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The impact of China's digital economy development on green total factor productivity

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Abstract

This study utilizes provincial panel data from China, spanning 2013 to 2022, to empirically analyze the impact of the digital economy on green total factor productivity (GTFP) and to investigate the factors driving this relationship. The results demonstrate that the digital economy substantially enhances GTFP via three primary mechanisms: streamlining industrial structure, fostering green technical innovation, and improving energy efficiency. A further regional examination indicates significant disparities in the magnitude of this influence. The digital economy has the most substantial positive effect on GTFP in the central region, followed by the eastern regions, while the western region exhibits relatively weaker effects. These regional disparities are intricately linked to variances in industrial composition, digital infrastructure, and resource accessibility. The report advocates for the establishment of a regional synergy mechanism to enhance coordinated growth by leveraging the distinct capabilities of eastern, central, and western China. The eastern region may enhance its position as a center for technological innovation, the middle region may concentrate on advancing industrial integration, and the western region may prioritize infrastructural enhancement. The implementation of a 'Trinity' digital empowerment framework may accelerate the integration of the digital economy with green development, providing a sustainable impetus for high-quality economic growth.

Keywords: Digital economy, Green total factor productivity, Mediating effect.

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1. Introduction

Since the commencement of economic reforms, China has achieved unprecedented growth, transforming itself into a global economic powerhouse. Leveraging its vast domestic market, abundant labor force, and effective institutional frameworks, China sustained an average annual GDP growth of 9% from 1978 to 2023, rising to become the world's second-largest economic entity and contributing over 24% to global economic expansion. However, this resource-intensive growth paradigm has incurred substantial environmental costs. In 2023, China accounted for 27% of global primary energy consumption, with per capita energy use 1.5 times the global average, and energy intensity per unit of GDP exceeding that of most developed nations, underscoring the urgent need for a sustainable and low-carbon transition.

In response, China has elevated ecological civilization to the core of its national development strategy. From the 17th to the 20th National Congress, green development has been consistently emphasized as a critical direction for structural transition. These strategic efforts have produced tangible outcomes: over the past decade, China reduced its carbon intensity by 34.4%, maintained an average annual energy consumption growth of only 3.0% despite 6.6% GDP growth, and established a world-leading clean energy system. However, regional disparities and entrenched reliance on traditional growth models continue to hinder the achievement of high-quality, sustainable development. A paradigm shift toward a green, efficient, and innovation-driven economy is increasingly necessary.

This transformation also calls into question the adequacy of traditional metrics used to assess development. While Total Factor Productivity (TFP), rooted in neoclassical growth theory [1], has long been a benchmark for efficiency, it fails to account for environmental degradation and may thus overstate actual progress. To address this limitation, scholars have advanced the connotation of GTFP, which integrates environmental and resource costs into the traditional TFP framework [2, 3]. GTFP is now widely recognized as a more holistic indicator of sustainable development, driven by green technological progress, cleaner energy systems, stringent environmental regulation, and industrial upgrading [4, 5]. However, traditional green policy tools often suffer from diminishing returns and implementation challenges, necessitating new levers for transformation.

The digital economy acts as a significant facilitator of this ecological shift. Characterized by low resource intensity, high efficiency in factor allocation, and increased transparency, digital technologies provide systemic benefits for improving resource use, reducing transaction costs, and enhancing environmental governance [6, 7]. Artificial intelligence, big data analytics, and the IoT are among the innovations that are rapidly transforming industries, from smart energy and green manufacturing to sustainable agriculture [3, 8]. These innovations are also facilitating new forms of green production and consumption. In this context, the digital economy is not only transforming industrial structures but also represents a novel engine for enhancing GTFP.

China has recognized the significance of digital transformation by highlighting it in its 14th Five-Year Plan and enacting various regulations to facilitate the integration of digital technologies with the real economy. According to the latest authoritative research [1, 9, 10], the sector achieved a market valuation of 53.9 trillion yuan last year, constituting nearly 43% of the country's total economic output. Notably, digital adoption rates varied significantly across economic sectors, with agriculture, manufacturing, and service industries demonstrating 10.8%, 25.0%, and 45.6% penetration, respectively. These statistics underscore the dual function of the digital economy: it stabilizes macroeconomic performance while promoting micro-level green innovation and efficient resource allocation.

Consequently, understanding the impact of the digital economy on GTFP is essential both theoretically and practically. Such inquiry is crucial not only for charting a new course for high-quality development but also for informing policy design in the global pursuit of sustainability.

2. Literature Review

2.1. Theoretical Basis

2.1.1. Evolving Growth Paradigms: From Productivity to Sustainability

The evolution of economic growth theory has progressively underscored the central role of productivity, particularly total factor productivity (TFP), as a key engine of long-term development [11, 12]. Yet, conventional TFP metrics neglect the negative externalities associated with environmental degradation, thereby risking systematic overestimation of the true quality of growth. In response to the growing salience of sustainability concerns, the concept of GTFP has emerged as a more inclusive measure that integrates both resource-use efficiency and environmental constraints [13, 14].

Growth theory itself has evolved across three principal stages: classical, neoclassical, and endogenous growth models. Classical economists, including Smith [9], focused on capital, labor, and land as growth drivers. Although a formal TFP construct was absent, their emphasis on division of labor and economies of scale laid a conceptual foundation for understanding how novel production factors, such as data, might yield synergistic returns.

