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Digital Economy and Energy Intensity: The Light and Dark Side

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ABSTRACT

Abstract

The digital economy exerts both positive and negative influences on urban sustainable development, yet there is a notable gap in the existing research concerning its impact on energy intensity and the underlying mechanisms. this study pioneers the investigation of a nonlinear relationship between the digital economy and energy intensity, revealing a significant inverted U-shaped relationship. Specifically, we observe a noteworthy reduction in energy intensity when the digital economy index surpasses 0.286. Our empirical findings indicate that the digital economy not only directly influences energy intensity but also exerts an indirect impact through initiatives such as the promotion of green innovation and the agglomeration of high-tech industries. Importantly, the promotional effects of the digital economy exhibit heterogeneity with respect to geographical location, resource endowment, and urban scale. This paper contributes to the theoretical understanding of information technology in urban green development by analyzing the mechanisms of the digital economy at the urban level and its intricate impact on energy intensity.

KEYWORDS

Digital Economy; Energy Intensity; Green Innovation; High-Tech Industrial Agglomeration

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1. Introduction

Energy input has consistently served as a pivotal driver for global industrialization and rapid economic expansion. Given the escalating concerns about climate change and significant shifts in the global energy landscape, governments, the academic community, and the general public have widely recognized the issue of energy intensity (Anu et al., 2023; Jiang et al., 2024; Sun et al., 2022). Notably, China has drawn particular attention due to its comparatively high unit energy consumption, which is approximately twice the world average, three times that of the United States, and seven times that of Japan (Song et al., 2023; Yang et al., 2023). As a result, enhancing energy efficiency and reducing energy-related carbon emissions have become indispensable pathways towards achieving carbon neutrality goals, considering the imperative of ensuring economic stability and development.

Energy Intensity (ENI[1]), defined as the energy consumed per unit of GDP, serves as a critical metric for assessing a nation's energy efficiency, carbon emissions, and overall sustainable development (Lin & Zhu, 2021; Wang et al., 2022; Wurlod & Noailly, 2018). Scholars have extensively explored the driving factors and constraints influencing ENI, encompassing technological advancements and environmental regulations (Balado-Naves et al., 2023; Bashir et al., 2021), providing valuable insights into the promotion of green energy development. However, the existing studies have predominantly concentrated on examining the influence of different factors on ENI within the context of traditional economic conditions. They have not adequately explored the changes in ENI under new economic paradigms. Moreover, most of these studies assume a linear relationship between influencing factors and ENI, potentially overlooking complex nonlinear dynamics.

With the rapid evolution of the global technological revolution and industrial transformation, DIGE has emerged as a powerful force driving economic transitions on a global scale. (Liu et al., 2023; Ma & Zhu, 2022; Skare et al., 2023). Existing studies have unveiled intricate links between the DIGE and diverse domains, including urban green development (Luo et al., 2022; Ma & Zhu, 2022; Zhang et al., 2022), carbon emissions (Meng et al., 2023; Zhang et al., 2022; Zhou et al., 2022), and air pollution mitigation (Yang et al., 2021; Zhang & Ran, 2023). However, whether the development of the DIGE truly lowers urban ENI remains underexplored, and the underlying mechanisms lack comprehensive investigation.

This article aims to fill these research gaps by elucidating the significant implications of the DIGE for urban sustainable development and exploring its nonlinear impact on ENI. Simultaneously, it seeks to offer guidance for formulating digitization and sustainable development policies, aligning with carbon neutrality strategies. The potential contributions of this study may be outlined as follows:

Integrated Research Framework and Empirical Evidence: This study integrates the DIGE and ENI into a unified research framework, revealing that DIGE has both positive ("light side") and negative ("dark side") impacts on ENI, resulting in an inverted U-shaped relationship. This finding challenges traditional linear assumptions in existing literature and provides new insights into the dynamic interplay between digitalization and energy efficiency. Empirical testing, conducted using data from 282 Chinese cities from 2011 to 2021, provides verified evidence for the specific effects, mechanisms, and heterogeneity analysis of the DIGE on ENI. The study demonstrates that while DIGE may initially increase ENI due to its "dark side" impacts, it ultimately reduces ENI by accelerating green innovation (GRI) and promoting high-tech industrial agglomeration (HTIA). This evidence facilitates the adoption of more effective measures by cities during the digital transformation process, enabling the simultaneous advancement of digitization and green development.

Mechanism Exploration and Heterogeneity Analysis: Further discussions unveil that the DIGE primarily mitigates its negative impact on ENI by accelerating green innovation (GRI) and promoting high-tech industrial agglomeration (HTIA), subsequently reducing ENI. Heterogeneity analysis indicates that the reduction of ENI due

[1] Abbreviations in the paper are as follows: digital economy(DIGE); energy intensity(ENI); green innovaiton(GRI); high-tech industrial agglomeration (HTIA)

to the DIGE is particularly prominent in eastern cities, southern cities, cities along the Yangtze River Economic Belt, resource-based cities, high-economic-development cities, and large cities. This nuanced understanding contributes to tailored policy recommendations for different city characteristics.

2. Literature review and hypothesis development

There are some gaps in the existing studies when discussing the relationship between DIGE and ENI. On the one hand, while some studies suggest that technological advancements reduce ENI (Lin & Xu, 2019; Wang & Zhou, 2018), they often assume a linear relationship and do not consider the potential nonlinear effects of the DIGE on ENI. On the other hand, the adverse effects of the DIGE on urban ENI remain underexplored, and consensus on research findings is lacking. Despite the potential of the DIGE to reduce ENI through technological innovation and improved resource allocation efficiency, digital devices, escalate energy consumption during the investment phase (Krause & Tolaymat, 2018; Li & Wang, 2022). Operational processes also sustain continuous energy consumption (Avom et al., 2020; Hu, 2023). Therefore, neglecting the nonlinear relationships among economic variables and employing conventional linear methods to investigate the impact of the DIGE on ENI might result in biased estimates (Liu et al., 2024; Luo et al., 2024).

2.1. Test of hypothesis 1: Nonlinear relationship between DIGE and ENI

2.1.1. The bright side of DIGE and ENI

The Digital Economy, an innovative economic paradigm emerging from the era of data and information, is instigating profound technological changes and digital empowerment. It reshapes resource allocation and modes of production, driving revolutions in energy production and consumption across various stages—from production and processing to transformation and end-use (Ma & Zhu, 2022; Zhou et al., 2022; Skare et al., 2023).

From a macro perspective of urban governance, the development of DIGE contributes significantly to reducing ENI. First, leveraging technological advantages such as big data, DIGE has the potential to upgrade traditional energy infrastructure. The rise of innovative digital, low-carbon, and energy-efficient technologies drives the real economy towards more sustainable, low-carbon production methods and smarter manufacturing processes. This optimization of energy resource allocation promotes large-scale utilization of clean energy, contributing to a decrease in ENI (Chen, 2022). Second, empowered by digital technology, digitized modes of production interlink diverse elements-technology, data, and energy-generating synergies within digital networks and consequently leading to a reduction in ENI (Li, 2022; Liu et al., 2024). Third, DIGE facilitates the acquisition and transmission of information. Environmental protection agencies can use digital platforms to monitor companies' energy usage and implement corresponding incentive measures (Yang et al., 2023).

From the viewpoint of enterprise production and operations, digital technologies provide multiple strategies for reducing ENI. First, digital technologies optimize existing production methods and processes, driving technological advancements and enhancing energy utilization efficiency within enterprises (Ding et al., 2024). Moreover, the integration of digital technologies, industrial robots, and other intelligent terminal systems elevates the digitalization level of enterprise production systems. This enhanced resource allocation efficiency contributes to a reduction in ENI (Du et al., 2023). Second, digital finance improves the fund circulation environment, reduces transaction costs for green financial products, and directly supports financing for innovative entities such as enterprises such as enterprises (Mu et al., 2023). By judiciously channeling capital into green and advanced technology sectors, financial organizations play a pivotal role in fostering technological advancements in the energy domain, thereby contributing to a reduction in ENI (Razzaq et al., 2023). Additionally, digital technologies also enhances enterprises' energy monitoring and management capabilities, promoting advancements in renewable energy technologies (Lange et al., 2020).

In the context of daily life, the widespread adoption of remote work has resulted in fewer non-essential offline economic activities among employees, subsequently decreasing carbon emissions linked to activities like commuting and physical work meetings (Li et al., 2023; Marz & Sen, 2022). In addition, smart home systems and interconnected devices can more accurately monitor and regulate energy usage. For instance, smart thermostats can automatically adjust indoor temperatures based on residents' habits and weather forecasts, optimizing energy usage and reducing wastage (Qin et al., 2022). Online shopping platforms frequently provide consumers with product energy efficiency labels and carbon footprint data, assisting them in choosing products with lesser environmental impact. Additionally, through shared mobility and accommodation models, resource utilization rates have significantly improved (Storch et al., 2021). Taking shared bicycles as an example, they reduce energy consumption and environmental pollution. Moreover, through route optimization and intelligent scheduling technologies, they decrease ENI (Chen et al., 2020).

2.1.2. The dark side of DIGE and ENI

While the energy-saving effects of digital economic development have garnered widespread attention, it is equally essential not to overlook the adverse impact of the DIGE on ENI.

