innovation ecosystem also serve as critical moderators. Government prioritization of ecological performance influences the allocation of digital resources toward green ends, while the regional capacity for innovation spillovers determines how green technologies diffuse across space(Wu et al., 2022; Agan & Balcilar, 2022). Thus, the mediating effect of green innovation is not uniform across cities.

H3: The impact of digital-economy development on GTFP is heterogeneous across cities.

Research Design

Data Sources and Sample Construction

This study employs a city-level panel dataset covering 281 prefecture-level and above cities in mainland China from 2011 to 2022. The study period is selected because the nationwide rollout of digital infrastructure, digital finance, and data governance policies accelerated notably after 2011, allowing for more standardized and continuous statistical reporting. The sample includes cities from all major regions—eastern, central, and western China–ensuring broad geographic representation and enabling subsequent heterogeneity analysis.

The dataset is compiled from multiple authoritative and publicly accessible sources. Core socioeconomic indicators, including GDP, labor force, fixed asset investment, and environmental emissions, are obtained from the China Urban Statistical Yearbook and the China Urban Construction Statistical Yearbook. Data on green technological innovation are sourced from the National Intellectual Property Administration (CNIPA), using official classifications of green patents. Measures of digital-economy development, such as digital infrastructure, telecommunications activity, and digital financial inclusion, are drawn from publications by the China Academy of Information and Communications Technology (CAICT), including the White Paper on China's Digital Economy Development, as well as the

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Peking University Digital Inclusive Finance Index. Additional control variables are supplemented using the Wind and CEIC commercial databases.

To ensure data reliability and comparability over time, cities with substantial missing observations, inconsistent reporting standards, or major administrative adjustments are excluded. After data cleaning and cross-source validation, the final balanced panel dataset consists of 281 cities observed over 12 years, yielding 3,372 city-year observations used in the empirical analysis. This structure supports the application of two-way fixed-effects models and mediation analysis in subsequent sections.

This study employs a combination of advanced analytical techniques, including the super-efficiency SBM–GML index for measuring green total factor productivity, principal component analysis (PCA) for constructing the digital economy index, a two-way fixed effects econometric model for baseline estimation, and the Baron and Kenny (1986) mediation framework to examine indirect effects. Robustness checks and instrumental-variable approaches are further applied to ensure the reliability of results.

To provide a clear overview of the empirical strategy, Figure 1 summarizes the overall research process employed in this study.

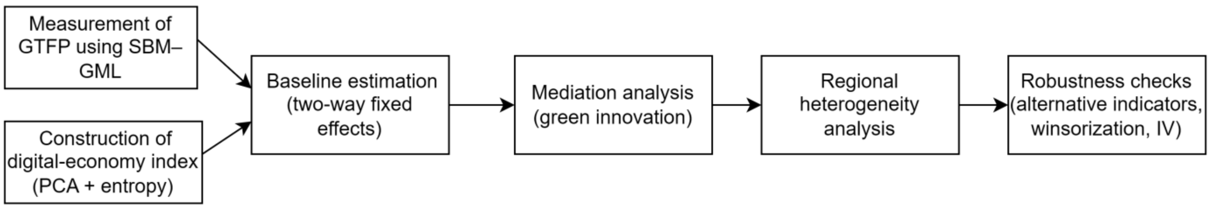

Figure 1: Research Process Flowchart Showing the Main Analytical Steps

Variable Definitions and Measurement Methods

Dependent Variable: Green Total Factor Productivity (GTFP)

Green Total Factor Productivity (GTFP) captures a city's capacity to generate output while accounting for undesirable environmental outcomes. Following the methodology proposed by Oh (2010), this study adopts a Super-Efficiency Slack-Based Measure (SBM) directional distance function that incorporates undesirable outputs, and further applies the Global Malmquist–Luenberger (GML) productivity index to measure GTFP for the 281 selected Chinese cities.