The neoclassical framework, anchored by Solow's exogenous growth model, established the Solow residual as a foundational tool for quantifying total factor productivity (TFP), while Arrow [15] the learning-by-doing mechanism offered early insights into innovation as an endogenous process shaped by experience. Empirical advances, including stochastic frontier analysis [10] and data envelopment analysis [16]. Later, it enabled rigorous TFP measurement, setting the stage for endogenous growth theories. [17, 18] that explicitly linked innovation to investments in knowledge and human capital, a paradigm further refined by Aghion and Howitt [10], creative destruction [19], which highlighted technology's dual role as both a disruptive and productivity-enhancing force.

These theoretical developments gain renewed relevance in the digital era. The non-rivalrous nature of data, network effects, and increasing returns to scale challenge classical production assumptions. In this new context, digital technologies act as accelerators of knowledge diffusion and collaborative innovation, creating fertile ground for enhancing GTFP through structural reorganization and biased technological progress.

We thus propose a conceptual framework of “factor reconfiguration technological innovation efficiency leap”. Classical theory contributes the foundational logic of factor input; neoclassical theory provides the quantitative lens; and new growth theory elucidates the endogenous drivers. Collectively, they facilitate a comprehensive understanding of how the digital economy might act as a transformative catalyst for sustainable development, connecting two hitherto neglected aspects: environmental limitations and digital efficiency.

2.1.2. Green Economy Theory: Measurement and Mechanisms of GTFP

Green economy theory arose in response to the ecological shortcomings of traditional economic paradigms. It promotes economic development that operates within ecological boundaries, aiming to harmonize resource efficiency with environmental integrity [20]. As defined by institutions such as the Wang and Wei [21] the green economy constitutes a policy framework that fosters environmental sustainability, resource conservation, and social equity, and has become an integral part of the global sustainable development agenda.

From a methodological perspective, green economy theory is closely aligned with GTFP measurement innovations. The integration of undesirable outputs into the DEA model by Feng et al. [2], the introduction of directional distance functions [22] and the “total factor green productivity” metric proposed by Romer [14] have expanded the empirical toolkit for evaluating green efficiency. These approaches allow for the simultaneous assessment of economic output and pollution abatement, thereby enabling a more accurate reflection of sustainable performance.

The "innovation offset hypothesis," proposed by Porter and Linde [7] posits that effectively structured environmental legislation can promote green innovation and improve corporate environmental efficiency. This proposition has been widely adopted in China’s green development strategy and empirically validated, including through the green [1].

At its core, green economy theory contends that high-quality growth is attainable even under stringent resource and environmental constraints. By incorporating elements such as natural capital, pollution intensity, and capital service efficiency, it provides a robust theoretical basis for the conceptualization and empirical assessment of GTFP. In the digital age, this theoretical lens is instrumental in identifying mechanisms through which digitalization and ecological civilization may reinforce one another.

2.1.3. Toward Theoretical Integration: A Synergistic Framework

This study integrates economic growth theory and green economy theory to establish a unified framework for understanding the drivers of GTFP in the digital era. On one hand, the digital economy reconfigures factor inputs and accelerates technological innovation through data-driven production systems and network-based knowledge diffusion. On the other hand, green economy theory emphasizes ecological constraints and regulatory mechanisms that channel innovation toward environmental objectives.

These two paradigms are not mutually exclusive; rather, they converge to produce synergistic effects on sustainable productivity. We therefore propose a three-stage pathway, "factor structure optimization, green innovation, and environmental performance enhancement," as the theoretical framework through which the digital economy might catalyze advancements in GTFP. This integrated perspective provides a nuanced and forward-looking foundation for analyzing how digitalization facilitates the broader transition to high-quality, sustainable development.

2.2. Literature Review

The coevolution of digital economies and sustainable development has emerged as a defining characteristic of China's economic metamorphosis, sparking intense scholarly debate about their interplay. A central research question concerns the measurable effects of digitalization on Green Total Factor Productivity (GTFP). Contemporary research coalesces around three critical axes: the architecture of digital economies, robust methodologies for GTFP assessment, and the underlying mechanisms by which digital transformation drives ecological efficiency gains.

First, research on the digital economy highlights its significance as a vital catalyst for contemporary economic expansion, propelled by the profound integration of digital technologies across various sectors. Researchers have developed multiple approaches to quantify the extent and structure of the digital economy. These include value-added accounting methods that quantify its direct economic contribution [23, 24], index-based indicator systems capturing its multi-dimensional characteristics [25, 26] and satellite accounting frameworks offering systematic evaluation [15]. Empirical findings underscore the digital economy’s transformative effects: it accelerates technological innovation [10] upgrades industrial structures [27], reshapes consumption behavior [28], and enhances governance capacity and public service efficiency [29]. Increasingly, its contribution to environmental sustainability through improved resource allocation and support for green technology has become a focal point [30].

Second, research on GTFP focuses on integrating environmental factors into productivity assessment. Early methodological innovations, such as the directional distance function (DDF) model introduced by Fokina and Barinov [31] enabled the inclusion of undesirable outputs like pollution. Subsequent refinements, including the slack-based SBM [20] and EBM models [32] facilitated more accurate estimation using dynamic panel data. Recent empirical applications, such as the SBM-GML index, have measured regional and sectoral GTFP across China [2, 3, 7], providing valuable inputs for different policy designs. Others have adopted the EBM-GML model to capture macro- and micro-level variations across logistics, tourism, agriculture, and enterprises [5]. Collectively, these studies identify key determinants of GTFP, including environmental regulation [4], technological progress [27] energy consumption [16]. urbanization [18], financial development [33] and globalization [22].