The digital industry, known for its high energy consumption, has been shown in existing research to contribute to an energy rebound effect due to its expansion in scale, thereby intensifying emissions (Li & Wang, 2022; Liu et al., 2024). On the one hand, various smart devices are continuously expanding, increasing the demand for stable electricity supply from households, businesses, and government agencies. The energy structure providing this electricity, especially in certain countries, still relies predominantly on fossil fuels. This undoubtedly further intensifies carbon emissions, making it difficult to reduce ENI (Su et al., 2024). The development and maintenance of digital infrastructure lead to a significant surge in electricity requirements, resulting in heightened energy consumption for the establishment, operation, and upkeep of such infrastructures (Avom et al., 2020; Luo et al., 2024).

On the other hand, the swift growth of the digital economy is paralleled by a considerable increase in electricity consumption. Data centers, tasked with processing, storing, and transmitting vast amounts of data globally, require substantial electrical support. Cooling systems, server maintenance, and network equipment all demand continuous power supply to remain operational (Jia et al., 2023). Furthermore, with the rising value of digital currencies, especially Bitcoin, the energy consumption associated with mining activities has attracted increasing attention. Several studies have noted that mining Bitcoin to the value of one US dollar demands over twice the energy needed to extract an equivalent value of gold (Krause & Tolaymat, 2018).

We also acknowledge that although technologies such as smart grids, remote monitoring, and data analytics hold tremendous potential for enhancing energy efficiency, underdeveloped regions lag far behind their developed counterparts in the adoption of digital technologies due to constraints related to funding, technical expertise, and policies (Du et al., 2023). This disparity directly results in the uneven application of energy efficiency optimization technologies across different regions (Liu et al., 2024). The digital divide might impede communication and collaboration among different regions, hindering the widespread adoption of certain energy technological innovations (Yang et al., 2023).

Therefore, considering both the positive and negative effects of the DIGE on ENI, it is essential to investigate the potential nonlinear relationship between them. Neglecting the nonlinearities might result in biased estimates and inadequate policy recommendations.Therefore, this paper posits hypothesis 1.

Hypothesis 1: The impact of DIGE on ENI follows an inverted U-shaped curve. In other words, as the level of DIGE increases, it initially leads to an elevation in ENI. However, when the DIGE reaches a certain

threshold, ENI subsequently decreases.

2.2. Test of hypothesis 2: DIGE, GRI and ENI

DIGE reduces the cost of GRI by facilitating factor mobility, reducing information asymmetry, and easing credit constraints, nurturing opportunities for GRI. First, by overcoming time and space limitations in the transfer of innovative resources like information, digital infrastructure amplifies the speed of information dissemination. This acceleration reduces the costs associated with information search and resource consumption within the industrial chain for businesses. The advent of internet applications allows innovation resources such as knowledge, talent, and funds to flow freely, giving rise to an open, collaborative, and cooperative innovation network (Yang et al., 2022). Second, DIGE promotes the integration of financial resources with GRI. With the widespread adoption of low-carbon consumption habits among consumers, financial institutions are compelled to innovate green financial products, driving regional GRI (Anu et al., 2023). Third, DIGE enhances public oversight of businesses. The application of urban big data monitoring systems significantly reduces the cost of environmental information acquisition. Coupled with the increasing public awareness of environmental information, this forces companies to promote GRI and gain a better external reputation.

Additionally, GRI contributes to reducing ENI. Technological advancement is pivotal, and GRI augments production efficiency and resource utilization for a win-win scenario in economic development and environmental conservation (Sun & Razzaq, 2022). For example, utilizing CCUS technology separates and captures carbon from industrial production and energy utilization processes, recycling it to reduce ENI. Furthermore, energy-intensive enterprises can prioritize low-carbon environmentally friendly materials during product design or improvement. Technological advancements, such as perovskite solar panels with potential efficiencies exceeding 30%, contribute to reducing ENI (Luo et al., 2022). Smart home technologies and green building designs also play a role in optimal energy usage efficiency and resource demand reduction in construction. Therefore, this paper proposes hypothesis 2.

Hypothesis 2: The DIGE reduces ENI by promoting GRI.

2.3. Test of hypothesis 3: DIGE, HTIA and ENI

DIGE effectively harnesses the spillover effects of knowledge and industrial upgrading, promoting high-tech industrial agglomeration (HTIA).

Regarding knowledge spillover effects, high-tech industries, which are technology-intensive, require knowledge and innovative resources at lower costs. DIGE, represented by technologies like 5G and the industrial internet stimulates the permeation, facilitating the flow of resources for high-tech industries and guiding similar enterprises to concentrate in regions abundant with innovative elements, fostering spatial clustering of high-tech industries (Peng et al., 2023). Furthermore, digital economy growth (DIGE) facilitates the accurate alignment of fund supply and demand, broadens the scope of financial services and financing avenues, and mitigates the external financing challenges encountered by the high-tech industries.

In terms of industrial upgrading effects, DIGE manifests in digital industrialization and industrial digitization, optimizing input-output structures within high-tech industrial parks. This optimization enhances the quality and efficiency of traditional production factors, markedly boosting production efficiency and overall factor productivity. It fosters the intelligent advancement of industries (Sturgeon, 2021). These developments attract external enterprises to relocate within the park, stimulating HTIA.

HTIA mainly reduces urban ENI by capitalizing on economies of scale and technology spillover effects. The clustering of high-tech industries encourages the use of shared public infrastructure, which diminishes energy consumption and transportation expenses. This communal infrastructure boosts energy utilization efficiency, thereby decreasing ENI (Liu & Zhang, 2021). HTIA accelerates research and development cooperation, personnel exchanges, and equipment sharing across the entire industry chain, strengthening spillover effects between high-tech and traditional industries, encouraging green technological transformations, and product upgrades. For example, in high-tech industrial parks, different companies collectively utilize pollution control and emission reduction facilities, sharing pollution control costs, thereby diminishing per capita carbon emissions, input of production factors, and resources, reducing overall urban ENI (Tanaka & Managi, 2021).

Regarding technology spillover effects, HTIA fosters better communication between technical experts and laborers, deepens the application of low-carbon technologies, and utilizes innovation clustering to reduce ENI. Simultaneously, traditional, resource-intensive industries like paper, steel, and cement manufacturing often exhibit high energy consumption. The intense competition among enterprises in agglomerated zones drives increased innovation investments, enhancing low-carbon technology capabilities. This dynamic stimulates comprehensive energy conservation and emission reduction within high-tech industry clusters, enhancing urban energy efficiency. Additionally, HTIA deepens specialization within and between industries, broadens channels for technological advancements, effectively enhancing production efficiency, reducing per capita carbon emissions, and diminishing urban ENI (Wang et al., 2022). Therefore, this paper proposes hypothesis 3.

Hypothesis 3: The DIGE reduces ENI by promoting HTIA.

3. Research design

3.1. Methodology

Building upon the theoretical analysis presented earlier and considering the potential nonlinear effects of DIGE on ENI as digital economic development advances, this study incorporates both the linear and quadratic terms of DIGE into the baseline regression model. This approach allows the research to comprehensively investigate both the positive and negative impacts of DIGE on ENI.

$$ENI_{it} = \alpha_0 + \alpha_1 DIGE_{it} + \alpha_2 DIGE_{it}^2 + \alpha_3 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), ENI_{it} represents the energy intensity of city *i* at time *t*, $DIGE_{it}$ denotes the level of digital economic development in city *i* at time *t*, and $DIGE_{it}^2$ represents the quadratic term of the level of digital economic development. Morever, this study introduces control variables represented by Z_{it}. Here, μ_i captures city-level fixed effects, δ_t represents time-level fixed effects, and ε_{it} represents the random disturbance term.

(1) The *regional economic development level* (*pgdp*) is expressed as the logarithm of per capita gross domestic product. Regions with greater economic capabilities are typically more proficient in environmental protection. Concurrently, the rise in corporate income strengthens their inclination to implement energy-saving and emission-reducing measures, consequently leading to a decrease in ENI.

(2) *Population density* (*pnd*) is computed as the ratio of the year-end population to the urban area's size. Regions with high population density have the potential to attract a larger pool of innovative talent. This concentration of skilled individuals aids in the advancement and implementation of green technologies, leading to a significant decrease in ENI (Hong et al., 2023).

(3) *Foreign Direct Investment* (*FDI*), as represented by the ratio of actual foreign investments in the current year to GDP, plays a pivotal role in augmenting corporate capital accumulation. A robust capital base ensures the maintenance of high levels of research and development, production technology, and managerial capabilities,

consequently leading to enhanced energy efficiency. Additionally, FDI can result in the relocation of highly polluting industries, consequently decreasing environmental impact.

(4) *Financial Development Leve*l (*fin*) is represented by the ratio of the amount of loans granted by financial institutions to GDP. Zhang et al. (2020), using enterprise-level data from World Bank surveys, found a significant correlation between financing opportunities for Chinese manufacturing firms and the reduction of ENI. Financial development provides funds for overall economic development, accelerates information dissemination, and enhances resource allocation, thereby reducing ENI (Ma & Zhu, 2022).

(5) The *Urbanization Rate* (*urban*) is calculated as the ratio of the urban population to the total population at the end of one year. The modification of consumption demand, factor supply, and infrastructure during urbanization aids in the refinement and advancement of industrial institutions, consequently leading to a reduction in ENI (Bilgili et al., 2017).

(6) *Environmental Regulations* (*regulation*) are quantified by the natural logarithm of the count of environmental protection personnel in the region. The implementation of environmental regulations incentivizes enterprises to expedite the upgrading and adoption of energy-saving equipment, consequently leading to a reduction in ENI (Liu et al., 2023; Wu et al., 2020).

