Sustainable Futures 10 (2025) 100858

Contents lists available at ScienceDirect

Sustainable Futures

journal homepage: www.sciencedirect.com/journal/sustainable-futures

Digital economy, energy consumption and urban carbon emission reduction: empirical evidence from 278 cities in China

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ARTICLE INFO

Keywords:
Digital economy
Energy consumption
Carbon emissions
Non-linear relationships
Spatial spillover effect

ABSTRACT

The intensifying challenge of global climate change has made accelerating energy conservation and emission reduction an urgent global imperative. As one of the world's largest carbon emitters, China plays a pivotal role in global decarbonization efforts. The digital economy, emerging as a key driver of China's economic transformation, provides novel pathways for advancing carbon reduction. This paper employs kernel density estimation and ArcGIS 10.8 to analyze the spatiotemporal dynamics of the digital economy and urban carbon emissions in China. Using panel data from 278 prefecture-level cities, the study applies fixed-effects models, mediation effect models, and spatial Durbin models to explore the mechanisms and spatial impacts of the digital economy on carbon reduction. The findings reveal that: (1) the development of the digital economy exerts a significant "inverted U-shaped" influence on urban carbon emission reduction; (2) energy consumption intensity is the critical mechanism underlying the nonlinear relationship between the digital economy and carbon emissions; (3) the digital economy's impact on carbon emissions exhibits spatial spillover effects, following a similar "inverted U-shaped" trajectory. These results contribute valuable empirical insights into the dual objectives of digital economic growth and carbon emission reduction, offering policymakers guidance on leveraging digitalization to achieve sustainable and coordinated regional development.

1. Introduction

Excessive greenhouse gas emissions have made global warming a pressing concern for nations worldwide, posing severe threats to human survival and sustainable development [1]. Addressing climate change has thus become a global consensus. In response to the escalating climate crisis, the Chinese government has intensified its environmental protection efforts. In 2020, China pledged at the United Nations General Assembly to achieve carbon peaking by 2030 and carbon neutrality by 2060. The "dual carbon" policy is not only a pivotal measure to enhance China's energy conservation and emission reduction but also a critical contribution to global climate governance. Historically, China's economic growth has been driven predominantly by secondary industries, prioritizing economic gains while overlooking environmental costs. This has led to a resource-intensive, high-consumption, high-pollution, and low-efficiency economic model, exacerbating resource constraints and environmental pressure [2]. According to publicly available data from the National Energy Administration and the National Bureau of Statistics, China's total energy consumption and carbon dioxide emissions in 2023 reached 5.72 billion tons and 12.6 billion tons, respectively—an increase of 5.7 % and 4.92 % from the previous year. These represent the highest annual growth rates worldwide to date and reflect the continued trajectory of carbon-intensive economic expansion in China following the COVID-19 pandemic. This trend not only poses challenges to China's ecological environment and sustainable development but also adds significant pressure to global climate change efforts.

Concurrently, the rapid development of China's digital economy has emerged as a crucial driver of stable economic growth, offering new avenues for energy conservation and emission reduction. According to the China Digital Economy Development Report (2023), the scale of China's digital economy reached 53.9 trillion yuan in 2023, with a nominal year-on-year growth rate of 10.3 %, accounting for 42.8 % of GDP. The National Bureau of Statistics defines the digital economy as a series of economic activities that use data as a core production factor, modern information networks as key infrastructures, and information and communication technologies to enhance efficiency and optimize

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https://doi.org/10.1016/j.sftr.2025.100858
Received 9 December 2024; Received in revised form 22 May 2025; Accepted 13 June 2025
Available online 14 June 2025

economic structures.[1] This encompasses green, coordinated, and shared development principles, whereby the digital economy can reduce urban carbon emissions by enhancing energy efficiency and breaking geographical constraints. Emerging technologies fueled by the digital economy — such as artificial intelligence — can significantly enhance energy efficiency [3] and optimize the structure of energy consumption [4,5], thereby helping to reduce the share of energy-intensive industries in China's urbanization process and contributing to urban carbon emission reduction [6].

As crucial platforms for digital economy development, cities face a pressing challenge: how to harness the rapid growth of the digital economy while balancing environmental benefits [7]. During this critical stage of China's low-carbon transition, fully unlocking the potential of the digital economy to drive urban low-carbon development is not only a key pathway toward achieving the country's "dual carbon" goals, but also offers valuable insights for promoting global sustainable development.