Third, an expanding corpus of work directly examines the impact of the digital economy on GTFP. The consensus is that digital transformation fosters green productivity through multiple channels. It accelerates the development and diffusion of clean technologies, enabling firms to adopt low-carbon production methods and reduce environmental footprints [14]. It also drives structural shifts toward digital-intensive, green industries, advancing industrial upgrading [17]. Furthermore, digital tools enhance transparency and control in energy systems, improving efficiency in energy production, transmission, and use [19]. The identified mechanisms reveal a fundamental convergence between economic development and environmental stewardship enabled by digital transformation.

In summary, existing research has established a solid foundation for understanding the role of the digital economy in promoting GTFP. However, gaps remain. Current studies often examine the mechanisms linking digitalization and green productivity in isolation, lacking a comprehensive framework that integrates green innovation, energy efficiency, and industrial upgrading. This research utilizes longitudinal data covering 30 provincial-level administrative regions in China (2013-2022) to systematically analyze how advancements in the digital economy influence environmentally sustainable production through identifiable causal pathways.

Integrating theoretical insights from economic growth and green economy literature, we devise the following framework (Figure 1): Integrating theoretical insights from economic growth and green economy literature, we devise the following analytical framework (Figure 1): First, a systems-based theoretical model is formulated to capture the multi-faceted interactions between digital economic development and GTFP. Second, rigorous empirical analysis is conducted using frontier econometric methods, with robustness ensured through endogenous treatments (e.g., double robustness tests and instrumental variable approaches). Furthermore, a mediation effects model is employed to identify critical transmission pathways, while regional heterogeneity tests reveal divergent impacts of digital economy development on GTFP across spatial contexts. Finally, the empirical evidence informs a targeted policy framework to align digital transformation with green, low-carbon development objectives.

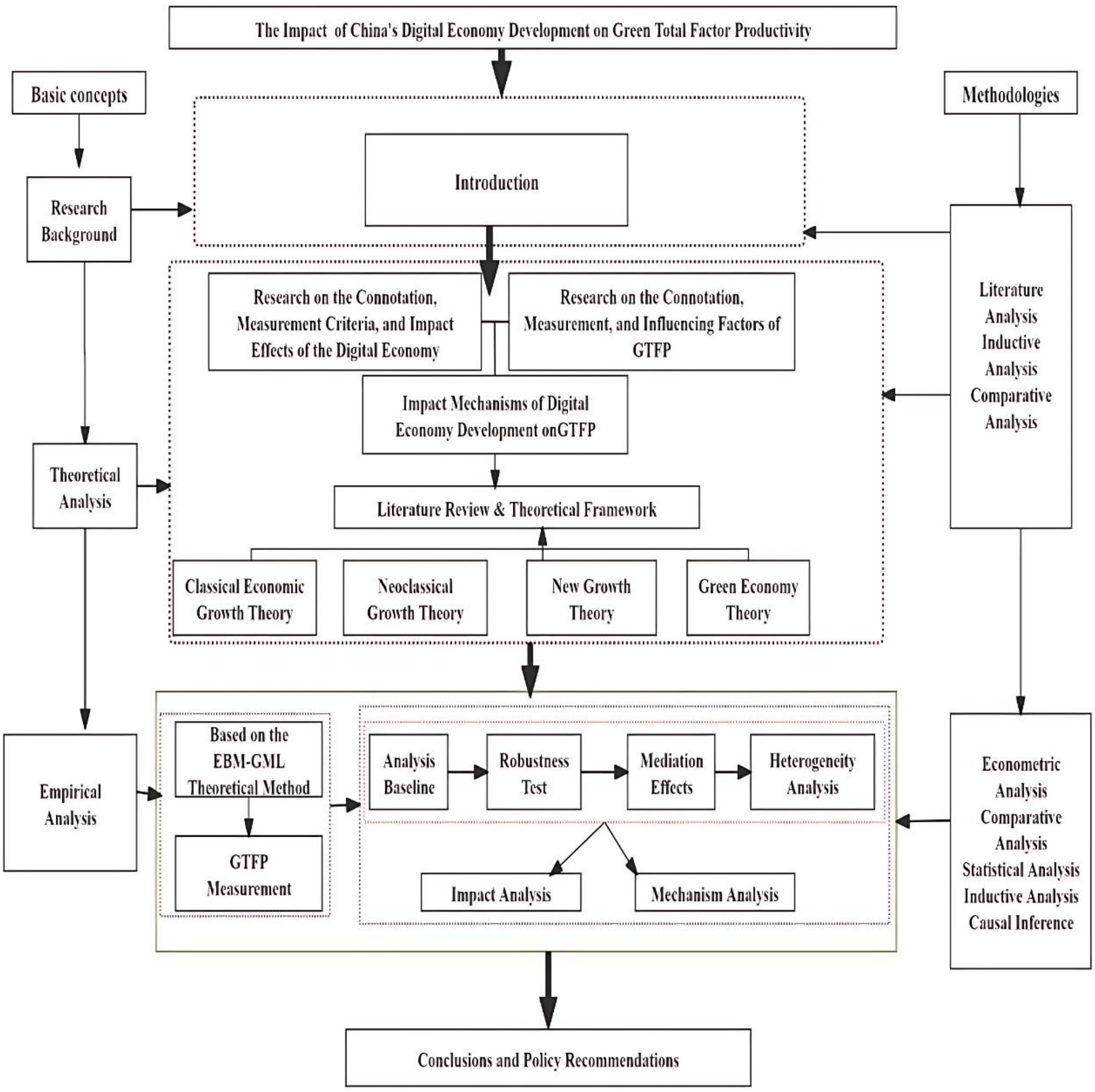

Figure 1.
Research Methodology Framework.

