Scholar Publishing Group
International Journal of Social Sciences and Economic Management
https://doi.org/10.38007/IJSSEM.2025.060114
ISSN 2789-715X Vol. 6, Issue 1: 157-178

Examining the Influence and Mechanisms of the Digital Economy on Urban Green Total Factor Energy Efficiency: Evidence from 240 Cities in China

Jun Xu and Wenbo Song

Associate Professor, School of Economics and Management, Xinjiang University, Urumqi 830046, China

Keywords: Digital economy; Green total factor energy efficiency; Green technology innovation; Energy electrification level; New quality productive forces

Abstracts: The digital economy has emerged as a pivotal driver in enhancing the green total energy efficiency of cities. Utilizing panel data from 240 prefecture-level cities in China spanning 2011 to 2022, this study develops an index system to evaluate urban digital economy development across five dimensions: digital infrastructure, digital industry, digital finance, digital innovation, and digital economic policy support. The analysis reveals that urban digital economy's advancement significantly enhances urban green total factor energy efficiency, persisting across various robustness tests. Moreover, the digital economy improves urban green total factor energy efficiency by fostering green technology innovation and advancing energy electrification. Notably, digital finance and digital innovation exhibit a more substantial impact on urban green total factor energy efficiency, with coastal cities and key environmental protection cities showing a more pronounced effect. The threshold effect analysis further indicates a dual threshold effect for new quality productive forces, where the digital economy exerts a significant influence on green total factor energy efficiency once these forces surpass the second threshold. Consequently, it is recommended to promote the development of the urban digital economy to comprehensively enhance energy use efficiency and establish a green, low-carbon urban energy system.

1. Introduction

Due to the constant growth of the Chinese economy, the total amount of energy consumed has tended continuous growth, thereby establishing China as a major energy-consuming country on the global stage(Wang et al., 2014). Meanwhile, the growth in energy demand has placed higher demands on energy supply and posed challenges to environmental protection and sustainable development(Crompton and Wu, 2005; Zhang et al., 2021). Despite the rapidly expanding use of renewable energy sources in the past few years, coal still constitutes a significant portion of China's

Copyright: © 2025 by the authors. This is an Open Access article distributed under the Creative Commons Attribution License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited (https://creativecommons.org/licenses/by/4.0/).

energy mix. Data from 2023 reveal that coal consumption comprises 55.3% of the nation's total energy use, posing a substantial challenge to further improvements in China's energy efficiency. In March 2021, the 14th Five-Year Plan was announced, the Chinese government emphasized the importance of transforming energy production and consumption, constructing a green and low-carbon energy system, enhancing energy efficiency, and promoting high-quality economic growth in China. The ongoing advancement of digital information technology has enabled China to achieve rapid growth in its digital economy (Huang and Chen, 2023). This has in turn given rise to a digital economy-driven mode of production that is integrated with the field of energy, energy production,and consumption. This integration has provided strong information technology support, enabling the linkage of resources and the promotion of green total energy efficiency(Xue et al., 2022). The aim of this paper is to examine how the digital economy affects urban green total factor energy efficiency. This holds substantial significance for enhancing energy efficiency in Chinese cities and advancing the achievement of the "double carbon" goals (H. Wang et al., 2024).

The study examines how the digital economy (DE) affects urban green total factor energy efficiency (GTFEE) through panel data collected from 240 prefecture-level cities in China from 2011 to 2022. This paper addresses four key research questions. The primary objective of this paper is to assess the immediate impact of urban DE on urban GTFEE. In addition, it is aimed at identifying the channels by which the DE affects GTFEE. Thirdly, it attempts to investigate the threshold effect of new quality productive force. Finally, the potential relationship between DE development and urban GTFEE is explored by exploring the heterogeneous characteristics of urban areas.

Each of the following four areas highlights the contributions of this paper. Firstly, building upon the existing DE framework, this paper utilizes the Python to extract the frequency of government concern words related to the DE from official reports. A new DE indicator system is built by taking into account government concerns. Second, we take into account the development level of the DE in the prefecture-level city to further explore its influence on urban GTFEE. Third, this paper finds that DE development can improve the urban GTFEE by impacting both green technological innovation and energy electrification through theoretical analyses and mediating effect models. This provides a new perspective for studying the impact of the DE on urban GTFEE. Fourth, the threshold effect of new quality productive forces (NQPF) is utilized to examine the impact of the DE on urban GTFEE, providing an invaluable complement to existing research.

2. Literature Review

The recent focus of scholars has been about the connection between energy efficiency and urban DE. As China strives for high-quality economic development, scholars are beginning to examine the effect of the DE on urban GTFEE. This topic is categorized into three categories in the current literature: the assessment of GTFEE, the factors that influence it, and the effects of the DE on GTFEE.

The first area of study is focused on measuring GTFEE. Firstly, Hu and Wang (2006) brought forth the idea of total factor energy efficiency, which is based on total factor productivity. Regarding subsequent measurement, various scholars have employed different methodologies. The use of a traditional DEA model was used by Al-Refaie et al.(2016) to assess energy efficiency, while Shang et al. (2020) used an SBM model to assess total factor energy efficiency that included undesired outputs. Wang (2022) proposed a new approach that incorporates the Shephard distance function and the meta-frontier model to create a model that can model total factor green efficiency by parameterizing it. The assessment of green efficiency requires consideration of technological heterogeneity in this approach. In recent years, Liu (2023) has carried out relevant measurements by applying the super-efficient SBM model. This provides a reference for measuring urban GTFEE.

In examining the determinants of GTFEE, the extant literature primarily concentrates on economic, financial, infrastructural, and digitalization aspects. For example, Tang and He (2021) posited that more resources and funds from economic development will be better spent on environmental management and sustainable development, resulting in further enhancements in energy efficiency. Concerning green finance, Yu et al. (2024) discovered that green finance policy pilots can markedly enhance the pilot cities' total energy efficiency factor. Furthermore, economically developed cities exhibited a more pronounced positive response to green finance policy pilots, and their total factor energy efficiency improvements were more pronounced. Additionally, Wu et al. (2024) found that digital finance has the potential to expand capital resources for financing options, improve capital allocation efficiency, and foster corporate production processes that are greener and low-carbon industries at a macro level. In terms of infrastructure, Lin and Zhu (2021) proposed that industrial agglomeration prompts local governments to prioritize infrastructure enhancements within these concentrations. This markedly enhances firms' energy scale and energy allocation efficiency through shared infrastructure. Simultaneously, broadband infrastructure can improve green energy efficiency by lowering transaction costs and promoting technology diffusion (Wen et al., 2022). Gao et al. (2022) demonstrated that digitization has a beneficial effect on GTFEE. However, the non-linear relationship with the level of resource matching influences the impact of digitization on GTFEE.

The third aspect is the investigation of how the DE affects GTFEE. Scholars have been evolving their research approach in this field by transitioning from measuring only single indicators in the early stages of the DE to building a comprehensive indicator system for the DE. This shift underscores both the depth and sophistication of the research and highlights the significant role of the DE in enhancing GTFEE. The early stages of the DE were explored in their investigation of the Internet and information and communications technology (ICT). The discovery made by Wu et al. (2021) was that Internet development can directly improve both local GTFEE and neighboring regions' GTFEE. Moreover, the advancement of the Internet can indirectly enhance GTFEE by mitigating resource misallocation, boosting regional innovation capabilities, and facilitating the upgrading of industrial structures(Wu et al., 2021; Yu and Luo, 2024). The impact of ICT on improving total energy efficiency was demonstrated by Ahmed et al.(2022), which is of great strategic importance in balancing energy supply and demand. In light of these findings, numerous scholars have endeavored to elucidate the impact of DE advancements on GTFEE. To assess the advancement of the DE, they have created a comprehensive indicator. Wu et al. (2023) discovered that ICT in the early stages of the DE can result in more energy consumption and even hinder improvements in energy efficiency. However, as the DE matures, its impact on energy efficiency demonstrates a U-shaped relationship. Below a certain threshold, the growth of the DE can promote the enhancement of the urban GTFEE. According to Song et al. (2023), the increase in the DE has a beneficial direct impact on the efficiency of utilizing energy. Additionally, they found that energy efficiency in neighboring regions correlates positively with the scale of the DE. With regard to the impact of mechanisms, Huang and Chen (2023) found through the promotion of technological innovation, industrial structuring, and improving the alignment between capital and labor, the DE positively impacts the GTFEE. As stated in the findings of (Wang et al., 2014), the DE's effect on urban energy efficiency is contingent upon city size, geographic region, and level of economic development.