Against this backdrop, this paper seeks to explore the following research questions: How the digital economy affects urban carbon emission intensity? How this relationship is shaped by energy intensity? Whether the carbon reduction effects of the digital economy exhibit spatial spillovers?

To address these questions, we first calculate the carbon emission intensity and digital economy index for 278 Chinese cities from 2011 to 2021, employing kernel density estimation and spatiotemporal evolution map to analyze the spatiotemporal dynamics of digital economy development and carbon emission intensity. Second, we construct fixed-effects models and mediation effect models to examine the nonlinear relationship between digital economy development and urban carbon emission intensity, focusing on the dominant role of energy consumption intensity. Finally, we employ a bidirectional fixed spatial Durbin model to explore the spatial spillover effects of digital economy development on carbon emission intensity.

The potential marginal contributions of this study are threefold:

(1) While most existing studies on China's digital economy rely on provincial-level data, this study constructs a digital economy development index for 278 Chinese cities using principal component analysis, and further investigates both the direction and mechanisms through which the digital economy influences carbon emission intensity.
(2) Unlike the majority of existing literature that examines linear or unidirectional mechanisms, this study introduces energy intensity as a mediating variable and empirically identifies a nonlinear relationship between the digital economy and carbon emission intensity based on a mediation effect model.
(3) Building on the analysis of this nonlinear relationship, the study further explores the potential spatial spillover effects of the digital economy on carbon emission intensity across cities, providing empirical evidence for how the digital economy may facilitate inter-city coordination in carbon reduction.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature to identify existing research gaps. Section 3 presents the theoretical framework and research hypotheses. Section 4 briefly introduces the methodology and data. Section 5 analyzes the spatiotemporal evolution of digital economy development and carbon emissions in China using kernel density estimation with MATLAB and ArcGIS10.8. Section 6 discusses the empirical results. Section 7 summarizes the key conclusions and proposes targeted policy recommendations. Finally, Section 8 reflects on the limitations of this study and suggests directions for future research.

[1] Source: https://www.stats.gov.cn/hd/cjwtjd/202302/t20230207_1902279.html

2. Literature review

2.1. Related research on the digital economy

2.1.1. Measurement of digital economy

Currently, there is no unified standard for measuring the digital economy, and various accounting methods have been proposed in academic research. Internationally, measurement approaches are generally categorized into two types: the direct method and the comparative method. The direct method involves estimating the scale of the digital economy within a defined scope by collecting relevant data for a specific region (DEBA, 2018[2]). The comparative method, on the other hand, assesses the relative development of the digital economy across different regions by using multidimensional indicators (OECD, 2017; ITU, 2015[3]).

In China, scholars predominantly adopt comprehensive evaluation frameworks to measure the development of the digital economy. Existing studies primarily follow two approaches in selecting indicators. The first approach is based on the digital economy industry framework developed by the China Academy of Information and Communications Technology (CAICT, 2020). This framework distinguishes between "digital industrialization" and "industrial digitalization" and selects corresponding secondary indicators for comprehensive measurement [8–10]. The second approach constructs indicators based on the practical context, scientific connotations, and developmental characteristics of the digital economy [11–13].

2.1.2. Spatial evolution patterns and driving factors

Existing studies indicate that China's digital economy is steadily advancing, with a spatial distribution characterized by a pronounced "east-high, west-low" gradient [14,15]. Additionally, the digital economy exhibits significant spatial agglomeration and polarization effects [16,17]. Furthermore, various studies have identified key drivers of regional digital economy development, including economic growth, government intervention, human capital, and household income level [18,19].

2.1.3. Practical functions

With the deepening of research on the digital economy, an increasing body of literature suggests that the rise of the digital economy has played a significant role in alleviating the pressure of intergovernmental economic competition [20], upgrading household consumption structures [21,22], and promoting technology transfer [23]. Moreover, the digital economy stimulates entrepreneurship and enhances employment quality [24], advances industrial upgrading [25], and narrows the urban-rural income gap [26,27]. In addition, it enhances the relative welfare of low- and medium-skilled worker [28] and facilitates China's high-quality development [29–31].