3. Research Methodology

3.1. Baseline Model

To assess the impact of the digital economy on GTFP, we employ a panel regression model as specified in Equation 1.

$$\mathrm{lngtfp}_{it} = \alpha_0 + \beta_1 \mathrm{lnde}_{it} + \beta_2 \mathrm{lnC}_{it} + \mu_i + \varepsilon_{ij} \quad (1)$$

In this formulation, subscripts i and t represent region and year. The dependent variable gtit captures The GTFP, whereas the core explanatory variable de_{it}signifies the extent of digital economy development.C_{it} is a vector of control variables,α_0 is the constant term, and μ_i andε_{ij} represent unobservable regional fixed effects and the idiosyncratic error term, respectively. The coefficient on de_{it},denoted as β_1 is the primary focus of this study. A notably favorable estimate would indicate that the digital economy serves a catalytic function in augmenting GTFP.

To further uncover the potential mechanisms underlying this relationship, we examine three mediating channels suggested by the theoretical framework: industrial structure optimization, green technological innovation, and energy efficiency. These mechanisms are operationalized through the mediation models in Equations 2 and 3

$$\mathrm{Med}_{it} = \theta_0 + \gamma_1 \mathrm{lnde}_{it} + \gamma_2 \mathrm{lnC}_{it} + \mu_i + \varepsilon_{ij} \quad (2)$$

$$\mathrm{lngtfp}_{it} = \alpha_0 + \beta_1 \mathrm{lnde}_{it} * \mathrm{lnMed}_{it} + \beta_2 \mathrm{lnC}_{it} + \mu_i + \varepsilon_{ij} \quad (3)$$

Med_{it}represents the mediating variable either industrial optimization, green innovation, or energy efficiency and β_1 denotes the estimated coefficient reflecting the mediation effect of digital economic development on GTFP through Med_{it}. The sign and significance of $\gamma_1$serve as indicators of the presence and direction of the mediating relationship. Control variables in Equation 2 remain consistent with those in Equation 1.

3.2. Variables and Research Methodology

The study utilizes an unbalanced provincial panel (2013-2022) covering 30 regions on the Chinese mainland, excluding Tibet due to data limitations. Dataset integration involved: (a) official statistical yearbooks, (b) ecological bulletins, and (c) financial databases (WIND), with missing observations imputed using Stata's linear interpolation procedures.

3.2.1. Dependent Variables

The GTFP index is calculated using the Epsilon-Based Measure (EBM) model, which integrates both radial and non-radial distance measures. Unlike traditional DEA or SBM models, the EBM framework captures inefficiencies more comprehensively. Given the inclusion of undesirable outputs in the GTFP framework, we implement a super-efficiency EBM model that incorporates variable returns to scale and non-oriented variables. Equation 4 illustrates the formulation.

$$\gamma^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{\omega_i^- s_i^-}{x_{ik}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{\omega_r^+ s_r^+}{y_{rk}} + \varepsilon_b \sum_{p=1}^{q} \frac{\omega_p^{b-} s_p^{b-}}{b_{pk}}}$$

$$\begin{aligned} \text{st.} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- - \theta x_{ik} = 0, i = 1, \cdots, m \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ - \varphi y_{rk} = 0, r = 1, \cdots, s \\ \sum_{p=1}^{n} b_{ij}\lambda_j + s_p^{b-} - \varphi b_{pk} = 0, p = 1, \cdots, q \\ \lambda_j \geq 0, s_i^-, s_r^+, s_p^{b-} \geq 0 \end{aligned} \quad (4)$$

The EBM model with scale rewards defines optimal efficiency asγ^*,where,θrepresents the radial planning parameter. The transition, coefficientε_x(0 <ε_x< 1) mediates between radial and non-radial conditions. The relative significance of each input indicator is denoted byω_i^-.s_i^- captures input relaxations.x_{ik} andy_{rk} are the i-th input and r-th output of the k-th DMU. lambdaλ_j is the linear combination coefficients of the DMUs.b_{pk} denotes the p-th undesirable output of the k-th DMU.

Because the EBM model operates on cross-sectional data, we integrate it with the GML index to analyze productivity dynamics over time. Following [30] GML allows for the measurement of intertemporal GTFP growth, as demonstrated in Equation 5.

$$\begin{aligned} \mathrm{GML}_t^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \\ = \frac{1 + D^t(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{1 + D^G(x^t, y^t, b^t)}{1 + D^t(x^t, y^t, b^t)} \times \frac{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \right] \end{aligned} \quad (5)$$

The GML index indicates the variation in green total factor productivity across time. The value of GML over 1 signifies an augmentation in GTFP; a value of 1 denotes stability; and a value below 1 indicates a reduction in GTFP.