Although numerous scholars have investigated the DE and its relationship with GTFEE, identifying a potential correlation, existing studies have notable limitations. (1) The majority of research material has been focused on how the DE affects economic variables, the measurement of GTFEE, and its influencing factors. Limited research has been done on the direct link between the

DE and urban GTFEE. By examining the impact of the DE on urban GTFEE, this paper is aimed at addressing this gap. (2) Most research samples are focused on provincial and national levels, but few studies address how the DE affects the GTFEE of prefecture-level cities. Given the significant development disparities among prefecture-level cities within the same province, analyzing regional heterogeneity is crucial for refining study results. (3) Concerning influence mechanisms, existing research primarily emphasizes advanced industrial rationalization and industrial structure, with insufficient exploration of other mechanisms. In this paper, the impact of DE on urban GTFEE is examined using green technological innovation and energy electrification.

3. Theoretical analysis and research hypotheses

3.1. The Influence of the Digital Economy on Urban Green Total Factor Energy Efficiency

The DE has become a significant catalyst for economic transformation and development due to the rise of ICT (Chen et al., 2023; Ji et al., 2023 and Zhang et al., 2023). Data resources, modern information, networks, and ICT have enabled the DE, which has facilitated innovation and development in a range of economic activities (Wang and Zhong, 2023a). In this context, it is first necessary to clarify the connotation of urban GTFEE. Optimizing energy structure, enhancing energy efficiency, and reducing environmental pollution are the steps required to decouple energy consumption from economic growth, while maintaining sustained urban economic growth, which is what this term means (Song et al., 2024). Rapidity and other attributes of the DE are what make it possible to continuously enhance inter-regional information networks, reduce costs associated with information acquisition and the exchange, and improve efficiency (S. Wang et al., 2024). These developments lead to increased inter-regional exchanges, effectively promoting the flow of talent and information sharing, and providing robust information technology support for the production and consumption of energy(Dian et al., 2024). Simultaneously, by directing the transition from high-energy-consuming industries to low-energy, high-value-added sectors, the DE can help optimize industrial structure. Additionally, the green consumption and low-carbon travel promoted by the DE help guide public engagement in energy conservation and emission reduction, fostering a consensus on green development. As a result, the urban green total energy efficiency is significantly enhanced. (Huang and Chen, 2023; Wang and Zhong, 2023). The preceding analysis leads to the formulation of Hypothesis 1.

H1. Urban GTFEE can be significantly enhanced by the DE.

3.2. The heterogeneous Effects of the Digital Economy on Urban Green Total Factor Energy Efficiency

The influence of the DE on GTFEE in urban areas is likely to be contingent upon the geographical location and developmental characteristics of the city in question. For instance, clean energy sources like wind and solar power are the most commonly used for energy in coastal cities. These cities generally exhibit higher GTFEE compared to inland cities due to their advanced economic development, abundant educational and financial resources, and the presence of a large, talented workforce. These factors collectively provide substantial capital for enterprises, further enhancing their energy efficiency (Y. Zhang et al., 2022; Y. Ren et al., 2022). Concurrently, key cities for environmental protection often receive more policy support and resources at the national or local level, and their energy consumption structure may be more rational and efficient, with a relatively high proportion of clean and renewable energy. Therefore, the implementation of digital technology in energy management, conservation, and consumption reduction can be more effective and contribute significantly to enhancing GTFEE. The preceding analysis leads to the formulation of Hypothesis 2.

H2. The GTFEE of cities can be impacted differently by the DE due to differences in geographical location and city characteristics.

3.3. Mechanisms Through Which the Digital Economy Affects Urban Green Total Factor Energy Efficiency

The exponential growth of the DE has led to a surge in investment in green technological innovation, with capital, talent, and technology all playing a pivotal role. Research, development, and application of green technology are being pushed forward by the intrinsic innovation in the DE (Luo et al., 2022). Through the collection, processing, and analysis of large volumes of data, the DE provides crucial data support for green innovation research and development (Ge et al., 2024). Secondly, the swift advancement of the DE offers significant technical support for the implementation of green innovations. More opportunities and avenues for implementing green innovations are generated by the continued development of artificial intelligence and other digital technologies. The DE acts as both an external environment and a fundamental driver, encouraging enterprises to adopt and leverage digital technologies to advance green innovation. Concurrently, the DE stimulates green innovation by facilitating the digitization of firms and improving access to trade credit, which reduces the financial constraints and debt costs of firms (Qiao et al., 2024). Concurrently, the transformation of traditional industries towards high technology and low pollution, optimizing the industrial structure, reducing pollutant emissions, and lowering the cost of urban environmental governance can be promoted by green technology innovation, which makes the limited resources invested more in economic activities to improve energy efficiency. Thus, green technological innovation within the traditional energy sector can be promoted by the DE, leading to reducing energy intensity and consumption across development, transportation, and storage processes. The demand for electricity is increasing due to the widespread use of technologies such as ICT due to the DE's expansion. (Yeager, 2004). The growth in demand for electricity is not only driving the growth in energy demand, but also prompting a shift in the energy mix. The increasing electricity demand has not been met by traditional fossil fuels, leading to the shift in energy demand from conventional fossil fuels to new energy sources (Berkhout and Hertin, 2001). The advent of numerous new energy technologies, including solar and wind power, has not only effectively increased the supply of electricity, but also improved energy efficiency (Liu and Wang, 2009). At the same time, energy electrification improves energy use efficiency by reducing energy waste and loss, thus effectively contributing to the improvement of the urban GTFEE. The preceding analysis leads to the formulation of Hypothesis 3.

H3. Urban GTFEE is influenced by the DE through mechanisms such as green technology innovation and energy electrification.

3.4. Threshold effects of new quality productive forces

Advanced productive forces driven by innovation are new quality productive forces (NQPF), which are different from traditional economic growth models and development paths. The New Development Concept is aligned with these forces, which are characterized by high technology, efficiency, and quality. China is a country that encompasses a large area, and local governments may adopt different approaches to the promotion of macroeconomic policies. Consequently, NQPF will vary between regions. Cities may experience varying effects on GTFEE from the DE depending on the level of NQPF. The impact of the DE on the GTFEE can be increased in regions with advanced NQPF. Cities can enhance technological innovation and industrial structure upgrades by including DE elements in production processes, which improves their GTFEE (Gao et al., 2022).

The preceding analysis leads to the formulation of Hypothesis 4.

H4. Urban GTFEE is affected by the impact of the DE through NQPF.

4. Methodology

4.1. Model setting

4.1.1. Dynamic Panel Data Model

This paper builds upon Wang and Shao (2023)'s research to examine how the DE affects urban GTFEE and introduces the following model for validation.

$$\mathrm{GTFEE}_{it} = \alpha_0 + \alpha_1 \mathrm{DE}_{it} + \alpha_2 \mathrm{Control}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(1)$$

In model (1), subscript i is used to represent the city, t is used to represent the year, GTFEE is the urban green total factor energy efficiency, and DE is the urban digital economy level. μ_i describes the fixed effect of cities, σ_t describes the fixed effect of time, and ε_{it} describes the random perturbation term. Control consists of the control variables that are ln_GDP, FIN, FDI, and GOV.