Furthermore, to rigorously assess the nonlinear relationship between DIGE and ENI, we leverage insights from prior studies (Hansen, 1999; Ma & Zhu, 2022; Wang & Shao, 2023) and apply panel threshold models for thorough examination.

$$ENI_{it} = \alpha_0 + \alpha_1 DIGE_{it} \cdot I(DIGE_{it} \leqslant \theta) + \alpha_2 DIGE_{it} \cdot I(DIGE_{it} > \theta) + \alpha_3 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

In Eq. (2), the threshold variable is denoted by DIGE, representing the threshold value. Equation (2) explores the single-threshold scenario, extendable to a multi-threshold situation based on econometric requirements.

Consistent with established research methodologies (Hao et al., 2023; Cheng et al., 2023; Zhang et al., 2022), this study adopts the classical three-step approach to scrutinize the impact pathway of DIGE on ENI, as outlined below:

$$MV_{it} = \beta_0 + \beta_1 DIGE_{it} + \beta_2 DIGE_{it}^2 + \beta_3 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

$$ENI_{it} = \alpha_0 + \alpha_1 DIGE_{it} + \alpha_2 DIGE_{it}^2 + \alpha_3 MV_{it} + \alpha_4 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

In Eq. (3), MV denotes the mediating variables (GRI and HTIA). The confirmation of a mediating effect occurs when MV exhibits a significant positive effect in Model (3) and maintains significance in Model (4). If the effect remains significant in Model (4), it signifies a partial mediating effect. If neither effect is significant, it implies a complete mediating effect.

3.2. Sample selection

3.2.1. Dependent variable

In measuring ENI, a common method used in numerous studies is to calculate the ratio of total annual energy consumption to the actual GDP, a technique exemplified by various researchers (Bashir et al., 2021; Guo et al., 2023). Nevertheless, current research faces limitations as it predominantly operates at the national and provincial levels due to data scarcity. This broad geographical focus obscures the heterogeneity in urban energy consumption within regions.

Previous research has established a notable positive correlation between nighttime light data and energy consumption (Chen et al., 2022; Zhang et al., 2023; Zhu et al., 2019). Hence, drawing on this literature, we adopted a top-down approach to estimate urban carbon emissions from provincial nighttime light data (Zhao et al., 2019;

Zhou et al., 2022). Initially, we employed provincial energy consumption data (measured in ten thousand tons of standard coal) as the dependent variable, with nighttime light brightness in each province serving as the independent variable. A panel data model was then constructed to ascertain the coefficients and residuals between these variables. Subsequently, a top-down approach was applied to estimate total energy consumption at the urban level based on nighttime light brightness values at the city level. Lastly, the ratio of energy consumption at the city level to the GDP was utilized as the measure of ENI.

3.2.2. Key independent variable

In measuring DIGE, considering the availability of urban-level data and drawing on the research of existing scholars (Lin & Huang, 2023; Wang & Shao, 2023), this study employs the following indicators to represent urban-level digital development: *internet penetration rate* (the number of broadband internet users per hundred people), *the workforce in relevant sectors* (the proportion of employees in the computer services and software industry to total urban employees), *relevant output* (per capita total volume of telecommunications services), and *mobile phone penetration rate* (the number of mobile phone users per hundred people). Additionally, the urban digital financial development level is gauged by the digital finance index calculated by *Peking University*. Finally, DIGE is computed through principal component analysis.

3.2.3. Mediating variables

GRI: Owing to the lack of official statistical data on urban green innovation in China, this study relies on insights from previous research (Chen et al., 2022; Li et al., 2023; Meng et al., 2023). The study aligns patent information from the Chinese State Intellectual Property Office with the green patent classification list published by the World Intellectual Property Organization (WIPO) in 2010, thus creating China's green patent dataset. Subsequently, these data are further harmonized at the urban level, serving as a proxy variable for GRI. In empirical testing, this variable undergoes natural logarithmic transformation after adding 1. A higher value denotes a greater level of GRI.

HTIA: Industrial agglomeration encompasses the effects and centripetal force arising when enterprises concentrate (Zheng & He, 2022). The heightened concentration of high-tech enterprises in a specific region fosters increased activities among similar enterprises. This concentration is measured by the ratio of the output value or employment in high-tech industries to the total industrial output value of the region. An upswing in the industrial agglomeration index signals augmented agglomeration, while a decline indicates either weakened agglomeration or industry diffusion (Liu & Zhang, 2021). Despite the availability of current data on specific sectors of high-tech industries from various bureaus of statistics and science and technology departments, detailed and comprehensive data on high-tech industries and their subdivisions are accessible at the provincial (*direct-administered municipality*) level. However, there are data gaps at the prefecture-level cities, necessitating supplementation with information published by the science and technology departments (Wang et al., 2022). Owing to data limitations, this study employs the location quotient method to calculate HTIA.

$$HTIA_{it} = (H_{it}|H_t)/(P_{it}|P_t) \tag{5}$$

In Eq. (5), the variables are defined as follows: H_{it} represents the number of employees working in high-tech enterprises in region i at time t, P_{it} represents the total number of employed individuals in region i at time t, and H_t and P_t represent the national number of employees in high-tech enterprises and the national total employment, respectively, at time t. A higher value of this ratio signifies a more substantial concentration of the high-tech industry in the respective region.

3.2.4. Instrumental variables

In the context of this study, the pursuit of reducing ENI may drive businesses to enhance production methods and adopt advanced technologies and production models, thereby fostering the development of local digital economies. Consequently, a reverse causal relationship between DIGE and ENI may exist. On the other hand, ENI is influenced by numerous factors, presenting challenges in controlling for all these variables and potentially leading to omitted variable bias. Acknowledging these potential issues, this study utilizes an instrumental variable (IV) approach to alleviate concerns related to endogeneity, facilitating the accurate identification of the specific effects of DIGE on ENI.

(1) The initial instrumental variable is the topographical ruggedness of cities, labeled as *IV_Land*. Greater topographical ruggedness, at the outset, suggests higher construction and operational costs for digital infrastructure. This circumstance might prompt local governments to curtail investments in digital infrastructure development in those areas, potentially constraining the growth of DIGE to some extent, thereby satisfying the relevance condition of the instrumental variable (Tang et al., 2021). Additionally, topographical ruggedness is exogenous and does not exert influence on urban ENI (Meng et al., 2023).

(2) The second instrumental variable selected for this study is the 1984 postal density, designated as *IV_Post*. The undeniable connection between digital technology and historical post and telegraph offices is well-established (Ma & Zhu, 2022). In an era before the widespread adoption of landline phones, people predominantly relied on post offices for communication, and these offices held responsibility for landline phone installations. The distribution of post offices played a pivotal role in the proliferation of landline telephones, shaping the contemporary landscape of internet technologies. This connection satisfies the relevance requirement for an instrumental variable. Moreover, the utilization of traditional telecommunication entities such as post offices has declined now, diminishing their impact on ENI and thereby fulfilling the exogeneity condition for instrumental variable selection.

As topographical ruggedness and postal density constitute cross-sectional data, we create interaction terms between these factors and the previous year's number of internet users in China. This approach, as elucidated by *Nunn and Qian* (2011), enables the generation of specific instrumental variables for our analysis.

3.3. Data

Selecting Chinese cities as the research sample is driven by multiple crucial factors:

(1) *Economic Scale and Representativeness*: China boasts a vast and diverse economic and social landscape. Owing to geographical, economic, and cultural disparities across the country, different cities demonstrate substantial variations in the DIGE and energy usage. This diversity ensures that the research findings are highly representative of the multifaceted nature of China's urban environments.

(2) *Rapid Development of the DIGE*: Over the past decade, advancements spanning from mobile payments to e-commerce and, subsequently, the sharing economy have positioned China at the forefront globally. This unique trajectory provides researchers with a valuable "*laboratory*" setting to observe and analyze the tangible impact of the DIGE on energy consumption within an environment that is highly digitized.

(3) *Transition in Energy Structure*: China is currently in the process of transitioning from a predominantly coal-based energy structure to one that is cleaner and more renewable. This ongoing shift underscores the importance of exploring how the DIGE influences ENI. Investigating this relationship in the context of China's evolving energy landscape holds significant implications for steering sustainable development both within the nation and on a global scale.

The study encompasses data from 282 prefecture-level cities in China, spanning the years 2011 to 2021. Diverse data sources, including the "*China City Statistical Yearbook*," *CSMAR, EPS, Wind*, and other databases, were utilized. To enhance the accuracy of regression analyses and mitigate the potential impact of varying units and outliers, certain variables underwent unit transformation, logarithmic transformation, and a winsorizing technique. This involved trimming extreme values at both ends by 1%. Following these meticulous preparations (Table 1), the study proceeded with a series of subsequent analyses and discussions.

Table 1. Descriptive statistics of variables.