This approach offers several methodological advantages:It explicitly incorporates undesirable outputs, such as industrial wastewater discharge and sulfur dioxide emissions, into the production technology;It does not rely on price information, making it suitable for evaluating environmental performance in contexts with heterogeneous environmental indicators;It captures dynamic shifts in production frontiers across periods, enabling the assessment of temporal changes in green productivity efficiency.The measurement process is as follows:

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Assuming that each city is a decision-making unit, each decision-making unit contains n kinds of input factors $x_{in} = (x_{i1}, x_{i2}, \cdots, x_{iN}) \in R_N^+$, m kinds of desired outputs $y_{im} = (y_{i1}, y_{i2}, \cdots, y_{iM}) \in R_M^+$, and k kinds of undesired outputs $b_{ik} = (b_{i1}, b_{i2}, \cdots, b_{iM}) \in R_K^+$, where i is the ist city. This study constructs the Production Possibility Set (PPS) containing all sample points, which are defined as follows.

$$P^G(x) = \begin{cases} (y^t, b^t): \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t y_{im}^t \geq y_{im}^t, \forall m; \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t b_{ik}^t, \forall k \\ \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t x_{in}^t \leq x_{in}^t, \forall n; \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t = 1, \beta_i^t \geq 0, \forall i \end{cases} \quad (1)$$

Therefore, the SBM directional distance function for further consideration of non-desired outputs is:

$$\begin{gathered} S_V^G(x^{t,i}, y^{t,i}, b^{t,i}, g^x, g^y, g^b) = \max \frac{\frac{1}{N}\sum_{n=1}^{N} \frac{s_n^x}{g_n^x} + \frac{1}{M+K}\left(\sum_{m=1}^{M} \frac{s_m^y}{g_m^y} + \sum_{k=1}^{K} \frac{s_k^b}{g_{ik}^b}\right)}{2} \\ \text{s.t.} \sum_{t=1}^{T} \sum_{i=1}^{I} z_i^t x_{in}^t + s_n^x = x_{in}^t, \forall n; \\ \sum_{t=1}^{T} \sum_{i=1}^{I} z_i^t y_{im}^t - s_{nm}^y = y_{in}^t, \forall m; \\ \sum_{t=1}^{T} \sum_{i=1}^{I} z_i^t b_{ik}^t + s_i^b = b_{ik}^t, \forall i; \\ \sum_{i=1}^{I} z_i^t = 1, z_k^t \geq 0, \forall i; \\ s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \end{gathered} \quad (2)$$

Of these, the$(x^{t,i}, y^{t,i}, b^{t,i})$、$(g^x, g^y, g^b)$ and(s_n^x, s_m^y, s_k^b) denote the input and output vectors, direction vector and slack vector of the city, respectively. If(s_n^x, s_m^y, s_k^b) is greater than 0,it means that the factor inputs and non-desired outputs exceed the inputs and non-desired outputs on the production frontier, while the actual outputs are lower than the outputs on the frontier. The traditional ML index often has the problem of linear programming without solution, but based on the SBM-GML method to measure the GTFP change can avoid the linear mis-solution problem arising as follows:

$$Gtfp_t^{t+1} = GML_t^{t+1} = \frac{1+\vec{S}_V^G(x^t, y^t, b^t, g^x, g^y, g^b)}{1+\vec{S}_V^G(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b)} \quad (3)$$

This study further decomposes the GTFP change into green technical progress index (GTC) and green technical efficiency index (GEC), where GEC and GTC measure the evaluation object in terms of proximity and tightness, respectively, and the productivity index reflects the level of production efficiency. The decomposition process is as follows:

$$Gtfp_t^{t+1} = GEC_t^{t+1} \times GTC_t^{t+1} \quad (4)$$

$$GEC_t^{t+1} = \frac{1+\vec{S}_V^t(x^t, y^t, b^t, g^x, g^y, g^b)}{1+\vec{S}_V^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b)} \quad (5)$$