4.1.2. Mediating effect model

Adapting to the previous theoretical study on how the DE affects urban GTFEE, it is hypothesized that the DE may influence this efficiency through two primary channels: green technology innovation (GI) and energy electrification (ELE). To empirically test the aforementioned hypotheses, this paper employs the following model for verification, drawing upon the framework established by Du and Li (2019).

$$\mathrm{GI}_{it} = \beta_0 + \beta_1 \mathrm{DE}_{it} + \beta_2 \mathrm{Control}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(2)$$

$$\mathrm{GTFEE}_{it} = \gamma_0 + \gamma_1 \mathrm{DE}_{it} + \gamma_2 \mathrm{Control}_{it} + \gamma_3 \mathrm{GI}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(3)$$

$$\mathrm{ELE}_{it} = \beta_0 + \beta_1 \mathrm{DE}_{it} + \beta_2 \mathrm{Control}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(4)$$

$$\mathrm{GTFEE}_{it} = \gamma_0 + \gamma_1 \mathrm{DE}_{it} + \gamma_2 \mathrm{Control}_{it} + \gamma_3 \mathrm{ELE}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(5)$$

In model (2) and model (3), GI denotes green technology innovation. In model (4) and model (5), ELE denotes the degree of energy electrification. Other variable interpretations are the same as in equation (1).

4.1.3.Threshold regression model

Validating the nonlinear relationship between the DE and GTFEE is accomplished by using a threshold effect model, which involves NQPF as the threshold variable.

$$\begin{gathered}\mathrm{GTFEE}_{it} = \alpha_0 + \alpha_1 \mathrm{DE}_{it} I(\mathrm{NQPF}_{it} \le \gamma_1) + \alpha_2 \mathrm{DE}_{it} I(\gamma_1 < \mathrm{NQPF}_{it} \le \gamma_2) \\ + \alpha_3 \mathrm{DE}_{it} I(\mathrm{NQPF}_{it} > \gamma_2) + \alpha_4 \mathrm{Control}_{it} + \mu_i + \sigma_t + \varepsilon_{it} \#(6)\end{gathered}$$

In Model (6), NQPF represents new quality productive forces, γ denotes the threshold, and the remaining variables are defined in accordance with the same conventions as in Equation (1).

4.2. Variables and data

4.2.1. Dependent variable: green total factor energy efficiency

The GTFEE is measured using the super-efficient SBM model as referenced by Liu (2023) and Zhao et al.(2023) in this paper. The study is designed to account for the presence of N decision-making units (DMUs) with m inputs, n1 expected outputs, and n2 unexpected outputs. The vector format used for i DMU includes the inputs x_i , the expected output y_i^a, and the unexpected y_i^b.

$$x_i = (x_{1i}, x_{2i}, x_{3i}, \cdots, x_{mi}) \in R^{m \times n}$$
$$y_i^a = \left(y_{1i}^a, y_{2i}^a, y_{3i}^a, \cdots, y_{n_1 i}^a\right) \in R^{n_1 \times n} \#(7)$$
$$y_i^b = \left(y_{1i}^b, y_{2i}^b, y_{3i}^b, \cdots, y_{n_2 i}^b\right) \in R^{n_2 \times n}$$

Where X, Y^a, and Y^b are matrixes, and $X = [x_1, x_2, x_3 \cdots x_n] \in R^{m \times n}$, $Y^a = [y_1^a, y_2^a, y_3^a \cdots y_n^a] \in R^{n_1 \times n}$, and $Y^b = [y_1^b, y_2^b, y_3^b \cdots y_n^b] \in R^{n_2 \times n}$.

The DMU set T_{DMU} is expressed as $T_{DMU} = \{(x_1, y_1^a, y_1^b), (x_2, y_2^a, y_2^b), (x_3, y_3^a, y_3^b), \cdots (x_n, y_n^a, y_n^b)\}$, then the possible set $T = \{(x, y^a, y^b) | x_k \geq X\lambda, y_k^a \geq Y^a\lambda, y_k^b \geq Y^b\lambda, \lambda \geq 0\}$,where $\sum_{k=1}^{n} \lambda_k = 1$; this refers to variable returns of scale. S^-, S^a, and S^brepresent the slack of inputs, expected outputs, and unexpected outputs, respectively(Liu, 2023 and Zhao et al.,2023) λ is the weight vector, which is used to set up the undesirable SBM model as follows:

$$\min p^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{ik}}}{1 + \frac{1}{n_1 + n_2}\left(\sum_{r=1}^{n_1} \frac{S_r^a}{y_{rk}^a} + \sum_{r=1}^{n_2} \frac{S_r^b}{y_{rk}^b}\right)} \#(8)$$

$$s.t.\begin{cases} x_k = X\lambda + S^- \\ y_k^g = Y^a\lambda - S^a \\ y_k^b = Y^b\lambda + S^b \\ \lambda \geq 0, S^- \geq 0, S^a \geq 0, S^b \geq 0 \end{cases}$$

Capital stock (K), labor force (L), and energy consumption (EU) are the input variables S^- in Eq. (8). The output results contain the desired output, which is the city's actual GDP. The unexpected outputs, are the carbon dioxide emissions of the city industry, the sulfur dioxide emissions of the city industry, and the wastewater emissions of the city industry.

4.2.2. Core explanatory variable: digital economy

By reviewing the existing literature on DE (Ren et al., 2022; Ma and Zhu, 2022; Zhang et al., 2022 and Lyu et al., 2023) and combining its definition. Table 1 provides detailed information about the indicator system developed in this paper to assess the level of urban DE. The system encompasses five dimensions and thirteen indicators, and employs the entropy value method for a comprehensive evaluation.

Table 1. Digital Economy (DE)

Primary index	Secondary index	Third indexes
DE	Digital Facilities	Mobile phone subscribers at the end of the year
		Number of international Internet users
	Digital Industry	Total postal operations
		Total telecommunication services
		The number of individuals working in the computer industry
		Number of artificial intelligence company

	Digital Finance	Breadth of digital financial coverage
		Depth of use of digital finance
		Digitalization of financial inclusion
	Digital Innovation	Number of digital economy patents
		The number of students currently enrolled in a general higher education program
	Digital economic policy support	Number of digital economy policy word frequencies
		Total word count of digital economy policy texts

4.2.3. Mediation variables

Energy electrification level (ELE). The study conducted by Zhao et al.(2023) is referred to in this paper. And measure the level of urban energy electrification by choosing urban electricity consumption as an indicator.

Green technological innovation (GI). To illustrate urban GI, this study employs the total of green invention patents and green utility model patents granted as a proxy variable.

4.2.4. Control variables

The selection of appropriate control variables is crucial when assessing the factors that impact GTFEE. Building upon the work of Li and Ma (2021) and Siyu Ren et al.(2022), additional control variables are integrated into Model (1). (1) The Level of Economic Development (ln_GDP): Urban per capita GDP's logarithm is represented by this variable. The logarithmic transformation is applied to mitigate the effects of data variability and to present a more consistent measure of economic development. (2) The Degree of Financial Development (FIN): In order to assess the city's financial development, the financial institutions' year-end loan balance to the GDP ratio is utilized. This metric provides a clear indication of the activity and support capacity of the city's financial system. (3) The Level of Openness to the Outside World (FDI): Quantifying this is based on the ratio of the city's actual foreign direct investment to its GDP. This indicator reflects the city's capability and success in attracting foreign investments and engaging in international economic activities. (4) The Level of Government Intervention (GOV): Assessing the extent of government intervention in economic development can be achieved by comparing public financial expenditure to urban GDP. This indicator reflects the government's influence on resource allocation, policy-making, and economic control.