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
DIGE	3102	6.901	0.523	4.470	8.552
ENI	3102	0.187	0.048	0.058	0.518
pgdp	3102	8.685	0.988	6.744	17.280
pnd	3102	7.352	4.028	0.043	15.435
fin	3102	1.674	3.632	0.025	49.500
fdi	3102	0.016	0.017	0.000	0.192
urban	3102	0.404	0.212	0.083	1.091
regulation	3102	3.325	1.460	-0.139	8.157
GRI	3102	4.753	1.675	0.693	10.454
HTIA	3102	4.072	0.136	3.621	4.556

4. Results and discussion

4.1. Baseline model

Table 3 presents the estimated results of DIGE on ENI. Columns (1) and (2) discuss the specific impact of DIGE on ENI based on Ordinary Least Squares (OLS) models. The findings reveal a notably positive coefficient for the independent variable (DIGE) and a significantly negative coefficient for the squared independent variable (DIGE2), indicating a pronounced inverted U-shaped relationship between DIGE and ENI. This supports *hypothesis 1*. Columns (3) and (4) exhibit the regression outcomes utilizing a fixed-effects model, corroborating the substantial inverted U-shaped effect between DIGE and ENI. This conclusion contradicts the findings of *Guo et al.* (2023) and *Matthess et al.* (2023). Their research identified a linear impact of DIGE on ENI, whereas our study delves into the nonlinear influence between DIGE and ENI, aligning more closely with real-world dynamics. In summary, DIGE, while consuming electricity, has also driven economic growth, ultimately leading to a reduction in ENI (Hong et al., 2023; Matthess et al., 2023). Furthermore, to enhance the robustness of the conclusions, we examined the relationship between the two using a threshold model. The results indicate when the independent variable DIGE < 0.286, DIGE reduces ENI. When *DIGE > 0.286*, DIGE can also decrease ENI, and the effect is significantly more pronounced than before the turning point.

Additionally, the regression results for the control variables align with our expectations and are consistent with the existing body of literature. The coefficient of "*pgdp*" exhibits a highly significant negative effect at the 1% level, implying that an increase in economic density is associated with a reduction in ENI. This outcome is consistent with the findings of Lin and Huang (2023). Simultaneously, our findings substantiate the presence of the "*pollution halo hypothesis*," as posited by *Jia et al.* (2021). This theory suggests that developed countries, with more stringent environmental regulations in comparison to developing nations, have a positive influence on the host country's environment due to the demonstration effect of environmentally friendly technologies, particularly when multinational corporations adhere to higher environmental standards (Shao et al., 2019). Additionally, the coefficient associated with the *urban* exhibits a statistically significant negative relationship, consistent with the results reported by Balado-Naves et al. (2023).

Table 2. Regression analysis results of the DIGE on ENI.

	(1)	(2)	(3)	(4)	(5)
	OLS		Fixed effects		Threshold model
DIGE	0.025***	0.248***	0.005**	0.068***	
	(0.001)	(0.023)	(0.002)	(0.010)	
DIGE2		-0.021***		-0.005***	
		(0.002)		(0.001)	
DIGE(DIGE≦0.286)					-0.016***
					(0.003)
DIGE(DIGE>0.286)					-0.039***
					(0.002)
pgdp	-0.013***	-0.012***	-0.002***	-0.002***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
pnd	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
fdi	-0.120***	-0.138***	-0.085***	-0.096***	0.062
	(0.033)	(0.032)	(0.024)	(0.024)	(0.068)
fin	0.002***	0.002***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
urban	-0.047***	-0.044***	0.075***	0.066***	-0.035
	(0.003)	(0.003)	(0.009)	(0.009)	(0.035)
regulation	0.003***	0.003***	0.055***	0.051***	-0.026***
	(0.000)	(0.000)	(0.006)	(0.006)	(0.007)
_cons	0.137***	-0.781***	-0.397***	-0.575***	0.290***
	(0.011)	(0.074)	(0.024)	(0.037)	(0.018)
City FE	×	×	√	√	√
Year FE	×	×	√	√	√
N	3102	3102	3102	3102	3102
adj. R^2	0.629	0.659	0.936	0.937	0.520

*Notes: Columns (1) and (2) present the results of the OLS model regression.Columns (3) and (4)presents the results of the fixed-effects model regression. Columns (5) to (6) present the results of the Threshold model regression. ***, **, * indicate significance at the level of 1%, 5%, and 10%.Parenthetically presented is the clustered robust standard error. The following table is the same as this.*

4.2. Robustness test results

4.2.1. Replace dependent and independent variables

In the section dedicated to robustness testing, this study, in alignment with prior research (Yang & Wei, 2019), reexamines the ENI by employing electricity consumption per unit of GDP as a metric. Whether examined globally or within the context of China, the persistent growth in electricity demand driven by the *DIGE* has underscored the pivotal role of electricity in the overall energy consumption framework. The most notable departure of the DIGE from traditional models is the pivotal role assigned to data as a critical production factor. Across all stages, from data generation and transmission to processing, storage, and application, electricity is an indispensable foundational energy source. Owing to the exponential expansion of data presentation, every facet of data processing generates a substantial demand for electricity, as noted by *Hong et al.* (2023) and *Lin and Huang* (2023).

In measuring urban digital economic development, we rely on insights from prior studies (Lin & Zhou, 2021; Ren et al., 2021; Zhang et al., 2023) and employ internet penetration as an replaceable indicator of DIGE. The results of the regression analysis, presented in Table 3, columns (1) and (2), incorporate the substituted variables. The findings indicate that the coefficient of DIGE on ENI remains statistically significant, offering additional proof of the robustness of our model.

4.2.2. Using pro*year interactive fixed effects

Traditional panel data models usually incorporate individual fixed effects and time fixed effects. These account for variations over time that are not influenced by individual factors and individual differences that remain constant over time. Conversely, panel interactive fixed effects models, in comparison to their classical counterparts, provide superior data fitting capabilities (Bai, 2013). Thanks to historical and geographical factors, unique regional characteristics are evident in the development of various Chinese cities. These distinctions can induce systematic trends in *DIGE* and ENI across different regions over time, potentially impacting the precision of the findings. Consequently, this study integrates province-year interactive fixed effects into Eq (1) to assess the influence of DIGE on ENI (Ma and Zhu, 2022). The findings in Table 3, column (3), reveal an inverted U-shaped relationship between DIGE and ENI.

4.2.3. Delete the sample data of Chinese municipalities

Owing to the distinctive political and economic traits of China's centrally administered municipalities, such as Beijing, Tianjin, Shanghai, and Chongqing, businesses within their jurisdictions may benefit from greater political support and digital advantages in contrast to enterprises in other areas. To alleviate the impact of this specific situation, we removed samples from these cities before carrying out the regression analysis (Wang & Dong et al., 2022). The results, displayed in Table 7, column (4), demonstrate that even after the exclusion of these samples, the inverted U-shaped relationship between DIGE and ENI remains intact, in accordance with the initial findings.

4.2.4. Replace the standard error clustering level

Acknowledging the inherent correlation among different cities, we employed double-clustered standard errors in our analysis, which take into account both individual and time dimensions. This adjustment effectively mitigates issues like autocorrelation and heteroscedasticity, thereby fortifying the robustness of our statistical inferences (Petersen, 2009). The results, as showcased in Table 3, column (5), persistently align with the baseline findings.

4.2.5. Considering the impact of significant public health crises

Considering our sample period from 2011 to 2021, it is crucial to acknowledge the profound impact of the COVID-19 on the DIGE, as highlighted by Liu et al. (2022). Therefore, we partitioned our sample into two periods, namely 2011-2019 and 2020-2021, to evaluate the effects of model estimation within these sub-intervals. The detailed regression results are showcased in Table 3, columns (6) and (7). Particularly noteworthy is that during the pandemic period, the impact of DIGE on reducing ENI became notably pronounced. This can be attributed to the widespread adoption of remote work and online education—activities that led to a reduction in energy consumption. This finding is consistent with existing literature (Li et al., 2023; Marz & Sen, 2022), thereby reinforcing the alignment of our results with conclusions from prior research.

Table 3. Robustness test results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alternative measure of ESI	Alternative measure of DIGE	Interactive fixed effect	Deleting Extreme Samples	Replacing the standard error clustering level	2011-2019	2020-2021
DIGE	2.405***		0.023*	0.040***	0.068**	0.068***	0.090**
	(0.132)		(0.012)	(0.010)	(0.028)	(0.012)	(0.039)
DIGE2	-0.163***		-0.001	-0.003***	-0.005**	-0.005***	-0.006**
	(0.010)		(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
dige2		2.613***					
		(0.510)					
dige22		-0.951***					
		(0.189)					

pgdp	-0.030***	0.173***	0.000	-0.002***	-0.002	-0.001	-0.035***
	(0.009)	(0.036)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
pnd	-0.012***	-0.003***	-0.002***	-0.003***	-0.003***	-0.003***	-0.010***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
fdi	0.790**	-0.089***	-0.029	-0.110***	-0.096	-0.104***	-0.807***
	(0.318)	(0.024)	(0.027)	(0.024)	(0.065)	(0.025)	(0.249)
fin	0.009***	0.000	0.000	0.000	0.000	0.000	0.003***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
urban	0.823***	0.078***	0.013	0.075***	0.066**	0.064***	-0.078***
	(0.112)	(0.009)	(0.010)	(0.008)	(0.027)	(0.010)	(0.018)
regulation	0.837***	0.051***	0.037***	0.045***	0.051***	-0.290**	0.019***
	(0.076)	(0.006)	(0.006)	(0.006)	(0.008)	(0.127)	(0.004)
City FE	×	√	√	√	√	√	√
Year FE	×	√	√	√	√	√	√
*Pro*Year FE*	×	×	√	×	×	×	×
_cons	-12.403***	-3.067***	-0.392***	-0.468***	-0.575***	0.547	-0.173
	(0.478)	(0.525)	(0.043)	(0.037)	(0.098)	(0.399)	(0.157)
N	3102	3102	3047	3058	3102	2538	564
adj. R^2	0.973	0.937	0.950	0.938	0.937	0.932	0.998

4.3. Endogeneity test

In Equation (1), the possibility of endogeneity arises due to potential omitted variables and measurement errors. Although the fixed effects model alleviates endogeneity to some degree, to enhance the robustness and reliability of our conclusions, in this study, we use instrumental variable methods to address concerns about endogeneity. The outcomes of the regression analysis, conducted with these instrumental variables, are displayed in Table 4.