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$$GTC_t^{t+1}=\frac{\left[1+\vec{S}_v^G\left(x^t,y^t,b^t,g^x,g^y,g^b\right)\right]/\left[1+\vec{S}_v^t\left(x^t,y^t,b^t,g^x,g^y,g^b\right)\right]}{\left[1+\vec{S}_v^G\left(x^{t+1},y^{t+1},b^{t+1},g^x,g^y,g^b\right)\right]/\left[1+\vec{S}_v^{t+1}\left(x^{t+1},y^{t+1},b^{t+1},g^x,g^y,g^b\right)\right]} \tag{6}$$

In the above equation, $\vec{S}_v^t(\cdot)$ and $\vec{S}_v^G(\cdot)$ the current and global directional distance functions, respectively. The GML index measures the dynamic change in GTFP between two periods. When the index GML_t^{t+1} is greater than 1, equal to 1, or less than 1, the change from period t to period t+1 indicates that the city's GTFP is increasing, remaining constant, or decreasing, respectively.

To empirically evaluate green total factor productivity (GTFP), it is necessary to specify the relevant input and output indicators that capture the production process. The input indicators include capital stock, labor, and energy consumption. Capital input is estimated using the perpetual inventory method proposed by Shan Houjie (2008). Labor input is measured by the total number of employed persons at the end of each year in each city. Energy input is proxied by the total annual electricity consumption of each city.

Regarding output indicators: Desirable output is measured by the real GDP of each city at year-end, reflecting the level of economic output. Undesirable outputs consist of environmental pollutants, specifically the volumes of industrial wastewater, sulfur dioxide (SO_2), and industrial dust emissions.

To calculate Green Total Factor Productivity (GTFP), this study employs the MaxDEA software and utilizes the Global Malmquist–Luenberger (GML) index. The GML index effectively captures productivity changes over time while incorporating undesirable outputs into the production technology framework.

It is important to note that the GML index reflects the growth rate of green total factor productivity, rather than its absolute level. Therefore, it measures the dynamic improvement in green productivity rather than the static performance level of a city's green development.

Table 1 Input Indicators and Output Indicators of Green Total Factor Productivity

Level 1 indicators	Level 2 indicators	Description of measurements
Input indicators	1.Capital stock 2.Labor input 3.Energy consumption	1.Estimated using the perpetual inventory method of Shan (2008) 2.Measuring labour input using total employment at the end of the year in each city 3.Measurement of energy consumption using the total annual electricity consumption of each city
Output indicators	1.NonExpected outputs 2.expected outputs	1.Measurement of desired output using year-end real GDP for each city. 2.Pollutants such as industrial wastewater emissions, industrial sulphur dioxide emissions, industrial soot emissions, and industrial nitrogen oxide emissions were selected as non-desired output measures.

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Core Explanatory Variable: Level of Digital Economy Development

The level of digital economy development serves as the core explanatory variable in this study. Drawing on the methodology proposed by Zhao Tao (2020), the measurement focuses on three key dimensions: digital industrialization, information development, and digital financial inclusion. These dimensions collectively capture the comprehensive development level of China's digital economy from 2011 to 2021.

To construct the composite index, we employ both the Principal Component Analysis (PCA) and the Entropy Weight Method (EWM), thereby ensuring the robustness of the indicator system and minimizing subjective bias in weighting schemes.

Table 2 Indicators of The Level of Comprehensive Development of The Digital Economy

Level1 indicators	Level 2 indicators	Level 3 indicators	Causality
Level of integrated development of the digital economy	informatization development level	- Information transmission, software and information technology - Employment in urban units of the service sector - Total telecommunications business - Number of mobile phone subscribers	Positive
	Level of Internet development	Number of Internet broadband access subscribers	Positive
	Level of development of digital finance	China Digital Inclusive Finance Index	Positive

Mediating Variable: Green Technological Innovation

Green technological innovation (green_innov) is measured by the number of granted green patents. Patent data are collected based on the classifications provided by the World Intellectual Property Organization (WIPO) and the China National Intellectual Property Administration (CNIPA), specifically focusing on green technology categories such as Y02 and B09B. To address data skewness and reduce heteroscedasticity, the variable is transformed using a natural logarithm.