4.2.5. Threshold variable

NQPF are advanced productive forces that are distinct from traditional productive forces, those in which innovation plays a leading role and that are free from traditional modes of economic growth. In this study, Python is utilized to analyze the government work reports from 240 prefecture-level cities. The frequency of 46 keywords associated with "new quality productive forces" is counted. This frequency is used as a proxy variable to evaluate the growth of NQPF.

This study conducts a thorough analysis of panel data from Chinese prefecture-level cities and above, covering the period from 2011 to 2022. Following a meticulous review of data availability and completeness, a total of 2,880 valid observations were selected for inclusion in the study, representing 240 prefecture-level cities and above. The Digital Inclusive Finance Index, released by the Digital Finance Research Centre at Peking University, is the source of the digital finance data used in this study.[1] The China Energy Statistics Yearbook, China Statistical Yearbook, China

[1] Available https://idf.pku.edu.cn/.

Urban Statistics Yearbook, and local statistical bureaus are the primary sources for the remaining data. These sources provide the foundational data for the comprehensive analysis conducted in this study.

The relevant variables can be found in Table 2, where descriptive statistics are presented. According to the data, the average value of urban GTFEE in the city is 0.354, with a range between 0.103 and 1.177, indicating significant variability in urban GTFEE. This variability may stem from disparities in economic development levels and the diversity of local energy consumption patterns. Furthermore, the data shows a significant range in the degree of DE development in Chinese cities, with an average value of 0.071. The need for a more nuanced examination of this issue is highlighted by the standard deviation being 0.098 and the coefficient of variation exceeding 1.

Table 2 . Descriptive statistics

Variable	Obs	Mean	Std.Dev	Min	Max
GTFEE	2880	0.354	0.146	0.103	1.177
DE	2880	0.071	0.098	0.008	0.868
Ln_GDP	2880	10.815	0.582	8.773	13.056
FIN	2880	1.053	0.593	0.132	7.450
FDI	2880	0.001	0.005	0	0.120
GOV	2880	0.197	0.103	0.044	0.916
GI	2880	506.354	1371.184	0	18959
ELE	2880	14.182	0.892	11.093	16.568
NQPF	2880	23.822	12.198	0	84

5. Empirical results

5.1. Relevance analysis

Table 3. Results of correlation analysis

Variable	GTFEE	DE	Ln_GDP	FIN	FDI	GOV
GTFEE	1.000					
DE	0.317***	1.000				
Ln_GDP	0.363***	0.461***	1.000			
FIN	0.095***	0.450***	0.305***	1.000		
FDI	0.048***	0.076***	0.080***	0.160***	1.000	
GOV	-0.248***	-0.227***	-0.605***	0.060***	-0.0230	1.000

Notes: The significance levels of 1%, 5%, and 10% are represented by the symbols ***, **, and * separately.

The correlation analysis between variables is provided in Table 3. It can be inferred that the DE and urban GTFEE have a significant positive correlation as indicated by the results. The enhancement of urban GTFEE is likely to be positively affected by the advancement of the urban DE. Secondly, none of the variables had correlation coefficients above 0.7, a range of values that indicates a low degree of covariance between the variables. This indicates that there is no strong linear dependence among the variables. In addition, the variance inflation factor was utilized to verify multicollinearity between the variables. All variables have variance inflation factors below 3, as revealed by the test results. It can be inferred that there is no concern about multicollinearity in this study (it is commonly assumed that multicollinearity may be an issue when the VIF is greater than 5 or 10). Consequently, multicollinearity among the variables is not a concern, which provides a robust foundation for subsequent regression analyses.

5.2. Baseline model results

Table 4 demonstrates that urban GTFEE is impacted by the DE. Column (1) of Table 4 displays the baseline regression model demonstrating that urban GTFEE is significantly influenced by the DE. Hypothesis 1 proposed in this study is supported by this statistically significant effect at the 1% level. Furthermore, the results coincide with the study of Luo et al.(2022) and Lyu et al.(2024). Column (2) of Table 4, The coefficient for the DE has been determined to be 0.378 by incorporating relevant control variables into the baseline regression model. This indicates that a one-unit increase in the level of the DE corresponds to a 0.378-unit increase in GTFEE. These findings indicate that urban GTFEE is significantly improved by the DE's advancement. A potential explanation for this finding is that DE development drives technological innovation and upgrades within the energy sector, thereby contributing to improved energy efficiency. Consequently, H1 is supported by the evidence.

Table 4. The Baseline results

Variable	GTFEE	GTFEE
	Model (1)	Model (2)
DE	0.5147***	0.4547***
	(0.1478)	(0.1481)
Ln_GDP		0.0053
		(0.0126)
FIN		0.0239***
		(0.0068)
FDI		1.0953*
		(0.6026)
GOV		-0.1831***
		(0.0595)
Constant	0.2815***	0.2422*
	(0.0121)	(0.1380)
Observations	2880	2880
Number of cities	240	240
City FE	YES	YES
Year FE	YES	YES

Notes: The t-statistics are represented by the values in parentheses. The significance levels of 1%, 5%, and 10% are represented by the symbols ***, **, and * separately. The following table is the same as this note.

The control variables in the model reveal that the ln_GDP, the FIN, the FDI, and the GOV all influence urban GTFEE. Specifically, It has been found that GTFEE is positively affected by both economic development and financial development, suggesting that cities with higher economic and financial development have greater energy efficiency. Furthermore, the FDI coefficient is 1.0953 and is statistically significant at the 10% level, indicating a significant impact on the urban GTFEE. It can be reasonably assumed that foreign investment is being directed into energy-intensive industries, which expands the sources of funding for energy-intensive enterprises and provides a large amount of available capital. The improvement of urban GTFEE is facilitated by this green transformation of energy-intensive industries. The regression coefficient for the degree of government intervention is -0.1831. This negative value may be attributed to the current inadequacy of governmental support in enhancing urban GTFEE, suggesting that the government's role in promoting these improvements has not yet reached its full potential.

5.3. Robustness and endogeneity tests

5.3.1. Robustness tests

To ensure the robustness of empirical results, multiple robustness checks are conducted using the following approaches. (1) Variable Substitution: The input-oriented super-efficiency CCR model was used to re-evaluate the urban GTFEE. The revised variables were then employed in the regression analysis. (2) The removal of outliers: To prevent the negative effects of extreme values on outcomes, the analysis involved trimming the top and bottom 1% of the data. (3) Inclusion of Additional Control Variables: To further validate the empirical findings, the model was augmented with an additional control variable representing the overall upgrading of industrial structure (UIS). Table 5 demonstrates that the regression coefficients for the benchmark results are consistent with the core explanatory variables, confirming what was already known.

5.3.2. Endogeneity tests

The use of a lagged term of GTFEE to test for endogeneity is necessary due to the potential lagged effect of the DE on urban GTFEE. Column (4) of Table 5 shows that the DE has a regression coefficient of 0.7272. Urban GTFEE is to be significantly impacted by the DE at the 1% level, as indicated by this coefficient. The results are consistent with the previous benchmark regression results, which bolsters the conclusion that the DE's impact on urban GTFEE remains significant.