2.2. Research on carbon emissions

2.2.1. Measurement methods and distribution characteristics

Given the inherent difficulties in directly measuring the total volume of carbon dioxide emissions generated across all sectors of economic and social activity, there is currently no official statistical indicator for carbon emissions in China. Nevertheless, a growing body of academic and institutional research has proposed various estimation approaches. Among the most commonly adopted methods are the carbon emission factor approach [32,33], the input-output method [34,35], and the super-efficiency Slack-Based Measure (SBM) model [36].

[2] Source:The Digital Economy Advisory Committee (DEBA) of the U.S. Department of Commerce released its ***First Report on the Digital Economy Committee***.

[3] Source:The International Telecommunication Union published the ***Measuring the Information Society*** Report in 2015..

In terms of overall distribution, existing research indicates that although China's total carbon dioxide emissions have continued to rise, the rate of increase has slowed, and carbon emission intensity has shown a clear downward trend. At the same time, significant changes have emerged in the internal structure of emission sources. Spatially, carbon emissions exhibit a pronounced pattern of "higher in the east and north, lower in the west and south," along with spatiotemporal dynamics marked by both agglomeration and differentiation [37,38].

2.2.2. Influencing factors

Domestic and international studies have identified key factors influencing carbon emissions, including economic growth [39], energy consumption intensity [40,41], industrial structure transformation [42, 43], and financial development [44]. Other factors such as environmental regulations [45], pilot policies for "zero-waste" cities [46,47], artificial intelligence technologies [48,49], green technological innovation [50,51], and have been shown to significantly impact carbon emissions.

2.3. Research on the digital economy and carbon emissions

Amid the escalating global climate crisis and the strategic implementation of China's dual carbon goals, the role of the digital economy in promoting energy efficiency and reducing emissions has increasingly become a focal point of academic inquiry in both domestic and international research. Empirical studies by Yi et al. [52] and Yan et al. [53] have demonstrated that the digital economy can significantly reduce carbon intensity, with region-specific effects. In addition to its direct impact on carbon reduction, several studies such as Li and Wang [54] and Bai et al. [55], have revealed a potential nonlinear relationship between the digital economy and carbon emissions—characterized by an initial intensification followed by a subsequent mitigation. Moreover, the associated spatial spillover effects have been found to exhibit an inverted-U shaped pattern.

Regarding the mechanisms through which the digital economy drives urban carbon reduction, existing studies indicate that it can facilitate reductions through multiple pathways, such as energy structure transformation [54,56], ICT industry development [53], industrial structure optimization [57], technological advancement [52], consumption structure upgrades [58], and enhancing household income [59].

2.4. Research gap and contributions

Through a synthesis of the existing literature, it is evident that substantial research has been conducted on digital economy, carbon emissions, and the impact of the digital economy on carbon emissions, providing a solid theoretical foundation for this study. However, current research still faces several limitations: (1) There is a lack of uniformity in the methods used to measure the level of digital economy development and carbon emissions, with varying results depending on the perspective taken. Most studies focus on the provincial level, and measurements at the city level remain underdeveloped. (2) Existing research on the mechanisms between the two has mainly been based on linear models, and further exploration of the nonlinear relationship between digital economy and carbon emissions is needed. (3) Although some studies have explored the spatial spillover effects of the digital economy, much of this research remains in its early stages, with insufficient investigation into the synergistic carbon reduction effects of digital economy and the differences in their impacts.

Against this backdrop, this study seeks to address the following three gaps in the existing literature: (1) Based on the conceptual foundations of both the digital economy and carbon emissions, we establish a comprehensive evaluation framework for measuring digital economy development and defining the scope of carbon accounting at the urban level. While previous research has examined digital economy development to some extent, there remains a lack of refined measurement at the city level, which this study aims to improve. (2) We investigate the dynamic impact of the digital economy on urban carbon emission intensity, with a particular focus on identifying the key mechanism of their nonlinear relationship from the perspective of energy consumption intensity. (3) We emphasize the spatial spillover effects of the digital economy. Although prior literature has explored its emission reduction effects, limited attention has been given to its spatial interdependencies. By focusing on the regional coordination effects of the digital economy in facilitating urban carbon reduction, this study provides empirical evidence to support city-level collaborative mitigation strategies.