Control Variables

To account for structural heterogeneity across cities, we incorporate the following control variables into the model:

Economic Development Level: measured by the natural logarithm of per capita GDP (lngdp). Environmental Regulation Intensity: proxied by the ratio of local government environmental expenditure to total fiscal expenditure (green_exp). Government Intervention: captured by the share of total fiscal expenditure in GDP (gov_intervention). Financial Development: measured by the total amount of deposits and loans of financial institutions (loan_balance).

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All continuous variables are either logarithmically transformed or standardized in the regression analysis to mitigate estimation bias stemming from scale differences.

Model Specification and Identification Strategy

To examine the impact of the digital economy on urban green total factor productivity (GTFP) in China, we first specify the following baseline panel regression model:

$$lnUGtfp_{it} = \alpha_0 + \alpha_1 Dige_{it} + \alpha_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

where $ln\ UGtfp_{it}$ denotes the logarithm of green total factor productivity for city i in year t; $Dige_{it}$ represents the level of digital economy development; $Control_{it}$ is a vector of control variables; μ_i and δ_t capture city-specific and year-specific fixed effects, respectively; and ε_{it} is the error term.

To further explore the potential mediating effect of green technological innovation in the relationship between the digital economy and GTFP, we adopt a three-step mediation analysis framework based on the classical approach proposed by Baron and Kenny (1986). The mediating model is specified as follows:

$$\begin{aligned} M_{it} &= \alpha_1 + \beta_1 X_{it} + \mu_{it} \\ Y_{it} &= \alpha_2 + \beta_2 X_{it} + \mu_{it} \\ Y_{it} &= \alpha_3 + \gamma_1 X_{it} + \gamma_2 M_{it} + \mu_{it} \end{aligned} \quad (8)$$

Here, X_{it} denotes the digital economy index (independent variable), M_{it} represents the mediating variable–green technological innovation, and Y_{it} stands for the outcome variable–green total factor productivity. This framework allows us to identify both the direct effect of the digital economy on GTFP and the indirect effect mediated through green innovation.

Empirical Results Analysis

Descriptive Statistics and Correlation Analysis

Table 3 reports the descriptive statistics. The mean of green_tfp is 1.051 with moderate dispersion (SD = 0.147). The digital economy index averages 0.131, indicating low but uneven digitalization. Green innovation (green_innov) shows a mean of 2.005, suggesting notable variation in green patent activity. Loan_balance ranges widely, reflecting heterogeneity in financial development.

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Table 4 shows the pairwise correlations. All coefficients are below 0.7, indicating no serious multicollinearity. Digital is positively associated with green_tfp (r = 0.169) and green_innov (r = 0.672), supporting the mediation pathway. Green_innov also correlates with green_tfp (r = 0.178), reinforcing its role as a potential mediator.Overall, the descriptive and correlation results provide initial support for the proposed relationships and justify the subsequent regression-based empirical strategy.

Table 3. Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max	N
green_tfp	1.051158	0.1467679	0.2622605	5.714087	3372
digital	0.1312005	0.0677375	0.0142018	0.6126746	3372
lngdp	10.4339	0.5971109	8.484372	11.9924	3372
gov_intervention	0.2022364	0.1044746	0.0438815	1.592673	3372
green_exp	0.0290875	0.01621	0	0.1930661	3372
loan_balance	0.0073129	1.009234	-0.4584563	11.09865	3372
green_innov	2.005056	0.7439131	0	4.277815	3372

Table 4 Pearson Correlation Matrix

	green_tfp	digital	green_innov	lngdp	gov_intervention	green_exp	loan_balance
green_tfp	1.0000	0.1685	0.1775	0.1823	-0.0627	0.0155	0.0844
digital		1.0000	0.6718	0.6432	-0.1893	0.0527	0.6352
green_innov			1.0000	0.6600	-0.4631	-0.0107	0.6412
lngdp				1.0000	-0.5382	0.0202	0.4166
gov_intervention					1.0000	0.1087	-0.1914
green_exp						1.0000	0.0136
loan_balance							1.0000

After conducting the Hausman test, the p-value was found to be less than 0.05, rejecting the null hypothesis and confirming the suitability of a two-way fixed effects model with city and year dummies. All models are estimated using robust standard errors. The regression results in Table 5 indicate that the digital economy significantly promotes green total factor productivity (GTFP). Across various model specifications, the coefficient of the digital economy variable remains consistently within the range of 0.381‑0.421 and is statistically significant at the 1% level, suggesting that digital development plays a critical role in enhancing green productivity.