Table 5. Robustness and endogeneity tests

Variable	Model (1)	Model (2)	Model (3)	Model (4)
	GTFEE-CCR	GTFEE	GTFEE	F.GTFEE
DE	0.4059**	0.4468***	0.5953***	0.7272***
	(0.1838)	(0.1480)	(0.1661)	(0.1560)
Ln_GDP	-0.0292*	0.0021	0.0186	-0.0023
	(0.0157)	(0.0127)	(0.0130)	(0.0134)
FIN	0.0328***	0.0225***	0.0390***	0.0158**
	(0.0085)	(0.0069)	(0.0091)	(0.0072)
FDI	0.4950	1.0016*	-2.7707	1.4850**

Variable	Model (1)	Model (2)	Model (3)	Model (4)
	GTFEE-CCR	GTFEE	GTFEE	F.GTFEE
	(0.7480)	(0.6038)	(2.4530)	(0.7246)
GOV	-0.3339***	-0.1754***	-0.1834***	-0.1589**
	(0.0738)	(0.0596)	(0.0599)	(0.0634)
UIS		0.0845**		
		(0.0392)		
Constant	0.8669***	0.0870	0.0846	0.3233**
	(0.1713)	(0.1556)	(0.1416)	(0.1462)
Observations	2880	2880	2880	2640
Number of cities	240	240	240	240
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: Model (1) is with replacement of explanatory variables. Model (2) is to exclude outliers. Model (3) is adding control variables. Model (4) is lagging the explanatory variables by one period.

5.4. Quantile regression analysis

Table 6. Results of quantile regression test

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	Q10	Q30	Q50	Q70	Q90
DE	0.220***	0.244***	0.291***	0.349***	0.801***
	(4.86)	(4.38)	(5.73)	(4.09)	(12.82)
Ln_GDP	0.014**	0.043***	0.053***	0.056***	0.071***
	(2.13)	(6.04)	(7.76)	(7.21)	(5.23)
FIN	-0.028***	-0.024***	-0.023***	-0.015*	-0.019**
	(-5.76)	(-3.91)	(-4.89)	(-1.92)	(-2.11)
FDI	2.171***	1.218***	0.904*	0.831	0.212
	(4.10)	(2.59)	(1.79)	(1.64)	(0.17)
GOV	-0.198***	-0.092***	-0.081***	-0.099**	0.073
	(-5.31)	(-4.28)	(-3.35)	(-2.54)	(0.99)
Constant	0.136*	-0.154**	-0.229***	-0.218**	-0.345**
	(1.85)	(-2.03)	(-3.07)	(-2.56)	(-2.29)
Observations	2,880	2,880	2,880	2,880	2,880
Number of cities	240	240	240	240	240
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

In order to characterize the distribution in greater detail and thus obtain a comprehensive analysis, a panel quantile regression was performed on the data. Table 6 provides a detailed explanation of the regression results. As demonstrated, the DE is positively related to urban GTFEE. Advancements in the DE are correlated with enhancements in GTFEE, as evidenced by the positive regression coefficients. Furthermore, the regression coefficients demonstrate a discernible pattern of gradual elevation as the quantile ascends, with a notable surge occurring between the quantile of 70-90. The GTFEE in higher-tier cities is more significantly affected by the advancement of the DE, as suggested by this. As GTFEE improves, the marginal impact of the DE on urban GTFEE increases.

5.5. Heterogeneity analysis

5.5.1. Dimensions of digital economy development

Table 7. Heterogeneity analysis of the digital economy by dimension

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	GTFEE	GTFEE	GTFEE	GTFEE	GTFEE
DFF	0.1498***				
	(0.0420)				
DI		0.0670			
		(0.1115)			
DTIF			0.6204*		
			(0.3692)		
DIF				0.1204	
				(0.3130)	
DEP					-0.0246
					(0.0218)
Ln_GDP	-0.0038	0.0053	0.0069	0.0079	0.0074
	(0.0242)	(0.0243)	(0.0232)	(0.0235)	(0.0237)
FIN	0.0218**	0.0251**	0.0214**	0.0251**	0.0254**
	(0.0102)	(0.0106)	(0.0099)	(0.0106)	(0.0106)
FDI	1.0598	1.0516	1.1246	1.0797	1.1012
	(0.7623)	(0.7756)	(0.7919)	(0.7725)	(0.7868)
GOV	-0.1609	-0.1917	-0.1763	-0.1901	-0.1907
	(0.1142)	(0.1214)	(0.1191)	(0.1212)	(0.1211)
Constant	0.2917	0.2709	0.2274	0.2427	0.2659
	(0.2542)	(0.2611)	(0.2517)	(0.2540)	(0.2550)
Observations	2,880	2,880	2,880	2,880	2,880
Number of cities	240	240	240	240	240
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

To investigate the diversity in DE development dimensions, this paper creates five distinct dimensions and investigates their impact on urban GTFEE. Table 7 contains the details of the findings. The results reveal that the digital financial foundation (DFF) and digital technology innovation (DTIF) have statistically significant impacts on urban GTFEE, with significance levels at 1% and 10%, respectively. Furthermore, these two dimensions are larger than the other three, which may be attributed to the inclusive nature of digital finance. This enables the energy industry to effectively broaden its financing channels and further increase research and development of GI, thus improving the efficiency of energy use. Concurrently, digital innovation has facilitated the implementation of nascent technologies. These technologies, by aggregating, analyzing and mining energy data to achieve intelligent prediction of energy utilization and precise demand matching, have enhanced the efficiency of energy allocation, thereby further optimizing the urban GTFEE.

5.5.2. Heterogeneity of City Characteristics

Table 8. Heterogeneous analysis of urban characteristics

Variable	Model (1)	Model (2)	Model (3)	Model (4)
	GTFEE	GTFEE	GTFEE	GTFEE
DE	0.7142***	-0.0743	0.3618**	-0.0318
	(0.2107)	(0.2157)	(0.1828)	(0.3224)
Ln_GDP	-0.0289	0.0682***	0.0245	0.0377**
	(0.0218)	(0.0162)	(0.0231)	(0.0151)
FIN	0.0363**	0.0179**	0.0613***	0.0100
	(0.0152)	(0.0073)	(0.0156)	(0.0069)
FDI	1.5616**	-0.8882	1.1992	-0.6533
	(0.7492)	(1.1715)	(0.7598)	(1.1531)
GOV	-0.5714***	-0.0204	-0.7263***	0.0390
	(0.1461)	(0.0643)	(0.1368)	(0.0619)
Constant	0.6413***	-0.4097**	0.0534	-0.0812
	(0.2426)	(0.1736)	(0.2597)	(0.1609)
Observations	1176	1704	1200	1680
Number of cities	98	142	100	140
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: Column (1) is for coastal cities and column (2) is for inland cities. Column (3) is for priority cities for environmental protection and column (4) is for non-priority cities for environmental protection.

The vastness of China, coupled with significant disparities in regional economic development and industrial positioning, necessitates a nuanced examination of urban heterogeneity. This paper, therefore, presents an analysis of urban characteristics, with the findings presented in Table 8. In coastal cities, the DE coefficient of regression falls within 0.7142 at the 1% level. In contrast, the DE in inland cities does not contribute significantly to the urban GTFEE. It can be posited that the greater prevalence of complete infrastructure and a greater abundance of educational resources, including numerous universities and scientific research institutions, in coastal cities may contribute to the cultivation and attraction of a larger pool of DE and green technology-related talent. This may facilitate technological innovation, thereby enhancing the urban GTFEE. Concurrently, financial resources are relatively concentrated in coastal cities, thereby providing robust financial backing for the research, development, and implementation of GI by enterprises. Coastal cities have a more significant role in advancing the DE, particularly in increasing GTFEE through green technologies, than their counterparts in the hinterlands. The correlation coefficient for the DE in environmental protection key cities is 0.3618, which is significant at the 5% level, as shown in Columns (3). Conversely, the DE's impact on GTFEE is not statistically significant in key cities that do not prioritize environmental protection. One potential explanation is that environmental protection key cities tend to receive greater policy support and resources at the national or local level, which are directed towards promoting urban green development, enhancing energy efficiency, and reducing environmental pollution. Additionally, the energy consumption structure of these key cities is likely to be more rational and efficient, characterized by a relatively high proportion of clean and renewable energy. In summary, H2 is supported by the evidence.