Following the EBM-GML methodology, we construct an index system comprising inputs (capital, labor, energy, and pollution control investment), desired output (GDP), and undesirable outputs. Capital and labor inputs are proxied by fixed asset investment and total employment, respectively; energy input is represented by aggregate energy consumption; and environmental inputs are quantified via completed investment in industrial pollution control.

3.2.2. Explanatory Variables

The level of digital economy development is assessed using a multidimensional indicator derived from Aigner, et al. [13]. According to the Statistical Classification of the Digital Economy and Charnes et al. [12], the index consists of three dimensions: (1) Digital infrastructure, which includes mobile phone penetration, broadband user density, and fiber-optic cable coverage. (2) Digital industrialization encompasses the share of telecommunications services, software industry revenue, and information services in GDP, along with the proportion of urban employment in information-related sectors.

(3) Industrial digitization includes the number of websites per 100 enterprises, the digital financial inclusion index, e-commerce turnover, and express delivery revenue. The composite index is computed using the entropy weighting method, which is tailored to panel data.

Control variables encompass: financial development level (fin), operationalized as financial institutions' credit-deposit volume relative to GDP. Openness to trade (od): proxied by the trade-to-GDP ratio. Human capital (hum): captured by enrollment in tertiary education (undergraduate and postgraduate). Industrialization level (ind): represented by the industrial sector's value-added contribution.

3.2.3. Mediating Variables

Industrial structure optimization. This study adopts a tripartite framework to capture industrial transformation: industrial structure advancement (stra), industrial structure upgrading (stru), and industrial structure rationalization (strr). Drawing on the Petty-Clark Law and the frameworks proposed by Aigner, et al. [13] we operationalize these dimensions as follows:

The industrial structure's advancement is quantified by the proportion of tertiary sector value-added relative to that of the secondary sector. An elevated value signifies a more sophisticated industrial framework, indicating a transition towards service-oriented economic endeavors.

The industrial structure index captures the transition from basic to secondary and tertiary sectors. The upgrading index is computed as follows:

$$\mathrm{stru}_{\mathrm{it}} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{i} \times \frac{\mathrm{Y_i}}{\mathrm{Y}} \qquad (6)$$

Yi /Y represents the share of value added from primary, secondary, and tertiary industries in the region's total output. A higher value indicates more advanced industrial restructuring.

The industrial rationalization is quantified utilizing the Theil index, as demonstrated below:

$$\mathrm{strr}_{\mathrm{it}} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{Y_i}}{\mathrm{Y}} \ln\left(\frac{\mathrm{Y_i}}{\mathrm{L_i}} / \frac{\mathrm{Y}}{\mathrm{L}}\right) \qquad (7)$$

Here, Yi /Y denotes the output share, Li /L the labor share of each sector (primary, secondary, tertiary). The Theil index captures the degree of mismatch between output and labor allocation. A lower index signifies a more rational industrial structure, where output and labor are better aligned across sectors, suggesting higher overall efficiency.

Green technological innovation is indicated by the quantity of green patents awarded, signifying the extent of ecologically friendly innovation.

Energy Efficiency is represented by total electricity consumption, following Bridgman, et al. [34] who found that electricity demand closely correlates with the elasticity of GDP relative to energy inputs. Thus, electricity consumption serves as a suitable proxy for gauging changes in energy use efficiency.

3.2.4. Descriptive Statistics

The study utilizes panel data spanning 2013-2022 from 30 Chinese provinces, excluding Tibet due to data availability limitations. Key variable statistics are summarized in Table 1. The GTFP displays high stability (mean = 1.021 ± 0.069), whereas the digital economy index (de) exhibits greater dispersion (0.141 ± 0.138), suggesting broader variability in adoption or intensity. Financial development (fin, 3.54 ± 1.075) and human capital (hum, 97.858 ± 58.790) demonstrate marked cross-sectional heterogeneity, with the latter spanning nearly two orders of magnitude (range: 5.07–282.33). Other variables similarly reflect diverse economic conditions. Collectively, these metrics confirm significant data variation, ensuring sufficient discriminatory power for econometric modelling.

Table 1.
Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
gtfp	270	1.021	0.069	0.709	1.337
de	300	0.141	0.138	0.013	0.865
fin	300	3.54	1.075	1.912	7.618
od	300	0.259	0.257	0.008	1.257
hum	300	97.858	58.79	5.07	282.33
indu	300	0.322	0.075	.1	.51
stra	300	1.422	0.757	.665	5.244
stru	300	2.413	0.118	2.132	2.836
strr	300	0.151	0.105	0.008	0.565
gil	300	4893.857	6833.215	31	45359
ei	300	0.736	0.457	0.166	2.199

4. Results

4.1. Baseline Regression Analysis

We commence by assessing multicollinearity among the explanatory factors. The variance inflation factor (VIF) values range from 1.09 to 3.01, well below the standard threshold of 10, indicating no significant issues with multicollinearity. To ensure accurate estimation, we utilize robust standard errors. The Hausman test shows significance at the 1% level, confirming the preference for a fixed-effects model over a random-effects model.