As for control variables, loan_balance exhibits a negative association with green productivity in some models, implying that excessive reliance on credit resources may hinder green efficiency improvements. The coefficient of lngdp is positive and significant at the 5% level in most models, indicating that higher levels of economic development contribute positively to GTFP. In contrast, variables such as gov_intervention, green_exp, and trade_depend fail to demonstrate statistical significance, suggesting their impact on GTFP is relatively weak or

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unstable in the current sample. Overall, the baseline regression robustly validates the pivotal role of the digital economy in promoting green total factor productivity.

Table 5 Main Regression Results

	(1)	(2)	(3)	(4)	(5)
	green_tfp	green_tfp	green_tfp	green_tfp	green_tfp
digital	0.381***	0.415***	0.409***	0.417***	0.421***
	(0.110)	(0.114)	(0.114)	(0.113)	(0.113)
loan_balance		-0.0113**	-0.00872	-0.00741	-0.00774
		(0.00564)	(0.00577)	(0.00565)	(0.00568)
lngdp			0.0483	0.0618**	0.0583*
			(0.0300)	(0.0306)	(0.0309)
gov_intervention				0.114	0.112
				(0.0785)	(0.0781)
green_exp					0.255
					(0.180)
N	3372	3372	3372	3372	3372

Standard errors in parentheses; all regressions control for city and year fixed effects.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Mediation Mechanism Analysis

Table 6 presents the baseline mediation analysis results without controlling for city and year fixed effects. The total effect of the digital economy on green TFP is positive and highly significant (0.221, $p < 0.01$). When decomposed, the indirect effect through green innovation is estimated at 0.083 ($p < 0.01$), accounting for 37.3% of the total effect, while the direct effect remains positive and significant at 0.139 ($p < 0.05$), representing 62.7% of the total effect. These findings suggest a partial mediation mechanism in the baseline specification, whereby the digital economy enhances green productivity not only directly—through efficiency improvements and structural upgrading—but also indirectly by promoting green innovation. Nevertheless, given that fixed effects are not included, the robustness of this mediating channel requires further verification once unobserved heterogeneity across regions and years is taken into account.

Table 6 Mediation Effect Of The Digital Economy On Green TFP

Effect Type	Coefficient	Std. Error	z value	P>|z|	95% CI	Proportion
Indirect Effect	0.083***	0.023	3.61	0.000	[0.038, 0.127]	37.3%
Direct Effect	0.139**	0.058	2.49	0.013	[0.030, 0.249]	62.7%
Total Effect	0.221***	0.053	4.14	0.000	[0.117, 0.327]	100%

Notes: 95% confidence intervals are reported in brackets. * p<0.1, ** p<0.05, *** p<0.01.

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Table 7 Three-Step Mediation Regression Results

	(1) green_innov	(2) green_tfp	(3) green_tfp
digital	0.124	0.421***	0.421***
	(0.134)	(0.113)	(0.113)
green_innov			-0.00122
			(0.0168)
Controls	Yes	Yes	Yes
Constant	1.037*	0.358	0.359
	(0.544)	(0.328)	(0.324)
Observations	3372	3372	3372

Standard errors in parentheses,all regressions control for city and year fixed effects.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To ensure the robustness of the mediation mechanism, we further compared different fixed effects specifications. When including both city and year fixed effects simultaneously (two-way fixed effects), the mediating role of green technological innovation becomes statistically insignificant,as shown in Table 7. However, when adopting a less restrictive specification-controlling only for city fixed effects or only for year fixed effects—the mediation effect remains significant and consistent with our theoretical expectation.