5.6. Mediating effect test

Table 9. Mediating effect test

Variable	Model (1)	Model (2)	Model (3)	Model (4)
	GI	GTFEE	ELE	GTFEE
DE	16.3847***	-0.1123	39.9389***	0.3957***
	(1.1812)	(0.1475)	(7.8232)	(0.1484)
GI		0.0346***		
		(0.0024)		
ELE				0.0015***
				(0.0004)
Ln_GDP	-0.7351***	0.0307**	-4.8613***	0.0125
	(0.1009)	(0.0123)	(0.6681)	(0.0127)
FIN	0.1510***	0.0187***	1.6728***	0.0214***
	(0.0545)	(0.0066)	(0.3609)	(0.0068)
FDI	-1.0347	1.1311*	-31.3345	1.1416*
	(4.8070)	(0.5794)	(31.8365)	(0.6010)
GOV	-2.7545***	-0.0878	-18.8179***	-0.1553***
	(0.4746)	(0.0576)	(3.1431)	(0.0597)
Constant	6.9646***	0.0012	67.4460***	0.1426
	(1.1009)	(0.1337)	(7.2913)	(0.1399)
Observations	2,880	2,880	2,880	2,880
Number of cities	240	240	240	240
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 9 provides a detailed analysis of the findings from correlation mechanism analysis. The regression coefficients for columns (1) and (3) of Table 9 are 16.3847 and 39.9389, respectively. The positive impact of the DE on GI and ELE is evident in these coefficients. Moreover, both coefficients are highly significant at the 1% level.

The coefficient for the DE is significantly reduced after taking into account the mediator variable, as indicated in column (2). According to this, the development of the DE encourages GI, which in turn positively impacts the GTFEE. Green technology has been accelerated due to the development of the DE, allowing the traditional energy sector to decrease energy intensity and consumption in areas such as development, transport, and storage. This has led to improvements in GTFEE. Moreover, the improvement of green technology leads to enhanced efficiency by minimizing energy waste and losses. The validity of Hypothesis 3 has been confirmed by concluding that the DE's influence on GTFEE via green technological innovation has been substantiated.

The advancement of the DE is linked to an increase in electricity consumption, as shown in Column (4), which positively influences GTFEE. The DE's growth and the popularity of technologies like the Internet and ICT will increase electricity demand. This surge in demand is not only expanding energy needs but also driving a transformation in the energy mix. The introduction of various new energy technologies has significantly boosted electricity supply and enhanced energy efficiency. Validation has been given to the mechanism by which the DE affects GTFEE through ELE, thus validating Hypothesis 3.

5.7. Analysis of threshold effects

This study uses a threshold effect model with NQPF as the threshold variable to examine the non-linear relationship between the DE and GTFEE. Using the bootstrap method with 300 iterations for the sampling test. Table 10 contains the detailed results. According to the analysis, the p-value for three thresholds is 0.360, which fails to support the hypothesis of three thresholds. However, both single and double thresholds are significant. Therefore, for further examination, the double-threshold model is chosen.

Table 10. Threshold effect test

Variables	Threshold Test	F-statistic	P-value	Critical value		
				10%	5%	1%
NQPF	Single	101.32	0.000	16.4639	22.7858	40.6096
	Double	38.62	0.000	11.5738	15.8129	27.2042
	Triple	21.11	0.360	30.3450	35.6195	48.4785

Table 11. Results of the regression estimates between the variables for different threshold effects

Variable	Model (1)
DE	0.1928
(NQPF≤29)	(0.3262)
DE	0.4301
(29<NQPF≤46)	(0.2825)
DE	0.7009**
(NQPF>46)	(0.3176)
Constant	-0.3066**
	(0.1361)
Control	YES
Observations	2,880
Number of cities	240

Table 11 and Figure 1 show the results of the regression estimates between the variables for different threshold effects. The results indicate that when the NQPF is below 29, the DE's impact on the energy efficiency of the green total factor is 0.193, as determined by the coefficient, and does not reach statistical significance. Similarly, when the NQPF is between 29 and 46, the coefficient is 0.430 and remains non-significant. The coefficient rises to 0.701 and becomes significant at the 5% level when the NQPF goes over 46. According to this, the DE's positive impact on GTFEE will intensify as the NQPF exceeds a certain threshold. Recently, China's DE has been rapidly progressing, coupled with the gradual implementation of policies supporting the development of NQPF, which has significantly enhanced productivity levels. This development makes use of the full potential of the DE and leads to a significant improvement in the urban energy efficiency of the green total factor. In summary, hypothesis H4 is confirmed.

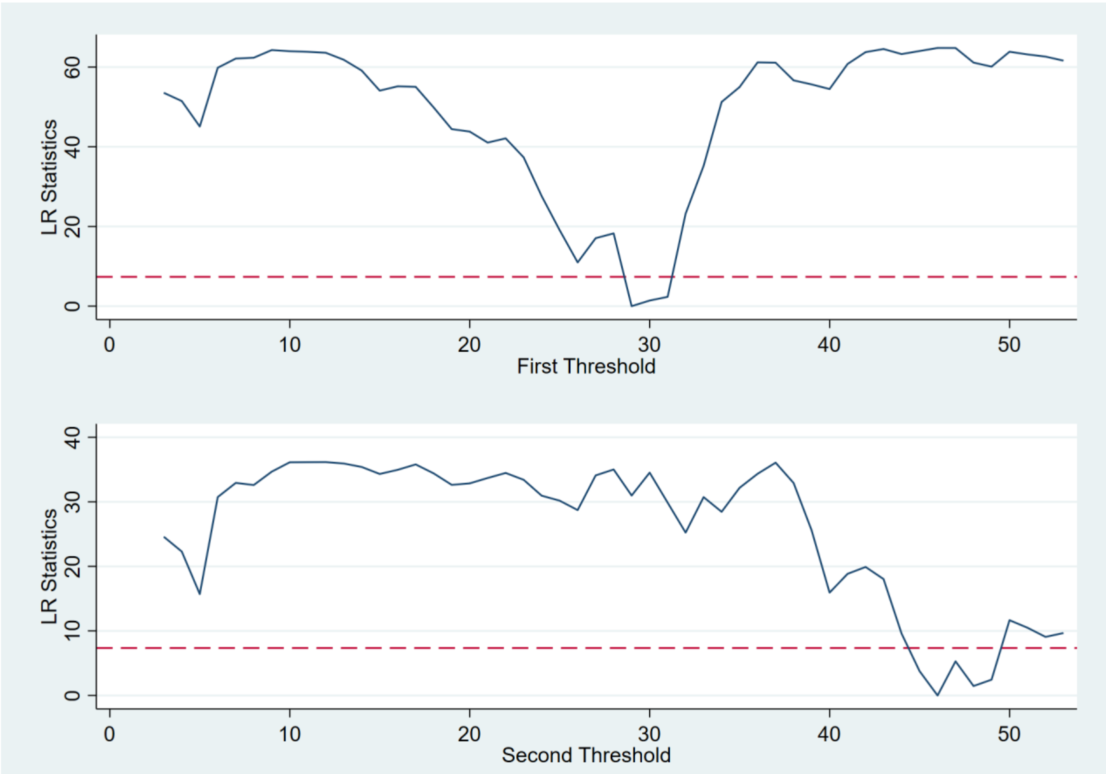

Fig. 1. Results at different thresholds.

6. Conclusion and implication

The enhancement of China's energy efficiency is an intrinsic requirement for the realization of the "dual-carbon" goal. The DE can have a significant practical value in advancing a green, low-carbon energy system and improving the ecological environment by making cities more energy efficient. The study examines how DE development can impact urban GTFEE by analyzing panel data from 240 Chinese cities spanning from 2011 to 2022. Additionally, this paper explores the mechanisms, providing insights into the pathways of this relationship. Based on the evidence presented, the conclusions were derived.