3. Theoretical mechanism analysis and research hypotheses

3.1. The carbon mitigation effects of the digital economy

With the deepening integration of digital technologies and the improvement of digital infrastructure, the environmental benefits of the digital economy have become increasingly evident. These benefits are reflected in the following three aspects:

First, by fostering collaborative innovation and technological advancement, the digital economy significantly enhances urban energy efficiency. Leveraging vast amounts of data and information, it facilitates coordination and interaction among economic agents, giving rise to emerging technologies and business models—such as artificial intelligence—that substantially improve energy use efficiency and accelerate the transition of the energy structure, thereby curbing carbon emissions [60].

Second, the digital economy drives the digital transformation of Chinese manufacturing enterprises, contributing to emission reductions [61]. In response to the "dual carbon" goals, manufacturing firms in China are under growing pressure to digitalize. The emergence of the digital economy helps alleviate the technological constraints associated with this transformation, while innovations such as digital financial tools ease financing bottlenecks, further facilitating the transition. The application of information and communication technologies (ICTs) enhances production flexibility, spurs technological upgrading, and promotes structural optimization—ultimately contributing to lower carbon emissions [62].

Third, the development of the digital economy generates positive social externalities. It raises public awareness of green and low-carbon lifestyles, and digital technologies not only improve living standards but also reshape consumer preferences. The increasing demand for energy-saving and low-carbon products and services promotes a societal shift toward sustainable consumption patterns [58].

3.2. The carbon-enhancing effects of the digital economy based on energy consumption intensity

Due to the high demand for dense technologies and equipment required for its operation and development, the digital economy may lead to substantial energy consumption in its early stages, thereby exerting upward pressure on urban carbon emissions. This effect can be observed in the following three aspects:

First, the digital economy intensifies energy consumption and carbon emissions in its early development stage due to its reliance on energy-intensive infrastructure. The operation of the digital economy depends heavily on data centers and network facilities, the production and maintenance of which consume considerable amounts of electricity. Given that China's energy mix is predominantly coal-based, increased electricity use inevitably results in higher coal consumption and, consequently, higher carbon emissions. With the widespread adoption of technologies such as cloud computing, big data, and artificial intelligence, the environmental impact of ICT extends beyond device efficiency to encompass the full lifecycle of equipment production, operation, and disposal—posing complex environmental challenges [63].

Second, while many digital economic activities appear to be low-carbon or even carbon-neutral, they may lead to indirect or “hidden” carbon emissions through the emergence of new industries. For instance, although online shopping reduces carbon emissions from consumer travel, it increases energy consumption associated with logistics and transportation. Empirical studies have confirmed this phenomenon; Lenzen et al. [64] found that the carbon footprint of e-commerce is primarily derived from logistics and warehousing activities.

Third, under the pressure of achieving the “dual carbon” goals, Chinese manufacturing enterprises are undergoing rapid digital transformation. However, in the initial stage of this transition, the replacement of production equipment and industrial restructuring may prompt firms to increase input intensity and energy usage in order to scale up output, which in turn elevates carbon emissions.

In summary, the initial phase of digital economy development is characterized by a strong demand for digital manufacturing sectors. However, due to the relative immaturity of supporting technologies, these industries are unable to offset the resulting surge in energy consumption. Consequently, carbon emissions are likely to increase in the short term. Therefore, this study posits that in its early stage, the digital economy does not suppress carbon emissions; instead, it contributes to increased energy intensity and, subsequently, higher carbon emissions. This implies that the relationship between the digital economy and carbon emissions is not linear, but follows an inverted-U shaped nonlinear pattern. Based on this rationale, the first and second hypotheses are proposed and denoted as **H1** and **H2**.

H1: The relationship between the digital economy and carbon emission intensity follows an “inverted U-shaped” nonlinear pattern, initially increasing before later suppressing emissions.
H2: The digital economy impacts urban carbon emission intensity through a nonlinear effect on energy consumption, first increasing and then decreasing it.