The instruments employed for columns (1) and (2) are labeled *Iv_post*, for columns (3) and (4) as *Iv_land*, and for columns (5) and (6) as *IV_Land*. The outcomes suggest that, even after addressing endogeneity concerns, the relationship between DIGE and ENI remains stable, with minor fluctuations in coefficient magnitudes, reaffirming the existence of an inverted U-shaped effect. All models in this analysis were estimated using the two-stage least squares method. Importantly, the Anderson LM and Wald F statistics, which passed the correlation test, affirm the appropriateness of the instrumental variables chosen for this study.

An important observation is that the estimates derived from instrumental variables are higher than the corresponding OLS estimates and fixed effects model results. Consistent with the research by *Nobel laureate Card* (2001), We attribute this phenomenon to the unobservable differences in the characteristics of the "treatment" and "control" groups inherent in the instrumental variable (IV) model. IV estimation tends to show a more substantial upward bias compared to the corresponding OLS estimates due to these unobserved distinctions.

Table 4. Endogeneity test results.

	Iv_post		*Iv_land*	
	Iv_post	*ENI*	*Iv_land*	*ENI*
	(1)	(2)	(3)	(4)
DIGE		0.787***		1.198***
		(0.096)		(0.117)
DIGE^2		-0.062***		-0.093***
		(0.007)		(0.009)
Iv_post	-0.002***			
	(0.001)			
Iv_ land			-0.028***	
			(0.002)	
pgdp	0.007***	-0.003*	0.005***	0.001
	(0.000)	(0.002)	(0.001)	(0.002)

pnd	0.002***	-0.002***	0.002**	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
fdi	-0.392***	-0.187***	-0.394***	-0.351***
	(0.051)	(0.060)	(0.051)	(0.076)
fin	0.001***	-0.001**	-0.001*	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
urban	-0.046***	-0.054***	-0.032***	-0.062***
	(0.017)	(0.016)	(0.001)	(0.021)
regulation	0.058***	0.011	-0.014	0.036***
	(0.006)	(0.008)	(0.008)	(0.011)
City FE	√	√	√	√
Time FE	√	√	√	√
Anderson LM		87.473***		100.655*** (0.0000)
Wald F		90.017***		104.084*** (0.0000)
F	90.017		104.084	
N	3102	3102	3102	3102
R^2	0.276	0.331	0.193	0.147

5. Further discussion

5.1. Mechanism analysis

The results of testing the mediating effects in GRI are presented in Table 5, with columns (1) and (2) focusing on GRI and columns (3) and (4) on HTIA. In column (1), it is observed that the coefficient of the squared term of DIGE is significantly positive. This suggests that DIGE has a positive impact on GRI once it reaches a certain threshold. Moving to column (2), it is demonstrated that GRI can effectively reduce ENI. The significance of both the linear and squared terms of DIGE in column (2) implies that GRI serves as a partial mediator in the influence of DIGE on ENI. These empirical findings provide support for the predictions of hypothesis 2. Our study results are consistent with findings from existing research (Dou & Gao, 2022; Chen et al., 2021; Wurlod & Noailly, 2018).

The results of testing the mediating effects in HTIA are presented in columns (3) and (4) of Table 5. In column (3), it is observed that both the first-order and squared coefficients of DIGE are significantly positive. This suggests that DIGE has a positive impact on HTIA. Moving to column (4), it is revealed that HTIA can effectively reduce ENI. Similarly, given the significance of both the first-order and squared terms of DIGE in column (4), it is suggested that HTIA plays a partial mediating role. These empirical results provide support for the predictions of *hypothesis 3*. Our results align with previous studies conducted by scholars, as referenced in works by Liu & Zhang (2021), Tanaka & Managi (2021), and Wang et al. (2022). HTIA facilitates the efficient allocation and utilization of resources, including labor and capital, within and between industries, leading to a reduction in ENI.

Table 5. Mediating effects.

	(1) GRI	(2) ENI	(3) HTIA	(4) ENI	(5) ENI
DIGE	0.443	0.069***	0.057**	0.069***	0.070***
	(0.276)	(0.010)	(0.026)	(0.010)	(0.010)
DIGE2	0.027**	-0.005***	0.007***	-0.005***	-0.005***
	(0.011)	(0.001)	(0.002)	(0.001)	(0.001)
GRI		-0.002***			-0.002***
		(0.001)			(0.001)
HTIA				-0.021***	-0.019***

				(0.007)	(0.007)
pgdp	0.088***	-0.002**	-0.001	-0.002***	-0.002**
	(0.019)	(0.001)	(0.002)	(0.001)	(0.001)
pnd	0.042***	-0.003***	-0.026***	-0.004***	-0.004***
	(0.006)	(0.000)	(0.001)	(0.000)	(0.000)
fdi	0.442	-0.095***	0.287***	-0.090***	-0.090***
	(0.664)	(0.024)	(0.063)	(0.024)	(0.024)
fin	-0.002	0.000	-0.000	0.000	0.000
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
urban	-1.538***	0.063***	-0.144***	0.063***	0.061***
	(0.234)	(0.009)	(0.022)	(0.009)	(0.009)
regulation	0.249	0.052***	-0.055***	0.050***	0.051***
	(0.159)	(0.006)	(0.015)	(0.006)	(0.006)
_cons	1.698*	-0.572***	3.769***	-0.497***	-0.500***
	(0.998)	(0.037)	(0.094)	(0.046)	(0.046)
City FE	√	√	√	√	√
Time FE	√	√	√	√	√
N	3102	3102	3102	3102	3102
adj. R^2	0.961	0.937	0.948	0.937	0.937

5.2. Heterogeneity analysis

5.2.1. Heterogeneity for geographical location

Considering significant disparities in foundational conditions and developmental statuses across regions, this study divides the sampled cities into three groups based on geographical locations: eastern, central, and western regions, and further categorizes them into northern and southern regions.This categorization aligns with Huang et al. (2021). The results of the regression analysis are presented in Table 6.

In columns (1) to (3) of Table 6, substantial variations in the impacts of DIGE on ENI become apparent. The eastern region, benefiting from its advantageous geographical position, displays a higher degree of market openness, frequent technological exchanges, and trading activities. Moreover, advanced high-tech industries often establish and concentrate in the eastern region, attributed to the presence of prestigious universities and research institutions that provide abundant research talent and innovation vitality (Hao et al., 2023; Hong et al., 2023). Consequently, the eastern region exhibits a stronger capacity for embracing digital technologies, leading to a significantly greater reduction in ENI compared to the central and western regions. This finding aligns with existing literature (Zhang et al., 2023; Zhang, 2022).

In columns (4) and (5), the presence of abundant coal resources in northern China has facilitated a resource-intensive economic growth model, primarily centered on coal-fired power generation, which has given rise to environmental challenges stemming from excessive emissions. In contrast, the southern region, particularly the southeast coastal areas, adopted openness at an earlier stage, nurturing a mature business environment (Wang et al., 2022). Combined with government support, convenient transportation, and superior natural environments, the southern region has attracted high-tech industries, financial enterprises, and tourism sectors. Consequently, the impact of DIGE in reducing ENI is more pronounced in southern cities.

Recognizing the strategic significance of the Yangtze River Economic Belt (YREB), we categorize our sample of cities into two groups: those located along the YREB (YREB=1) and those outside it (YREB=0). The regression results in columns (6) and (7) of Table 6 reveal a significantly more pronounced decline in ENI in cities situated along the YREB, attributed to the influence of DIGE. Compared to areas outside the YREB, these cities attract more foreign investment, leading to the introduction of advanced technologies and management practices (Shao et al., 2019; Zhu et al., 2017). This technical edge facilitates the adoption of new technologies, endowing the YREB region with improved capabilities, potential, and receptivity for digital economic development.

Table 6. Heterogeneity for geographical location.

	(1) East	(2) Central	(3) West	(4) North	(5) South	(6) YREB=0	(7) YREB=1
DIGE	0.193***	0.025	0.028**	0.028*	0.103***	0.040***	0.099***
	(0.022)	(0.027)	(0.012)	(0.016)	(0.013)	(0.013)	(0.015)
DIGE2	-0.015***	-0.001	-0.002**	-0.002*	-0.007***	-0.003**	-0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pgdp	-0.002	-0.009***	-0.000	-0.000	-0.003***	-0.002**	-0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pnd	-0.004***	-0.001***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
fdi	-0.141***	-0.023	-0.005	0.062	-0.244***	-0.081***	-0.099**
	(0.033)	(0.045)	(0.068)	(0.040)	(0.031)	(0.029)	(0.049)
fin	0.001	0.001**	-0.000	-0.000	0.000	-0.000	0.002**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
urban	0.157***	0.028**	0.011	-0.007	0.098***	0.095***	-0.014
	(0.016)	(0.014)	(0.014)	(0.015)	(0.011)	(0.011)	(0.014)
regulation	0.059***	0.054***	0.024**	0.077***	0.040***	0.048***	0.050***
	(0.010)	(0.011)	(0.009)	(0.012)	(0.007)	(0.009)	(0.007)
_cons	-1.012***	-0.408***	-0.331***	-0.527***	-0.657***	-0.500***	-0.635***
	(0.077)	(0.101)	(0.050)	(0.064)	(0.046)	(0.049)	(0.054)
City FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
N	1100	1089	913	1132	1969	1936	1166
adj. R^2	0.951	0.872	0.946	0.906	0.953	0.929	0.953

5.2.2. Heterogeneity of city characteristics

(1) Resource endowment heterogeneity

Previous studies suggest that resource-rich regions often experience lower energy prices, reducing incentives for businesses to pursue technological innovation and decrease ENI. Wei et al. (2019) found that energy-intensive enterprises in coal-rich areas might lack motivation for technological progress, significantly impacting both individual enterprises and the region's overall ENI. To better understand this phenomenon, we follow Zhang et al. (2022) and categorize sampled cities into two groups: resource-based and non-resource-based cities.