Table 2 the report presents the baseline regression results, with models estimated both with and without control variables. The coefficient for digital economy development (de) is positive and statistically significant at the 1% or 5% levels across all specifications. This indicates that the digital economy substantially boosts GTFP, perhaps via enhanced information distribution and more efficient resource allocation. These findings support the hypothesis that digital infrastructure and technologies act as enablers of green economic growth.

Moreover, human capital (hum) shows a significantly positive effect in Models 4 and 5, highlighting the critical role of a well-educated workforce in supporting green technology adoption and innovation. Enhancing human capital emerges as a key policy lever for advancing green development.

In contrast, financial development (fin) and openness to trade (od) exhibit significant negative effects on GTFP at the 5% and 10% levels, respectively. This may reflect inefficient financial resource allocation, with capital disproportionately favoring high-emission industries over environmental sectors. Similarly, increased trade openness may be associated with the expansion of pollution-intensive and energy-intensive export industries, thereby intensifying environmental pressures and hindering green productivity growth. The level of industrialization (indu) does not show a statistically significant impact on GTFP. This null effect may stem from the continued dominance of traditional manufacturing sectors, which are yet to transition to greener production modes.

In summary, the results suggest that while the digital economy and human capital are pivotal to advancing green total factor productivity, careful policy attention is needed to redirect financial flows and trade structures to better align with environmental sustainability goals.

Table 2.
Baseline Regression Results of the Impact of the Digital Economy on Green Total Factor Productivity.

Variables	**-1**	**-2**	**-3**	**-4**	**-5**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
lnde	0.222***	0.288***	0.266***	0.130**	0.135**
	-0.0419	-0.0511	-0.0517	-0.057	-0.0573
lnfin		-0.086**	-0.083**	-0.105***	-0.084*
		-0.0386	-0.0383	-0.0369	-0.0451
lnod			-0.148**	-0.188***	-0.196***
			-0.0697	-0.0671	-0.0678
lnhum				0.0820***	0.0837***
				-0.017	-0.0172
lnindu					0.11
					-0.132
Constant	0.673***	0.793***	0.823***	0.525***	0.456***
	-0.0059	-0.0543	-0.0557	-0.0818	-0.116
Observations	270	270	270	270	270
R-squared	0.105	0.124	0.14	0.217	0.219
Number of id	30	30	30	30	30

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1.

4.2. Robustness and Endogeneity Tests

This study conducted three different tests to validate the robustness of the projected influence of the digital economy on GTFP by creating new proxy variables and re-evaluating the relationship between the core explanatory variable and the dependent variable.

First, the GTFP index was recalculated to address potential measurement errors. In addition to the original approach, this paper employed the SBM-GML method to re-estimate green productivity. As shown in Column (1) of Table 3, even after using this alternative measurement technique, the digital economy variable remained significantly positive at the 5% level, thereby confirming the robustness of the initial findings.

Second, the construction of the digital economy index was revised. The entropy weight approach previously employed to assess the digital economy was replaced with the TOPSIS method, resulting in a new variable (de2). Column (2) of Table 3 indicates that the coefficient for the newly developed digital economy index remains notably positive at the 1% level. This further substantiates the persistent and substantial favorable impact of the digital economy on GTFP.

Third, to mitigate potential endogeneity issues, the one-period lag of the digital economy variable (L_lnde) was utilized as an instrumental variable in a two-stage regression analysis. The findings displayed in Column (3) of Table 3 demonstrate that the favorable correlation between the digital economy and GTFP persists as statistically significant. Collectively, these robustness checks, alternative measurement methods, and instrumental variable regressions validate the hypothesis that the digital economy greatly boosts GTFP, thereby increasing the dependability of the conclusions.

Table 3.
Regression Results of Robustness Tests.

	-1	-2	-3
	lngtfp	lngtfp	lngtfp
lnde	0.135**		
	-2.347		
lnde2		0.367***	
		-3.78	
L_lnde			0.110*
			-1.764
lnfin	-0.084*	-0.105**	-0.078*
	(-1.852)	(-2.346)	(-1.703)
lnod	-0.196***	-0.186***	-0.205***
	(-2.884)	(-2.808)	(-3.016)
lnhum	0.084***	0.041*	0.088***
	-4.873	-1.845	-5.009
lnindu	0.11	0.186	0.1
	-0.832	-1.406	-0.752
_cons	0.456***	0.575***	0.440***
	-3.921	-4.748	-3.709
Observations	270	270	270
R-squared	0.219	0.247	0.211
Number of id	13.18	15.376	12.58

Note: ***p<0.01, **p<0.05, *p<0.10.

4.3. Mediating Effect Tests

Having established that the digital economy significantly improves GTFP, this section further explores the mediating mechanisms through which this effect occurs, focusing on industrial structure optimization, green technological innovation, and energy efficiency.

Table 4.
Results of the Mediating Effect of Industrial Structure Optimization.