Firstly, the urban DE has been shown to significantly impact urban GTFEE, with this conclusion remaining robust across various tests. Secondly, the enhancement of urban GTFEE is particularly attributed to digital finance and digital innovation, among the dimensions of DE development.

Analysis by city characteristics reveals that the DE's influence is more pronounced in coastal cities compared to inland ones, with a more substantial impact observed in key environmental protection cities. Through the advancement of GI and ELE, the DE has a positive effect on urban GTFEE, as demonstrated by the mechanism of influence. Fourthly, the presence of NQPF introduces a double threshold effect; specifically, when these forces surpass the second threshold, the DE greatly increases the urban GTFEE.

This paper proposes suggestions to enhance the contribution of the DE to urban GTFEE based on the findings of the study. (1) Increase investment in the DE: It's necessary to increase investment in urban DE initiatives due to the rapid global expansion of the DE. China's DE will benefit from this comprehensive development across all dimensions. Additionally, regional characteristics should be taken into account when implementing customized DE development strategies. (2) Enhance energy efficiency: While investment in the DE is vital, improving energy efficiency remains paramount. Efforts should be concentrated on advancing GI, reducing the energy consumption associated with the DE, and lowering its carbon emissions. These measures will ensure more efficient energy use and support the achievement of the "dual carbon" goals. (3) Promote new energy sources: As the DE expands and electricity demand increases, reliance on traditional fossil fuels becomes insufficient. Developing renewable energy sources will help increase electricity supply, reduce energy waste, and improve overall energy efficiency. This approach will significantly enhance the city's green energy performance. (4) Develop new quality productive forces: It is essential to vigorously cultivate high-quality productive forces to foster a transformation in production methods aimed at resource conservation and environmental protection. Emphasis should be placed on integrating economic, social, and environmental benefits to achieve the objectives of green, efficient, and sustainable urban development.

References

[1] Ahmed, J., Raies, Farooq, U., & Subhani, B. H., 2022. The moderating role of information and communication technology in the nexus between financial development, economic growth and energy consumption. OPEC Energy Review, 46(4), 399–412. https://doi.org/10.1111/opec.12262

[2] Al-Refaie, A., Hammad, M., & Li, M.-H., 2016. DEA window analysis and malmquist index to assess energy efficiency and productivity in jordanian industrial sector. Energy Efficiency, 9(6), 1299–1313. https://doi.org/10.1007/s12053-016-9424-0

[3] Berkhout, F., Hertin, J., 2001. Impacts of information and communication technologies on environmental sustainability: Speculations and evidence. Report to the OECD, Brighton, 21.

[4] Chen, Y., Xu, S., Lyulyov, O., Pimonenko, T., 2023. China's Digital Economy Development: Incentives and Challenges. TECHNOLOGICAL AND ECONOMIC DEVELOPMENT OF ECONOMY 29, 518–538. https://doi.org/10.3846/tede.2022.18018

[5] Crompton, P., Wu, Y., 2005. Energy consumption in China: Past trends and future directions. Energy Econ. 27, 195–208. https://doi.org/10.1016/j.eneco.2004.10.006

[6] Dian, J., Song, T., Li, S., 2024. Facilitating or inhibiting? Spatial effects of the digital economy affecting urban green technology innovation. Energy Econ. 129, 107223. https://doi.org/10.1016/j.eneco.2023.107223

[7] Du, K., Li, J., 2019. Towards a green world: How do green technology innovations affect total-factor carbon productivity. Energy Policy 131, 240–250. https://doi.org/10.1016/j.enpol.2019.04.033

[8] *Gao, D., Li, G., Yu, J., 2022a. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. Energy 247, 123395. https://doi.org/10.1016/j.energy.2022.123395*

[9] *Gao, D., Li, G., Yu, J., 2022b. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. Energy 247, 123395. https://doi.org/10.1016/j.energy.2022.123395*

[10] *Ge, Y., Xia, Y., Wang, T., 2024. Digital economy, data resources and enterprise green technology innovation: Evidence from a-listed Chinese firms. Resources Pol. 92, 105035. https://doi.org/10.1016/j.resourpol.2024.105035*

[11] *Hu, J.-L., Wang, S.-C., 2006. Total-factor energy efficiency of regions in China. Energy Policy 34, 3206–3217. https://doi.org/10.1016/j.enpol.2005.06.015*

[12] *Huang, S., Chen, L., 2023a. The impact of the digital economy on the urban total-factor energy efficiency: Evidence from 275 cities in China. Sustainability 15, 3195. https://doi.org/10.3390/su15043195*

[13] *Huang, S., Chen, L., 2023b. The impact of the digital economy on the urban total-factor energy efficiency: Evidence from 275 cities in China. SUSTAINABILITY 15, 3195. https://doi.org/10.3390/su15043195*

[14] *Huang, S., Chen, L., 2023c. The impact of the digital economy on the urban total-factor energy efficiency: Evidence from 275 cities in China. Sustainability 15, 3195. https://doi.org/10.3390/su15043195*

[15] *Ji, Z., Zhao, L., Song, X., Gao, X., 2023. Digital economy impact on inclusive green growth: Intermediary and spatial spillover effects in China. Environ. Sci. Pollut. R. 30, 123657–123678. https://doi.org/10.1007/s11356-023-30898-7*

[16] *Li, X., Ma, D., 2021. Financial agglomeration, technological innovation, and green total factor energy efficiency. Alexandria Engineering Journal 60, 4085–4095. https://doi.org/10.1016/j.aej.2021.03.001*

[17] *Lin, B., Zhu, R., 2021. Energy efficiency of the mining sector in China, what are the main influence factors? Resources, Conservation and Recycling 167, 105321. https://doi.org/10.1016/j.resconrec.2020.105321*

[18] *Liu, B., 2023. An analysis of energy efficiency of the pearl river delta of China based on super-efficiency SBM model and malmquist index. Environ. Sci. Pollut. R. 30, 18998–19011. https://doi.org/10.1007/s11356-022-23465-z*

[19] *Liu, L., Wang, Z., 2009. The development and application practice of wind–solar energy hybrid generation systems in China. Renewable and Sustainable Energy Reviews 13, 1504–1512. https://doi.org/10.1016/j.rser.2008.09.021*

[20] *Luo, K., Liu, Y., Chen, P.-F., Zeng, M., 2022. Assessing the impact of digital economy on green development efficiency in the yangtze river economic belt. Energy Econ. 112, 106127. https://doi.org/10.1016/j.eneco.2022.106127*

[21] *Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., Hao, Y., n.d. Digitalization and sustainable development: How could digital economy development improve green innovation in China? https://doi.org/10.1002/bse.3223*

[22] *Lyu, Y., Wang, W., Wu, Y., Zhang, J., 2023. How does digital economy affect green total factor productivity? Evidence from China. Science of The Total Environment 857, 159428. https://doi.org/10.1016/j.scitotenv.2022.159428*

[23] *Lyu, Y., Xiao, X., Zhang, J., 2024. Does the digital economy enhance green total factor productivity in China? The evidence from a national big data comprehensive pilot zone. Struct. Change Econ. Dynam. 69, 183–196. https://doi.org/10.1016/j.strueco.2023.12.009*

[24] *Ma, D., Zhu, Q., 2022. Innovation in emerging economies: Research on the digital economy driving high-quality green development. J. Bus. Res. 145, 801–813. https://doi.org/10.1016/j.jbusres.2022.03.041*

[25] *Qiao, P., Liu, S., Fung, H.-G., Wang, C., 2024. Corporate green innovation in a digital economy. Int. Rev. Econ. Financ. 92, 870–883. https://doi.org/10.1016/j.iref.2024.02.073*

[26] *Ren, Siyu, Hao, Y., Wu, H., 2022. The role of outward foreign direct investment (OFDI) on green total factor energy efficiency: Does institutional quality matters? Evidence from China. Resources Pol. 76, 102587. https://doi.org/10.1016/j.resourpol.2022.102587*