The findings in columns (1) and (2) of Table 6 show that the reduction in ENI due to DIGE is more pronounced in resource-based cities, consistent with existing literature (Meng et al., 2023). In the era of DIGE, resource-based cities face challenges like economic structural imbalances, limited capabilities to transition to alternative industries, and severe environmental degradation. Thus, while the digital industry in these cities holds significant potential for reducing ENI, it faces substantial obstacles (Hao et al., 2023).

(2) Economic Development Heterogeneity

To explore heterogeneity among cities with different economic development levels, we use the criteria proposed by Li et al. (2022), utilizing per capita GDP. We classify all sampled cities into high-economic-development cities (ED=1) and low-economic-development cities (ED=0) based on the median value. The results are shown in columns (3) and (4) of Table 6.

An inverted U-shaped effect of DIGE on ENI is evident in both groups, but it is more pronounced in low-economic-development cities. This disparity may be because these cities, striving for economic catch-up, rely more on energy-intensive growth models. Furthermore, DIGE is still in its early stages in these cities, accentuating its negative impact on ENI (Wang et al., 2024). In contrast, high-economic-development cities have robust industrial foundations, abundant resources, and inherent advantages in data elements. They lead in various aspects of the digital economy ecosystem, including data center construction, content development, and data processing. Consequently, DIGE has a greater positive effect on reducing ENI in these cities.

(3) Urban size heterogeneity

Large cities are more likely to receive significant fiscal funds, serve as regional transportation hubs, and possess superior digital infrastructure. Consistent with previous scholarly work, we categorize sampled cities into three groups based on population size: large cities (population over 5 million), medium cities (1-5 million), and small cities (less than 1 million). The regression results are presented in Table 7, columns (5) to (7).

The results in columns (5) to (7) of Table 6 indicate that the impact of DIGE on ENI is more significant in large cities, aligning with existing literature (Ren et al., 2021). Large cities have robust resource mobilization capabilities and intricate energy systems covering production, dispatch, and consumption. Additionally, large cities demonstrate higher prevalence and utilization rates of internet infrastructure. The agglomeration effects of digital technology applications, along with network effects, reduce the average cost of digital infrastructure deployment. At the same time, these factors facilitate convenient data collection, processing, and sharing. Consequently, digital technologies can effectively leverage their energy-saving and emission-reducing positive externalities, thereby accelerating the transition toward energy decarbonization.

Table 7. Heterogeneity of cities characteristics.

	(1) Resource-based	(2) Non-resource-based	(3) ED=1	(4) ED=0	(5) Small	(6) Medium	(7) Large
DIGE	0.077***	-0.034*	0.050***	0.093***	0.034	0.036***	0.096***
	(0.012)	(0.020)	(0.017)	(0.017)	(0.074)	(0.013)	(0.019)
DIGE2	-0.006***	-0.003*	-0.014***	-0.004***	-0.001	-0.003***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)
pgdp	-0.002*	-0.001	-0.017***	-0.000	0.002	-0.001*	-0.001
	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
pnd	-0.003***	-0.003***	-0.002***	-0.004***	-0.004**	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
fdi	-0.087***	-0.188***	-0.054	-0.230***	0.571**	-0.098***	-0.110***
	(0.028)	(0.048)	(0.033)	(0.037)	(0.257)	(0.028)	(0.041)
fin	0.000	0.000	0.000	-0.000*	0.002	0.000	0.003*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)
urban	0.108***	0.031***	0.077***	0.053***	-0.061*	0.116***	0.065**
	(0.014)	(0.010)	(0.019)	(0.010)	(0.034)	(0.010)	(0.030)
regulation	0.060***	0.028***	-0.010	0.053***	0.014	0.049***	0.065***
	(0.008)	(0.009)	(0.040)	(0.007)	(0.026)	(0.007)	(0.010)
_cons	-0.636***	-0.153**	0.148	-1.032***	-0.389	-0.482***	-0.707***
	(0.046)	(0.073)	(0.150)	(0.061)	(0.249)	(0.048)	(0.073)
City FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
N	1881	1221	1537	1533	123	1842	1088
adj. R^2	0.939	0.918	0.894	0.950	0.924	0.953	0.925

6. Conclusion

Using urban panel data from China covering the period from 2011 to 2021, this paper utilizes a fixed-effect model, a threshold model, and an intermediary effect model to examine the specific impact of DIGE on ENI, as well as to explore the mechanisms of this impact at different levels.

First, the relationship between DIGE and ENI exhibits an inverted U-shaped pattern, suggesting that urban ENI can be effectively lowered once DIGE attains a certain level. This finding contrasts with several existing studies (Guo et al., 2023; Hong et al., 2023; Matthess et al., 2023). These studies only investigated linear relationships among variables, overlooking potential nonlinear impacts. Second, the mechanism analysis reveals that DIGE affects ENI by accelerating GRI and promoting HTIA. Our findings further support existing research in this area (Sturgeon, 2021; Wang et al., 2022; Wurlod & Noailly, 2018). Finally, our study investigated the diverse impacts of DIGE on ENI across cities, taking into account their varied geographical locations and factor endowments.

7. Policy Recommendation

Drawing upon the findings discussed above, we present these recommendations:

First, local governments are encouraged to actively promote and support local enterprises in accelerating the development of digital, energy-saving, and carbon-reducing services and products. Additionally, they should focus on enhancing the application of digital technology in energy carbon reduction devices. Furthermore, the government should strategically harness the unique advantages of digital technology to establish a standardized system for energy carbon reduction guided by the digital era. This systematic approach ensures that all stakeholders in energy production and consumption adhere to consistent guidelines, thereby offering effective institutional support for high-quality economic development with a focus on green and low-carbon practices.

Second, this dual approach optimizes industrial structures for high efficiency and low consumption. Additionally, the government should increase investments and research efforts in GRI projects. Accelerating the digitalization of businesses closes the digital development gap among enterprises of varying scales. Financial and technological support should especially target small-scale enterprises with low production costs, ensuring the establishment of high-tech industrial clusters. This synergy effectively empowers sustained economic and social development.

Third, central government should take regional differences into careful consideration during policy formulation. Policies should adapt to local conditions, fostering the development of biomass energy and exploring new energy sources such as geothermal and marine energy, while also establishing comprehensive nuclear power demonstration bases in an organized manner. This approach lays a solid foundation for promoting green, low-carbon economic and social transformations. Additionally, policies should be tailored to support underdeveloped regions, narrowing the regional gap, and effectively harnessing the economic and social welfare benefits resulting from digital economic development.

8. Limitations and Future Research

Due to the diverse institutional backgrounds and economic environments among nations, our results may be more applicable to developing countries than to all countries. Future research could include comparative studies between emerging economies and developed nations to assess the applicability of our research model in various contexts. Second, although we measured the GRI and HTIA mechanisms, the impact of DIGE on ENI is multifaceted and may involve other distinct pathways. These pathways should be explored in future studies.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

References

Anu, Singh, A. K., Raza, S. A., Nakonieczny, J., and Shahzad, U. (2023). Role of financial inclusion, green innovation, and energy efficiency for environmental performance? Evidence from developed and emerging economies in the lens of sustainable development. *Structural Change and Economic Dynamics*, 64, 213-224. http://doi.org/10.1016/j.strueco.2022.12.008

Avom, D., Nkengfack, H., Fotio, H. K., and Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technological Forecasting and Social Change*, 155, 120028. http://doi.org/10.1016/j.techfore.2020.120028

Bai, J. S. (2013). Fixed-effects dynamic panel models, a factor analytical method. *Econometrica*, 81(1), 285-314. http://doi.org/10.3982/ECTA9409

Balado-Naves, R., Banos-Pino, J. F., and Mayor, M. (2023). Spatial spillovers and world energy intensity convergence. *Energy Economics*, 124, 106807. http://doi.org/10.1016/j.eneco.2023.106807

Bashir, M. F., Ma, B. J., Shahbaz, M., Shahzad, U., and Vo, X. V. (2021). Unveiling the heterogeneous impacts of environmental taxes on energy consumption and energy intensity: Empirical evidence from OECD countries. *Energy*, 226, 120366. http://doi.org/10.1016/j.energy.2021.120366

Bilgili, F., Kocak, E., Bulut, U., and Kuloglu, A. (2017). The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. *Energy*, 133, 242-256. http://doi.org/10.1016/j.energy.2017.05.121

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, 69(5), 1127-1160. http://doi.org/10.1111/1468-0262.00237

Chan, H. K., Yee, R. W. Y., Dai, J., and Lim, M. K. (2016). The moderating effect of environmental dynamism on green product innovation and performance. *International Journal of Production Economics*, 181, 384-391. http://doi.org/10.1016/j.ijpe.2015.12.006

Chen, J., Liu, J., Qi, J., Gao, M., Cheng, S., Li, K., and Xu, C. (2022). City- and county-level spatio-temporal energy consumption and efficiency datasets for China from 1997 to 2017. *Scientific Data*, 9(1), 101. http://doi.org/10.1038/s41597-022-01240-6