3.3. Spatial spillover effects of digital economy in promoting carbon reduction

The carbon-reduction effect of the digital economy may exhibit a certain degree of spatial spillover, meaning that the development of the digital economy in one locality not only curbs local carbon emissions but may also contribute to emission reductions in neighboring regions. This spatial spillover effect of the digital economy manifests in the following three aspects:

First, technological spillovers associated with the digital economy may lead to the voluntary or involuntary diffusion of digital technologies from a given locality to adjacent regions during the process of promoting digital development [65]. As an economic factor, the digital economy is not constrained by spatial isolation; it alleviates information asymmetry and mitigates the traditional difficulties of economic interaction caused by geographic distance [66].

Second, core cities with relatively advanced digital economy development may drive the improvement of digitalization in neighboring cities. When a particular city accelerates its digital transformation, nearby cities may engage in adaptive behavior based on the "demonstration effect" or "imitation effect" [67], adjusting their own production models and industrial structures to enhance their digital economic development.

Third, carbon dioxide emissions are characterized by negative externalities and inherent spatial spillover. An increase in carbon emissions in one locality can affect the air quality and carbon levels in adjacent areas. Accordingly, cities with advanced digital development may exert an involuntary driving force on neighboring cities, generating positive externalities for regional carbon reduction.

Based on this reasoning, the following hypothesis is proposed as **H3**:

H3: The nonlinear impact of the digital economy on urban carbon emission intensity may exhibit spatial spillover effects.

Building on the above theoretical analysis, this study categorizes the impact mechanisms of the digital economy on carbon emissions into three main pathways: the carbon-reduction effect of the digital economy, the carbon-enhancing effect based on energy consumption intensity, and the spatial spillover effect. The conceptual framework of this study is illustrated in Fig. 1.

4. Empirical design

4.1. Model construction

4.1.1. Kernel density estimation

To explore the dynamic evolution characteristics of the Digital Economy Development Index and carbon emission intensity in China, this paper applies kernel density estimation to the core explanatory variables and dependent variables, and draws kernel density curves. Kernel density estimation (KDE) is a non-parametric method that estimates an unknown density function directly from the sample. It uses continuous density curves to describe the distribution characteristics of random variables [68,69]. The kernel density estimation formula is as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - X}{h}\right)$$

Where $K\left(\frac{x-X_i}{h}\right)$ is the kernel function, h is the bandwidth, n is the number of observations, X_i is the observation value, and x is the mean of the observations. In this study, a Gaussian kernel function is used. The position of the curve distribution reflects the relative levels of each variable, while the height and width of the peaks characterize the spatial differences. The distribution's spread reflects the spatial differences between the highest (or lowest) value regions and other areas, and the number and shape of the peaks indicate the degree of polarization.

4.1.2. Fixed effects model

Based on the above three hypotheses, first, in order to study the relationship between the digital economy and carbon emission intensity, a two-way fixed effects model is constructed, denoted as Model 1. The specific form is as follows:

$$Cei_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2\ Dig_{it}^2 + \sum \alpha_3 Controls_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \tag{1}$$

4.1.3. Mediation effect model

Next, based on the perspective of energy consumption intensity, the main mechanism through which the development of the digital economy non-linearly affects urban carbon emissions is explored. A stepwise regression mediation effect model is constructed, denoted as Model 2. The specific form is as follows:

$$\begin{aligned} Pegh_{it} &= \beta_0 + \beta_1 Dig_{it} + \beta_2\ Dig_{it}^2 + \sum \beta_3 Controls_{it} + \mu_i + \vartheta_t + \varepsilon_{it} Cei_{it} \\ &= \beta_0 + \beta_1 Dig_{it} + \beta_2\ Dig_{it}^2 + \beta_3 Pegh_{it} + \beta_4 (Pegh)_{it}^2 + \sum \beta_5 Controls_{it} \\ &\quad + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

4.1.4. Spatial durbin model

Finally, in order to study the spatial effects of the digital economy on carbon emissions, this research is based on the first law of geography from existing literature. A spatial weight matrix is constructed using the inverse distance between two locations, based on the inverse distance matrix, named W_1:

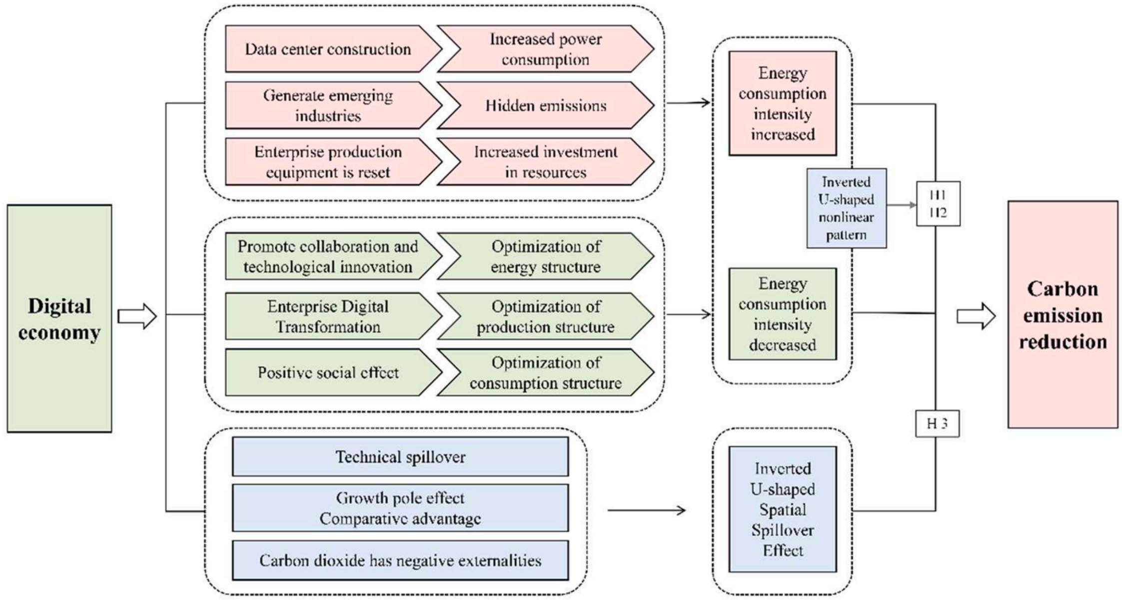

Fig. 1. Mechanisms of the digital economy to promote carbon emission reduction in cities.

$$W_2 = \begin{cases} GDP_i * GDP_j \Big/ d_{ij}^2 & ,i \neq j \\ 0 & ,i = j \end{cases}$$

Where d_{ij} denotes the center distance between city i and city j.

In addition, based on model robustness considerations, this study also constructs an economic geospatial matrix about the combination of geographic location and economic linkages based on the gravity model W_2:

$$W_2 = \begin{cases} GDP_i * GDP_j \Big/ d_{ij}^2 & ,i \neq j \\ 0 & ,i = j \end{cases}$$

Where d_{ij} denotes the center distance between city i and city j, the GDP is selected and averaged to measure the GDP per capita from 2011 to 2021.

Based on the two spatial weight matrices constructed above, this paper uses the global Moran' I index in the exploratory spatial data analysis ESDA to test the spatial autocorrelation between the urban digital economy and the urban carbon emission intensity, and the formula of Moran' I index is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

Based on the above series of test results, in order to verify the spatial spillover effect of the digital economy, this paper constructs a spatial Durbin model with time and individual double-fixed, which is denoted as Model III, in the following form:

$$\begin{aligned} Lncei_{it} = {} & \delta_0 + \rho WLncei_{it} + \delta_1 Lndigzcf_{it} + \delta_2 Ln(digzcf)_{it}^2 + \sum \delta_3 Controls_{it} \\ & + \gamma_1 WLndigzcf_{it} + \gamma_2 WLn(digzcf)_{it}^2 + \sum \gamma_3 WControls_{it} + \sigma_i + \varphi_t \\ & + \varepsilon_{it} \end{aligned} \tag{3}$$

4.2. Variable selection

4.2.1. Dependent variable

Carbon Emission Intensity (Cei). The total carbon dioxide emissions for each city at the prefecture level were first calculated for each year, and then the total carbon emissions were divided by the Gross Domestic Product (GDP) of the region to obtain carbon emission intensity (Cei), which was then log-transformed.

The calculation of total carbon dioxide emissions follows the method of Cong et al. [34], which involves summing emissions from three major scopes: Scope 1 refers to all direct emissions within the city's jurisdiction, including emissions from transportation, construction, industrial production processes, agriculture, forestry, land-use changes, and waste management activities; Scope 2 refers to indirect emissions associated with energy consumption outside the city's jurisdiction, including emissions from electricity, heating, and/or cooling purchased to meet urban consumption; Scope 3 refers to indirect emissions from activities within the city that occur outside the jurisdiction, but excluding Scope 2 emissions, such as the emissions generated from the production, transportation, use, and disposal of all goods purchased from outside the city.