[27] *Ren, Shuming, Li, L., Han, Y., Hao, Y., Wu, H., 2022. The emerging driving force of inclusive green growth: Does digital economy agglomeration work? Busi. Stra. Envir. 31, 1656–1678. https://doi.org/10.1002/bse.2975*

[28] *Ren, Y., Zhang, X., Chen, H., 2022. The impact of new energy enterprises' digital transformation on their total factor productivity: Empirical evidence from China. Sustainability 14, 13928. https://doi.org/10.3390/su142113928*

[29] *Shang, Y., Liu, H., Lv, Y., 2020. Total factor energy efficiency in regions of China: An empirical analysis on SBM-DEA model with undesired generation. Journal of King Saud University - Science 32, 1925–1931. https://doi.org/10.1016/j.jksus.2020.01.033*

[30] *Song, J., Liu, Z., Leng, X., 2024. The impact of the digital economy on provincial carbon emissions in China. Applied Spatial Analysis and Policy. https://doi.org/10.1007/s12061-024-09582-x*

[31] *Song, M., Pan, H., Vardanyan, M., Shen, Z., 2023. Evaluating the energy efficiency-enhancing potential of the digital economy: Evidence from China. J. Environ. Manage. 344, 118408. https://doi.org/10.1016/j.jenvman.2023.118408*

[32] *Tang, L., He, G., 2021. How to improve total factor energy efficiency? An empirical analysis of the yangtze river economic belt of China. Energy 235, 121375. https://doi.org/10.1016/j.energy.2021.121375*

[33] *Wang, H., Wang, Y., Zeng, G., Qian, Z., Lu, S., 2024. The differential impact of the digital economy on urban energy efficiency in China: The mediating mechanism of FDI. Environment, Development and Sustainability. https://doi.org/10.1007/s10668-024-04475-y*

[34] *Wang, S., Song, Y., Min Du, A., Liang, J., 2024. The digital economy and entrepreneurial dynamics: An empirical analysis of urban regions in China. Research in International Business and Finance 71, 102459. https://doi.org/10.1016/j.ribaf.2024.102459*

[35] *Wang, X., Zhong, M., 2023a. Can digital economy reduce carbon emission intensity? Empirical evidence from China's smart city pilot policies. Environ. Sci. Pollut. R. 30, 51749–51769. https://doi.org/10.1007/s11356-023-26038-w*

[36] *Wang, X., Zhong, M., 2023b. Can digital economy reduce carbon emission intensity? Empirical evidence from China's smart city pilot policies. Environ. Sci. Pollut. R. 30, 51749–51769. https://doi.org/10.1007/s11356-023-26038-w*

[37] *Wang, Y.F., Li, K.P., Xu, X.M., Zhang, Y.R., 2014. Transport energy consumption and saving in China. Renewable Sustainable Energy Rev. 29, 641–655. https://doi.org/10.1016/j.rser.2013.08.104*

[38] *Wang, Z., 2022. Measuring the total-factor green efficiency in China's industrial sectors: A parametric approach. Discrete Dyn. Nat. Soc. 2022, 5634702. https://doi.org/10.1155/2022/5634702*

[39] *Wen, H., Liang, W., Lee, C.-C., 2022. Urban broadband infrastructure and green total-factor energy efficiency in China. UTILITIES POLICY 79, 101414. https://doi.org/10.1016/j.jup.2022.101414*

[40] Wu, H., Hao, Y., Ren, S., Yang, X., Xie, G., 2021a. Does internet development improve green total factor energy efficiency? Evidence from China. Energy Policy 153, 112247. https://doi.org/10.1016/j.enpol.2021.112247

[41] Wu, H., Hao, Y., Ren, S., Yang, X., Xie, G., 2021b. Does internet development improve green total factor energy efficiency? Evidence from China. Energy Policy 153, 112247. https://doi.org/10.1016/j.enpol.2021.112247

[42] Wu, H., Wen, H., Li, G., Yin, Y., Zhang, S., 2024. Unlocking a greener future: The role of digital finance in enhancing green total factor energy efficiency. J. Environ. Manage. 364, 121456. https://doi.org/10.1016/j.jenvman.2024.121456

[43] Wu, J., Lin, K., Sun, J., 2023. Improving urban energy efficiency: What role does the digital economy play? J. Cleaner Prod. 418, 138104. https://doi.org/10.1016/j.jclepro.2023.138104

[44] Xue, Y., Tang, C., Wu, H., Liu, J., Hao, Y., 2022. The emerging driving force of energy consumption in China: Does digital economy development matter? Energy Policy 165, 112997. https://doi.org/10.1016/j.enpol.2022.112997

[45] Yeager, K.E., 2004. Electricity for the 21st century: Digital electricity for a digital economy. Technol. Soc., Technology and Science Entering the 21st Century 26, 209–221. https://doi.org/10.1016/j.techsoc.2004.01.031

[46] Yu, R., Luo, Z., 2024. Influencing factors of industrial transformation in resource-based cities: Comprehensive measurement method based on resource price distortion. Heliyon 10. https://doi.org/10.1016/j.heliyon.2024.e32797

[47] Yu, S., Wang, S., Cheng, X., Li, L., 2024. Green finance and total factor energy efficiency: Theoretical mechanisms and empirical tests. FRONTIERS IN ENVIRONMENTAL SCIENCE 12, 1399056. https://doi.org/10.3389/fenvs.2024.1399056

[48] Zhang, C., Yang, Q., Zhang, J., Gou, L., Fan, H., 2023. Topic mining and future trend exploration in digital economy research. Information 14, 432. https://doi.org/10.3390/info14080432

[49] Zhang, J., Lyu, Y., Li, Y., Geng, Y., 2022. Digital economy: An innovation driving factor for low-carbon development. Environ. Impact Assess. Rev. 96, 106821. https://doi.org/10.1016/j.eiar.2022.106821

[50] Zhang, S., Ma, X., Cui, Q., 2021. Assessing the impact of the digital economy on green total factor energy efficiency in the post-COVID-19 era. Front. Energy Res. 9. https://doi.org/10.3389/fenrg.2021.798922

[51] Zhang, Y., Xie, P., Liao, C., Zhao, D., Wang, P., 2022. Planning and implementation of renewable energy in coastal cities - a case study of huangpu district, guangzhou. Environmental Engineering & Management Journal (EEMJ) 21, 219–224. https://doi.org/10.30638/eemj.2022.021

[52] Zhao, S., Peng, D., Wen, H., Wu, Y., 2023a. Nonlinear and spatial spillover effects of the digital economy on green total factor energy efficiency: Evidence from 281 cities in China. Environ. Sci. Pollut. R. 30, 81896–81916. https://doi.org/10.1007/s11356-022-22694-6

[53] Zhao, S., Peng, D., Wen, H., Wu, Y., 2023b. Nonlinear and spatial spillover effects of the digital economy on green total factor energy efficiency: Evidence from 281 cities in China. Environ. Sci. Pollut. R. 30, 81896–81916. https://doi.org/10.1007/s11356-022-22694-6

[54] Peng, Y. "Research on Exploring the Path of Financial Risk Management and Standardization Based on Artificial Intelligence Technology and Intelligent Investment Advisory Regulatory Framework." Financial Engineering and Risk Management 7.3 (2024): 110-117.

[55] Dong, P. (2024). Research and Analysis of Financial Crisis Prediction Model Based on the Fusion of Financial and Non-Financial Data with CSO Algorithm. Academic Journal of Business & Management, 6(11), 56-60.

[56] Ma, K. (2024). Employee Satisfaction and Firm Performance: Evidence from a Company Review Website. International Journal of Global Economics and Management, 4(2), 407-416.