Chen, J., Zhou, D., Zhao, Y., Wu, B., and Wu, T. (2020). Life cycle carbon dioxide emissions of bike sharing in China: Production, operation, and recycling. *Resources Conservation and Recycling*, 162, 105011. http://doi.org/10.1016/j.resconrec.2020.105011

Chen, P. (2022). Is the digital economy driving clean energy development? -New evidence from 276 cities in China. *Journal of Cleaner Production*, 372, 133783. http://doi.org/10.1016/j.jclepro.2022.133783

Cheng, Y., Zhang, Y., Wang, J., and Jiang, J. (2023). The impact of the urban digital economy on China's carbon intensity: Spatial spillover and mediating effect. *Resources Conservation and Recycling*, 189, 106762. http://doi.org/10.1016/j.resconrec.2022.106762

Ding, C., Chen, H., Liu, Y., Hu, J., Hu, M. J., Chen, D., and Irfan, M. (2024). Unleashing digital empowerment: Pioneering low-carbon development through the broadband China strategy. *Energy*, 295, 131034. http://doi.org/10.1016/j.energy.2024.131034

Du, J. T., Shen, Z. Y., Song, M. L., and Zhang, L. D. (2023). Nexus between digital transformation and energy technology innovation: An empirical test of A-share listed enterprises. *Energy Economics*, 120, 106572. http://doi.org/10.1016/j.eneco.2023.106572

Guo, Q., Wu, Z., Jahanger, A., Ding, C., Guo, B., and Awan, A. (2023). The spatial impact of digital economy on energy intensity in China in the context of double carbon to achieve the sustainable development goals. *Environmental Science and Pollution Research*, 30(13), 35528-35544. http://doi.org/10.1007/s11356-022-24814-8

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93(2), 345-368. http://doi.org/10.1016/S0304-4076(99)00025-1

Hao, Y., Guo, Y. X., and Wu, H. T. (2022). The role of information and communication technology on green total factor energy efficiency: Does environmental regulation work? *Business Strategy and the Environment*, 31(1), 403-

424. http://doi.org/10.1002/bse.2901
Hong, J. J., Shi, F. Y., and Zheng, Y. H. (2023). Does network infrastructure construction reduce energy intensity? Based on the "Broadband China" strategy. *Technological Forecasting and Social Change*, 190, 122437. http://doi.org/10.1016/j.techfore.2023.122437
Huang, H., Wang, F., Song, M., Balezentis, T., and Streimikiene, D. (2021). Green innovations for sustainable development of China: Analysis based on the nested spatial panel models. *Technology in Society*, 65, 101593. http://doi.org/10.1016/j.techsoc.2021.101593
Jia, R. N., Shao, S., and Yang, L. L. (2021). High-speed rail and CO2 emissions in urban China: A spatial difference-in-differences approach. *Energy Economics*, 99, 105271. http://doi.org/10.1016/j.eneco.2021.105271
Jia, S. H., Guo, N. N., and Liu, Y. K. (2023). Electricity shortage and corporate digital transformation: Evidence from China's listed firms. *Finance Research Letters*, 57, 104260. http://doi.org/10.1016/j.frl.2023.104260
Jiang, H., Han, Y., and Qin, Y. (2024). Influencing Factors as well as Implementation Path of Synergistic Development of Digitalization and Greening in Manufacturing Industry: Analysis from a Configuration Perspective. *Review of Economic Assessment*, 3(1), 26. http://doi.org/10.58567/rea03010004
Krause, M. J., and Tolaymat, T. (2018). Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability*, 1(11), 711-718. http://doi.org/10.1038/s41893-018-0152-7
Li, D., Xia, Z., and Shi, Y. (2023). The Impact of Executive Academic Experience on Green Innovation in Manufacturing Corporations. *Review of Economic Assessment*, 2(3), 18. http://doi.org/10.58567/rea02030003
Li, J. L., Chen, L. T., Chen, Y., and He, J. W. (2022). Digital economy, technological innovation, and green economic efficiency-Empirical evidence from 277 cities in China. *Managerial and Decision Economics*, 43(3), 616-629. http://doi.org/10.1002/mde.3406
Li, L. X. (2022). Digital transformation and sustainable performance: The moderating role of market turbulence. *Industrial Marketing Management*, 104, 28-37. http://doi.org/10.1016/j.indmarman.2022.04.007
Li, W., Liu, N., and Long, Y. (2023). Assessing carbon reduction benefits of teleworking: A case study of Beijing. *Science of the Total Environment*, 889, 164262. http://doi.org/10.1016/j.scitotenv.2023.164262
Li, Z. G., and Wang, J. (2022). The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. *Journal of Cleaner Production*, 351, 131570. http://doi.org/10.1016/j.jclepro.2022.131570
Lin, B. Q., and Zhou, Y. C. (2021). Does the Internet development affect energy and carbon emission performance? *Sustainable Production and Consumption*, 28, 1-10. http://doi.org/10.1016/j.spc.2021.03.016
Lin, B. Q., and Zhu, J. P. (2021). Impact of China's new-type urbanization on energy intensity: A city-level analysis. *Energy Economics*, 99, 105292. http://doi.org/10.1016/j.eneco.2021.105292
Lin, B., and Huang, C. (2023). How will promoting the digital economy affect electricity intensity? *Energy Policy*, 173, 113341. http://doi.org/10.1016/j.enpol.2022.113341
Liu, X. P., and Zhang, X. L. (2021). Industrial agglomeration, technological innovation and carbon productivity: Evidence from China. *Resources Conservation and Recycling*, 166, 105330. http://doi.org/10.1016/j.resconrec.2020.105330
Liu, X., Cifuentes-Faura, J., Zhao, S., and Wang, L. (2023). Government environmental attention and carbon emissions governance: Firm-level evidence from China. *Economic Analysis and Policy*, 80, 121-142. http://doi.org/10.1016/j.eap.2023.07.016
Liu, X. Q., Qin, C., Liu, B. L., Ahmed, A. D., Ding, C. J., and Huang, Y. J. (2024). The economic and environmental dividends of the digital development strategy: Evidence from Chinese cities. *Journal of Cleaner Production*, 440, 140398. http://doi.org/10.1016/j.jclepro.2023.140398
Liu, Y. J., Cui, L. J., Xiong, Y. Y., and Yao, X. G. (2023). Does the development of the Internet improve the allocative efficiency of production factors? Evidence from surveys of Chinese manufacturing firms. *Structural Change and Economic Dynamics*, 66, 161-174. http://doi.org/10.1016/j.strueco.2023.04.017
Liu, Y., Zhao, X., and Kong, F. (2023). The dynamic impact of digital economy on the green development of traditional manufacturing industry: Evidence from China. *Economic Analysis and Policy*, 80, 143-160. http://doi.org/10.1016/j.eap.2023.08.005
Liu, Z., Liu, B., Luo, H., and Chen, S. (2024). Digital economy and fiscal decentralization: Drivers of green innovation in China. *Heliyon*, 10(13), e33870. https://doi.org/10.1016/j.heliyon.2024.e33870
Luo, H., Yang, B., Liu, Z., Ding, C. J., and Liu, B. (2024). The bright and dark sides: Unpacking the effect of digital economy on resource curse. *Journal of Cleaner Production*, 485, 144351. https://doi.org/10.1016/j.jclepro.2024.144351
Luo, K., Liu, Y. B., Chen, P. F., and Zeng, M. L. (2022). Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. *Energy Economics*, 112, 106127.