Variables	-1	-2	-3	-4	-5	-6
	lnstra	lngtfp	lnstru	lngtfp	lnstrr	lngtfp
lnde	0.0962**		0.0193**		0.153***	
	-0.0372		-0.0085		-0.0474	
lnde*lnstra		0.0685*				
		-0.0412				
lnde*lnstrh				0.101**		
				-0.0439		
lnde*lnstrr						2.267***
						-0.633
Constant	1.582***	0.395***	1.311***	0.448***	0.649***	0.389***
	-0.076	-0.111	-0.0174	-0.115	-0.0968	-0.107
control variable	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300	270	300	270	300	270
R-squared	0.936	0.21	0.832	0.218	0.594	0.242
Number of id	30	30	30	30	30	30

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 displays the regression results regarding the mediating impacts of industrial structure optimization. Columns (1), (3), and (5) illustrate that the digital economy exerts a substantial influence on all three aspects of industrial structural adjustment. Specifically, the coefficients for industrial structure advancement, industrial structure upgrading, and industrial structure rationalization are 0.0962 (significant at the 5% level), 0.0193 (significant at the 1% level), and 0.153 (significant at the 1% level), respectively. These results suggest that the proliferation of digital technologies has facilitated systemic upgrades to the industrial structure, enhancing technological capabilities while improving inter-industry coordination.

To investigate the extent to which these mediating elements influence the impact of the digital economy on GTFP, this study incorporates interaction terms between the digital economy and each industrial structure variable into the baseline regression model. As shown in Columns (2), (4), and (6) of Table 4, all interaction terms are significantly positive. The interaction coefficients for industrial structure advancement, upgrading, and rationalization are 0.0685 (significant at the 10% level), 0.101 (significant at the 5% level), and 2.267 (significant at the 1% level), respectively. These findings suggest that the digital economy further enhances GTFP through its positive influence on industrial upgrading, particularly by promoting more rational resource allocation across sectors. Among the three, the mediating effect of industrial structure rationalization is the strongest, indicating that more balanced and efficient inter-sectoral coordination is especially effective in facilitating green productivity improvements. Thus, the optimization of industrial structure serves as a crucial pathway for the digital economy to facilitate the transition toward a green economy.

Table 5.
Results of the Mediating Effect of Green Technological Innovation.

Variables	-1	-2
	lngil	**lngtfp**
lnde	2.270***	
	-0.48	
lnde*lngil		0.0121**
		-0.005
Constant	-4.797***	0.461***
	-0.98	-0.117
control variable	Yes	Yes
Observations	300	270
R-squared	0.807	0.219
Number of id	30	30

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1.

Column (1) of Table 5, indicates that the digital economy substantially enhances green technological innovation, exhibiting a coefficient of 2.270 (significant at the 1% level). To further validate the mediating role of green innovation in increasing GTFP, an interaction term between the digital economy and green innovation (lnde*lngil) is incorporated into the model. Column (2) presents a significantly positive coefficient of 0.0121 at the 5% level, suggesting that the digital economy promotes GTFP by fostering green innovation.

This effect can be ascribed to the availability of digital tools and platforms that facilitate the advancement of green technology. Technologies like big data analytics and AI enable the generation and distribution of green patents, encourage the implementation of clean production techniques, and ultimately enhance the ecological efficiency of economic activities.

Table 6.
Results of the Mediating Effect of Energy Efficiency.

Variables	-1	-2
	lnei	**lngtfp**
lnde	-0.218***	
	-0.0625	
lnde*lnei		1.051***
		-0.289
Constant	1.636***	0.558***
	-0.128	-0.12
control variable	Yes	Yes
Observations	300	270
R-squared	0.729	0.243
Number of id	30	30

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column (1) of Table 6 indicates that the coefficient of the digital economy on energy efficiency is -0.218 (significant at the 5% level), suggesting that the digital economy leads to a decrease in energy intensity. This may result from the extensive use of digital technologies, including smart manufacturing and the industrial internet, which enhance energy allocation efficiency in production and foster the growth of less energy-intensive service industries.

To further validate this mediating effect, the interaction between the digital economy and energy efficiency (lnde*lnei) is examined. The results in Column (2) show a significantly positive coefficient of 1.051 at the 1% level, confirming that improvements in energy efficiency serve as a key pathway through which the digital economy enhances GTFP.

This mechanism may function in two ways. First, digital technologies streamline production processes, reducing energy consumption at the source. Second, by lowering transaction and information costs, the digital economy improves market matching efficiency, reducing dependence on traditional energy sources on both the supply and demand sides. These factors jointly contribute to higher energy utilization efficiency and support the green transformation of the economy.

4.4. Heterogeneity Analysis

This research examines the disparate effects of the digital economy across various areas in China, including significant regional variances in resource availability, technological innovation, and industrial composition. The analysis categorizes the sample into eastern, central, and western regions based on the geographical classification issued by the National Bureau of Statistics.

Dummy variables (MID and WEST) were constructed to capture regional variations, and interaction terms between these variables and the digital economy index were included in the regressions. Table 7 presents the results.

Table 7.
Estimates of the digital economy's impact across different development regions.

VARIABLES	ln_gtfp
ln_de	0.159***
	-0.0576
ln_de×mid	0.315*
	-0.166
ln_de× west	0.112
	-0.163
ln_fin	-0.124**
	-0.0488
ln_od	-0.222***
	-0.071
ln_hum	0.0630***
	-0.0223
ln_indu	0.163
	-0.139
Constant	0.575***
	-0.124
Observations	270
Number of id	30
R-squared	0.247

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 The analysis reveals that the baseline coefficient of the digital economy (ln_de) on GTFP is 0.159, significant at the 1% level, indicating that in the eastern region (the reference group), the digital economy substantially enhances GTFP. For the central region, the interaction term coefficient (ln_de×mid) is 0.315, significant at the 10% level, suggesting that the digital economy's impact on GTFP in the central region is stronger than in the east, with a total effect of 0.474 (0.159 + 0.315). In contrast, the interaction term coefficient for the western region (ln_de×west) is 0.112 but does not reach statistical significance, implying that the digital economy currently has no discernible impact on GTFP in the west.