This divergence suggests that the mediating channel is sensitive to the choice of fixed effects. The disappearance of significance under the two-way fixed effects model may indicate that part of the variance explained by green innovation is absorbed by unobserved city-specific factors or common time shocks. In other words, the contribution of green innovation to GTFP enhancement could be partially masked when controlling too strictly for heterogeneity.

Overall, this result highlights that the mediating effect of green innovation should be interpreted with caution. Nevertheless, the consistency of results under alternative specifications lends support to the proposed mechanism, while the sensitivity under two-way fixed effects underscores the importance of regional heterogeneity and temporal shocks in shaping the digital economy—GTFP nexus.

Heterogeneity Analysis

Table 8 presents the results of the heterogeneity analysis across eastern, central, and western regions. The digital economy exhibits a significant and positive impact on GTFP in both the eastern ($\beta = 0.344$, $p < 0.01$) and central regions ($\beta = 0.783$, $p < 0.05$), suggesting that digitalization fosters green productivity where infrastructure and innovation capacity are relatively stronger. The larger coefficient in the central region may reflect the higher marginal benefit of digital transformation in resource-dependent sectors. However, the effect in the western region is statistically insignificant, likely due to lagging digital infrastructure and a dominance of resource-based industries.

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Among control variables, loan balance shows a significant negative effect in the western region (β =–0.0400, $p < 0.01$), implying that financial resources may be misallocated toward high-emission industries. In contrast, the effect is insignificant in other regions. Economic development (lngdp) positively correlates with GTFP in the central region (β=0.114, $p < 0.05$), indicating a virtuous cycle between growth and environmental efficiency. Other variables, including government intervention and environmental expenditure, remain insignificant across all sub-samples.Overall, the digital economy plays a critical role in promoting green productivity in the eastern and central regions, while its effect in the west remains constrained by structural and institutional barriers.

Table 8. Heterogeneous Effects Of the Digital Economy On Green Total Factor Productivity Across Regions

Region	(Eastern) green_tfp	(Central) green_tfp	(Western) green_tfp
digital	0.344^{***}	0.783^{**}	0.292
	(0.129)	(0.348)	(0.213)
loan_balance	-0.00760	0.00331	-0.0400^{***}
	(0.00613)	(0.0265)	(0.0124)
lngdp	0.0908	0.114^{**}	-0.0477
	(0.0720)	(0.0460)	(0.0691)
gov_intervention	0.231	0.0850	-0.0123
	(0.401)	(0.0756)	(0.0965)
green_exp	0.322	0.370	-0.286
	(0.370)	(0.233)	(0.418)
N	1200	1176	996

Standard errors in parentheses; all regressions control for city and year fixed effects.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Robustness Checks

Robustness checks are reported in Table X. In Column (1), the measurement of digital economy development is replaced, using the principal component analysis (PCA) method instead of the entropy-weighting method. In Column (2), the non-expected output component of GTFP is winsorized at the 1% and 99% levels to mitigate the influence of extreme values. In both specifications, the estimated coefficients of digital economy remain positive and significant at the 1% level (0.721 and 0.421, respectively), which are consistent with the baseline findings. These results confirm that the positive effect of digital economy development on green total factor productivity is robust to alternative measurement methods and tail-risk adjustments.

Table 9. Robustness Tests: Alternative Measurement of Digital Economy and Winsorization Of GTFP

	(1) green_tfp	(2) green_tfp
digital	0.721^{***}	0.421^{***}
	(0.189)	(0.113)
loan_balance	-0.00986^{*}	-0.00774
	(0.00587)	(0.00568)
lngdp	0.0595^{*}	0.0583^{*}

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	(0.0309)	(0.0309)
gov_intervention	0.114	0.112
	(0.0783)	(0.0781)
green_exp	0.258	0.255
	(0.180)	(0.180)
N	3372	3372

Standard errors in parentheses, all regressions control for city and year fixed effects.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To examine the potential endogeneity of the digital economy variable, this study employs its one-period lag as an instrumental variable and conducts the Durbin–Wu–Hausman test. The results (F=0.985, p=0.322) fail to reject the null hypothesis of exogeneity, suggesting that the digital economy variable does not suffer from significant endogeneity bias. Accordingly, the baseline regressions in this paper rely on the two-way fixed effects estimation results.