http://doi.org/10.1016/j.eneco.2022.106127
Ma, D., and Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *Journal of Business Research*, 145, 801-813. http://doi.org/10.1016/j.jbusres.2022.03.041
Marz, W., and Sen, S. (2022). Does telecommuting reduce commuting emissions? *Journal of Environmental Economics and Management*, 116, 102746. http://doi.org/10.1016/j.jeem.2022.102746
Matthess, M., Kunkel, S., Dachrodt, M. F., and Beier, G. (2023). The impact of digitalization on energy intensity in manufacturing sectors-A panel data analysis for Europe. *Journal of Cleaner Production*, 397, 136598. http://doi.org/10.1016/j.jclepro.2023.136598
Meng, Z. Y., Li, W. B., Chen, C. F., and Guan, C. H. (2023). Carbon Emission Reduction Effects of the Digital Economy: Mechanisms and Evidence from 282 Cities in China. *Land*, 12(4), 773. http://doi.org/10.3390/land12040773
Mu, W. W., Liu, K. F., Tao, Y. Q., and Ye, Y. W. (2023). Digital finance and corporate ESG. *Finance Research Letters*, 51, 103426. http://doi.org/10.1016/j.frl.2022.103426
Nunn, N., and Qian, N. (2011). The potato's contribution to population and urbanization: evidence from a historical experiment. *Quarterly Journal of Economics*, 126(2), 593-650. http://doi.org/10.1093/qje/qjr009
Peng, H., Lu, Y. B., and Wang, Q. W. (2023). How does heterogeneous industrial agglomeration affect the total factor energy efficiency of China's digital economy. *Energy*, 268 http://doi.org/10.1016/j.energy.2023.126654
Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies*, 22(1), 435-480. http://doi.org/10.1093/rfs/hhn053
Qin, P., Liu, M., Su, L., Fei, Y., and Tan-Soo, J. (2022). Electricity consumption in the digital era: Micro evidence from Chinese households. *Resources Conservation and Recycling*, 182, 106297. http://doi.org/10.1016/j.resconrec.2022.106297
Ren, S. Y., Hao, Y., Xu, L., Wu, H. T., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Economics*, 98, 105220. http://doi.org/10.1016/j.eneco.2021.105220
Shao, S., Chen, Y., Li, K., and Yang, L. (2019). Market segmentation and urban CO2 emissions in China: Evidence from the Yangtze River Delta region. *Journal of Environmental Management*, 248, 109324. http://doi.org/10.1016/j.jenvman.2019.109324
Skare, M., de Obesso, M. D., and Ribeiro-Navarrete, S. (2023). Digital transformation and European small and medium enterprises (SMEs): A comparative study using digital economy and society index data. *International Journal of Information Management*, 68, 102594. http://doi.org/10.1016/j.ijinfomgt.2022.102594
Song, P., Mao, X. Q., Li, Z. Y., and Tan, Z. X. (2023). Study on the optimal policy options for improving energy efficiency and Co-controlling carbon emission and local air pollutants in China. *Renewable & Sustainable Energy Reviews*, 175, 113167. http://doi.org/10.1016/j.rser.2023.113167
Storch, D., Timme, M., and Schroeder, M. (2021). Incentive-driven transition to high ride-sharing adoption. *Nature Communications*, 12(1), 3003. http://doi.org/10.1038/s41467-021-23287-6
Sturgeon, T. J. (2021). Upgrading strategies for the digital economy. Global Strategy Journal, 11(1), 34-57. http://doi.org/10.1002/gsj.1364
Su, Y. Q., Tian, G. G., Li, H. C., and Ding, C. J. (2024). Climate risk and corporate energy strategies: Unveiling the Inverted-N relationship. *Energy*, 310, 132968. http://doi.org/10.1016/j.energy.2024.132968
Sun, H. P., Edziah, B. K., Sun, C. W., and Kporsu, A. K. (2022). Institutional quality and its spatial spillover effects on energy efficiency. *Socio-Economic Planning Sciences*, 83, 101023. http://doi.org/10.1016/j.seps.2021.101023
Sun, Y. P., and Razzaq, A. (2022). Composite fiscal decentralisation and green innovation: Imperative strategy for institutional reforms and sustainable development in OECD countries. *Sustainable Development*, 30(5), 944-957. http://doi.org/10.1002/sd.2292
Tanaka, K., and Managi, S. (2021). Industrial agglomeration effect for energy efficiency in Japanese production plants. *Energy Policy*, 156, 112442. http://doi.org/10.1016/j.enpol.2021.112442
Tang, C., Xu, Y. Y., Hao, Y., Wu, H. T., and Xue, Y. (2021). What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. *Energy Economics*, 103, 105576. http://doi.org/10.1016/j.eneco.2021.105576
Wang, E. Z., Lee, C. C., and Li, Y. Y. (2022). Assessing the impact of industrial robots on manufacturing energy intensity in 38 countries. *Energy Economics*, 105, 105748. http://doi.org/10.1016/j.eneco.2021.105748
Wang, H., and Zhou, P. (2018). Multi-country comparisons of CO2 emission intensity: The production-theoretical decomposition analysis approach. *Energy Economics*, 74, 310-320. http://doi.org/10.1016/j.eneco.2018.05.038
Wang, L., Yang, D., and Luo, D. D. (2022). Policy Uncertainty, Official Social Capital, and the Effective Corporate Tax Rate-Evidence From Chinese Firms. *Frontiers in Psychology*, 13, 899021. http://doi.org/10.3389/fpsyg.2022.899021

Wang, J., Dong, K., Dong, X., and Taghizadeh-Hesary, F. (2022). Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Economics*, 113, 106198. http://doi.org/10.1016/j.eneco.2022.106198

Wang, J., Sun, F. R., Lv, K. J., and Wang, L. S. (2022). Industrial agglomeration and firm energy intensity: How important is spatial proximity? *Energy Economics*, 112, 106155. http://doi.org/10.1016/j.eneco.2022.106155

Wang, L., Liu, X. Q., Liu, R. W., and Pan, J. Y. (2024). Structural tax reform and local government non-tax revenues - evidence from rural tax reform of China. *Applied Economics*, 1-16. http://doi.org/10.1080/00036846.2024.2331024

Wang, L., and Shao, J. (2023). Digital economy, entrepreneurship and energy efficiency. *Energy*, 269, 126801. http://doi.org/10.1016/j.energy.2023.126801

Wei, T. Y., Zhou, J. J., and Zhang, H. X. (2019). Rebound effect of energy intensity reduction on energy consumption. *Resources Conservation and Recycling*, 144, 233-239. http://doi.org/10.1016/j.resconrec.2019.01.012

Wu, H. T., Hao, Y., and Ren, S. Y. (2020). How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Economics*, 91, 104880. http://doi.org/10.1016/j.eneco.2020.104880

Wurlod, J., and Noailly, J. (2018). The impact of green innovation on energy intensity: An empirical analysis for 14 industrial sectors in OECD countries. *Energy Economics*, 71, 47-61. http://doi.org/10.1016/j.eneco.2017.12.012

Yang, G. Q., Nie, Y. M., Li, H. G., and Wang, H. S. (2023). Digital transformation and low-carbon technology innovation in manufacturing firms: The mediating role of dynamic capabilities. *International Journal of Production Economics*, 263, 108969. http://doi.org/10.1016/j.ijpe.2023.108969

Yang, Q. C., Zheng, M. B., and Chang, C. P. (2022). Energy policy and green innovation: A quantile investigation into renewable energy. *Renewable Energy*, 189, 1166-1175. http://doi.org/10.1016/j.renene.2022.03.046

Yang, S. B., Jahanger, A., and Hossain, M. R. (2023). Does China's low-carbon city pilot intervention limit electricity consumption? An analysis of industrial energy efficiency using time-varying DID model. *Energy Economics*, 121, 106636. http://doi.org/10.1016/j.eneco.2023.106636

Yang, X. D., Wu, H. T., Ren, S. Y., Ran, Q. Y., and Zhang, J. N. (2021). Does the development of the internet contribute to air pollution control in China? Mechanism discussion and empirical test. *Structural Change and Economic Dynamics*, 56, 207-224. http://doi.org/10.1016/j.strueco.2020.12.001

Yang, Z., and Wei, X. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross-efficiency DEA. *Journal of Cleaner Production*, 209, 439-450. http://doi.org/10.1016/j.jclepro.2018.10.271

Zhang, D., Li, J., and Ji, Q. (2020). Does better access to credit help reduce energy intensity in China? Evidence from manufacturing firms. *Energy Policy*, 145, 111710. http://doi.org/10.1016/j.enpol.2020.111710

Zhang, J. N., Lyu, Y. W., Li, Y. T., and Geng, Y. (2022). Digital economy: An innovation driving factor for low-carbon development. *Environmental Impact Assessment Review*, 96, 106821. http://doi.org/10.1016/j.eiar.2022.106821

Zhang, W., Liu, X. M., Wang, D., and Zhou, J. P. (2022). Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy*, 165, 112927. http://doi.org/10.1016/j.enpol.2022.112927

Zhang, X., Cai, Z., Song, W., and Yang, D. (2023). Mapping the spatial-temporal changes in energy consumption-related carbon emissions in the Beijing-Tianjin-Hebei region via nighttime light data. *Sustainable Cities and Society*, 94, 104476. http://doi.org/10.1016/j.scs.2023.104476

Zhang, Y. R., and Ran, C. J. (2023). Effect of digital economy on air pollution in China? New evidence from the "National Big Data Comprehensive Pilot Area"policy. *Economic Analysis and Policy*, 79, 986-1004. http://doi.org/10.1016/j.eap.2023.07.007

Zhang, Z. (2022). Research on the Impact of Digital Finance on China's Urban-Rural Income Gap. *Review of Economic Assessment*, 1(1), 5. http://doi.org/10.58567/rea01010005

Zhao, J., Ji, G., Yue, Y., Lai, Z., Chen, Y., Yang, D., Yang, X., and Wang, Z. (2019). Spatio-temporal dynamics of urban residential CO2 emissions and their driving forces in China using the integrated two nighttime light datasets. *Applied Energy*, 235, 612-624. http://doi.org/10.1016/j.apenergy.2018.09.180

Zheng, H., and He, Y. (2022). How does industrial co-agglomeration affect high-quality economic development? Evidence from Chengdu-Chongqing Economic Circle in China. *Journal of Cleaner Production*, 371, 133485. http://doi.org/10.1016/j.jclepro.2022.133485

Zhou, X. Y., Zhou, D. Q., Zhao, Z. Y., and Wang, Q. W. (2022). A framework to analyze carbon impacts of digital economy: The case of China. *Sustainable Production and Consumption*, 31, 357-369. http://doi.org/10.1016/j.spc.2022.03.002

Zhou, Y., Chen, M., Tang, Z., and Zhao, Y. (2022). City-level carbon emissions accounting and differentiation integrated nighttime light and city attributes. *Resources Conservation and Recycling*, 182, 106337. http://doi.org/10.1016/j.resconrec.2022.106337

Zhu, C. (2019). Big Data as a Governance Mechanism. *Review of Financial Studies*, 32(5), 2021-2061. http://doi.org/10.1093/rfs/hhy081

Zhu, J., Fan, Y., Deng, X., and Xue, L. (2019). Low-carbon innovation induced by emissions trading in China. *Nature Communications*, 10(1), 4088.

Zhu, X. H., Zou, J. W., and Feng, C. (2017). Analysis of industrial energy-related CO2 emissions and the reduction potential of cities in the Yangtze River Delta region. *Journal of Cleaner Production*, 168, 791-802. http://doi.org/10.1016/j.jclepro.2017.09.014