Several factors may explain these regional differences. In the central region, the reception of industrial transfers has been coupled with active digital upgrading, creating a virtuous cycle between digital economy development and industrial transformation, thereby amplifying the green productivity effects. In the eastern region, despite a high level of digital economy maturity, the marginal returns of digitalization have started to diminish, leading to relatively smaller impacts. Meanwhile, the western region lags in digital infrastructure and talent reserves, constraining the digital economy's ability to drive GTFP improvements.

5. Conclusions

In the context of China's ongoing pursuit of high-quality growth, the digital economy has become a key catalyst for green transformation. However, the country's history of resource-intensive and pollution-heavy development presents persistent challenges to sustainability. Understanding the relationship between digital economy development and GTFP is crucial for informing policies aimed at promoting more efficient and environmentally sustainable growth. This study presents several significant findings based on provincial panel data from 2013 to 2022.

First, the expansion of the digital economy has substantially advanced gains in GTFP; however, there are notable regional disparities. Baseline regression findings demonstrate that a 1% increase in the digital economy correlates with a 0.135% rise in GTFP, a relationship that remains robust after multiple sensitivity and endogeneity checks. However, effects vary across regions: the central region shows a stronger enhancement effect than the eastern region, while no statistically significant effect is observed in the west. These findings highlight the importance of regionally tailored policies that align digital development strategies with local conditions and development needs.

Second, the digital economy fosters green growth through multiple interlinked transmission mechanisms. Specifically, it drives deep optimization of industrial structures, especially via industrial rationalization, significantly promotes green technological innovation, and enhances energy efficiency. Among the three pathways of industrial optimization, industrial advancement, upgrading, and rationalization, the mediating role of rationalization emerges as the most salient. This indicates that the digital economy not only reshapes the industrial ecosystem but also provides pivotal support for the transition toward a greener economy. In parallel, green technological innovation and energy efficiency improvements also serve as vital mediators. The digital economy not only expedites the research, development, and dissemination of green patents, dramatically boosting the supply capacity of green technologies, but also fosters the optimization of energy consumption patterns and a reduction in energy intensity. Enhancing resource-use efficiency at the unit level provides sustainable momentum for improvements in green total factor productivity (GTFP) while simultaneously charting a pathway towards the construction of a modernized green economic system.

6. Policy Recommendations

To fully harness the digital economy's capacity to promote sustainable development, we recommend the following policy initiatives:

First, develop a cross-regional collaborative mechanism to reduce disparities in digital economy development. Despite the overall upward trajectory of China's digital economy, regional imbalances are widening, particularly between the east, center, and west. In particular, the western region remains significantly lagging. To address this, it is imperative to strengthen regional collaboration, led by initiatives such as "East Counting Supports West Counting," to promote cross-regional infrastructure construction and digital resource sharing. The eastern region should focus on leading digital innovation, developing frontier technologies, and creating new industries and models. The central area should prioritize industrial digital transformation to improve resource allocation efficiency, and the western region should concentrate on upgrading new infrastructures, including 5G networks and data centers, to bridge the digital gap. Build a national-level coordinated development evaluation system to facilitate the logical allocation and gradual dissemination of digital economy resources via financial transfers, industry investment guidance, and collaborative innovation platforms.

Second, construct a comprehensive action system for digital-enabled green transformation to systematically improve GTFP. To translate the mechanism advantages of the digital economy into policy effectiveness, we recommend a three-pronged approach:

(i) Accelerate the green and intelligent transformation of traditional industries by creating dedicated funding for digital green upgrades, offering subsidies and tax incentives, and promoting technologies such as the industrial internet, edge computing, and digital twins for real-time emissions monitoring and process optimization. Establishing a "green digital enterprise rating system" will prioritize support for firms that achieve green transformation targets.

(ii) Enhance the development of green technology innovation platforms and promote regional collaborative innovation by utilizing high-tech zones, industrial research institutes, and universities, while encouraging joint research and development initiatives between enterprises and research organizations in fields such as green artificial intelligence algorithms, energy-efficient sensors, and blockchain for sustainability. Regional collaboration mechanisms combining "cross-provincial joint research" with "local pilot applications" should be established to efficiently match eastern technology supplies with green application needs in central and western regions.

(iii) Advance digitalization and enhancement of the energy system by expediting the establishment of municipal "energy data centres" and "real-time carbon emission management platforms," thereby enabling integrated data sharing across electricity, heating, and gas sectors, and facilitating real-time monitoring, early warning, and precise management of energy consumption. Through a combination of governmental guidance and market-based incentives, blockchain- and big data-enabled carbon accounting systems and green energy credit mechanisms should be established, encouraging enterprises to optimize energy use proactively. Large firms should be incentivized to develop internal digital platforms for energy management, benchmarking energy efficiency, and carbon emissions performance to shift corporate behavior from passive compliance to active optimization.

By building an integrated system spanning industrial transformation, technological innovation, and energy governance, these measures will not only resolve existing impediments but also establish a clear and systematic framework for attaining China's leap toward green, high-quality development.

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