Conclusions and Policy Implications

For both academia and policy circles, the interaction between the digital economy and green total factor productivity (GTFP) has become a key issue in promoting global low-carbon transition and high-quality development. Although prior studies have examined factors such as digital transformation, green innovation, and environmental regulation, systematic investigations into the impact of the digital economy on GTFP—particularly empirical analyses based on city-level data from China—remain relatively limited. Drawing on panel data from 281 cities during 2011-2022, this paper conducts a comprehensive study through baseline regressions, mechanism analysis, heterogeneity tests, and robustness checks to explore how the digital economy influences city-level GTFP. The following conclusions merit attention.

First, the baseline regression results show that the digital economy significantly improves GTFP, and this effect remains robust after controlling for city and year fixed effects. This finding indicates that digital transformation plays an active role in optimizing resource allocation and promoting green development.

Second, the mechanism analysis reveals that green technological innovation exhibits a significant mediating effect under certain model specifications. This suggests that the digital economy may promote information flows, enhance R&D efficiency, and accelerate technology diffusion, thereby stimulating green innovation activities and, to some extent, improving GTFP. Although the results of the two-way fixed effects model are less robust, the mediating pathway remains supported under one-way fixed effects and various robustness checks. Thus, green technological innovation can be regarded as an important potential mechanism through which the digital economy affects green productivity.

Third, the heterogeneity analysis shows that the effect of the digital economy on GTFP varies significantly across regions and city types. The promotion effect is more pronounced in eastern regions and large urban agglomerations, while it is relatively weaker in central and western regions and resource-based cities. This reflects the uneven characteristics of digital economy development across regions.

Fourth, robustness tests further confirm the reliability of the findings. Whether by adopting alternative measures of the digital economy or by applying winsorization to the data, the core conclusions remain consistent.

Based on the above findings, the following policy implications deserve attention:

First, accelerate the construction of digital infrastructure and narrow the "digital divide." The government should increase investment in networks, computing power, and data platforms in central, western, and resource-based cities, thereby improving access to digital factors and ensuring that the benefits of digital economy development are shared across regions.

Second, strengthen incentive mechanisms for green innovation. Through policy instruments such as green credit, tax reductions, and R&D subsidies, enterprises should be guided to increase investment in green technologies. At the same time, the deep integration of digital platforms and green industries should be promoted to foster a digitally-driven green innovation ecosystem.

Third, advance region-specific policies according to local conditions. Eastern regions should continue exploring high-level integration models of digitalization and greening, while central and western regions and resource-dependent cities should accelerate industrial restructuring under policy guidance to leverage the potential role of the digital economy in energy conservation, emission reduction, and resource efficiency improvement.

Fourth, improve digital environmental governance mechanisms. The application of big data, blockchain, and artificial intelligence in environmental monitoring, emission control, and policy enforcement should be encouraged, which can enhance regulatory efficiency while aligning technological empowerment with institutional safeguards in the green transition.

Research limitations: (1) This study uses city-level panel data from 2011 to 2022, and the sample coverage is limited, with missing data in some regions that may affect the precision of spatial effect analysis; (2) The paper focuses on the mediating role of green innovation, but the digital economy may also affect GTFP through other channels such as industrial upgrading, green finance development, or foreign capital flows, which remain to be explored; (3) The composite index of the digital economy adopted in this study has certain measurement limitations. Future research may combine micro-level enterprise data and more fine-grained digitalization indicators to improve the generalizability and explanatory power of the conclusions.

Overall, the empirical analyses and robustness tests confirm that all research objectives established in the Introduction have been successfully accomplished.

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