4.2.2. Core explanatory variable

Digital Economy Development Index (Dig). Based on the research by Zhao et al. [29], and considering the availability of relevant data at the city level, the digital economy development level was measured using principal component analysis, with a focus on both internet development and digital inclusive finance.

For measuring internet development, the method of Huang et al. [70] was followed, using indicators such as internet penetration rate (number of internet users per 100 people), employment related to information technology (proportion of computer services and software workers), telecommunications output per capita, and mobile phone penetration rate (number of mobile phone users per 100 people). For measuring digital inclusive finance, the Chinese Digital Inclusive Finance Index, jointly developed by Peking University Digital Finance Research Center and Ant Financial, was used [71]. Additionally, to explore the potential non-linear relationship between digital economy and carbon emissions, the squared term of the Digital Economy Development Index (Dig2) was added to the model. Details of the indicator construction can be found in Table 1.

4.2.3. Control variables

After analyzing the methods for measuring carbon emission intensity and reviewing existing research, the following control variables were selected:

Economic Development Level (Pgdp): Real per capita GDP.

Urbanization Rate (Urb): The proportion of the urban population in the total population.

Table 1
Indicators for building digital economy in Chinese cities.

Level indicators	Secondary indicators	Tertiary indicators	Indicator properties
Digital Economy Development Index	Internet penetration	Internet users per 100 population	+
	Relevant practitioners	Percentage of employees in computer services and software	+
	Status of related outputs	Total telecommunication services per capita	+
	Cell phone penetration rate	Cell phone subscribers per 100 population	+
	Digital Inclusive Finance	China Digital Financial Inclusion Index	+

Degree of Industrialization (Decy): The ratio of the secondary industry's added value to GDP.

Degree of Openness (Fdi): The ratio of actual foreign direct investment to GDP.

Greening Level (Lhcd): The city's green space coverage rate.

To eliminate the effect of heteroscedasticity on the results, all control variables were log-transformed in this study.

4.2.4. *Mediating variable*

Energy Consumption Intensity (Pegh). Following the study by Chen [72], energy consumption was measured in terms of standard coal in tons, and the energy consumption level was further depicted by energy consumption per unit of GDP, which is inversely related to energy efficiency. The lower the energy consumption intensity, the lower the energy consumption per unit of GDP, indicating better energy efficiency. Similarly, to explore the mechanism of the non-linear relationship between digital economy and the dependent variable, the squared term of energy consumption intensity (Pegh2) was included in the analysis. The definitions and calculation formulas of all variables are presented in Table 2.

4.3. *Data sources and descriptive statistics*

This study selects panel data from 278 prefecture-level and above cities across China from 2011 to 2021 as the research sample. The data are sourced from the National Bureau of Statistics, the Digital Finance Research Center of Peking University, the National Energy Administration, *China City Statistical Yearbook*, and *China Urban-Rural Construction Statistical Yearbook*. Specifically, data for the sub-indicator of digital inclusive finance within the digital economy index are obtained from the officially authorized dataset provided by the Peking University research team, while total energy consumption data used to calculate energy consumption intensity are derived from the National Energy Administration.

To ensure the accuracy of the subsequent empirical analysis, the data are processed as follows: First, regions with continuous missing data across years are manually identified and excluded from the sample, while sporadic missing values are filled using a scientifically grounded linear interpolation method. Second, cities that were abolished during the study period (e.g., Chaohu and Laiwu) are also excluded. Third, to minimize the influence of outliers, the sample data are winsorized at the 5 % level from both tails.

As a result, the final sample covers approximately 82.8 % of prefecture-level and above cities, 47.6 % of China's land area, and 81.3 % of the national population, yielding a total of 3058 observations. Table 3 reports the descriptive statistics of each variable.

Table 2
The definitions and calculation formulas of variables.

Variable Type	Variable Name	Calculation Method
Independent Variable	Digital Economy Development Index	Constructed using a comprehensive indicator system
Dependent Variable	Urban Carbon Emission Intensity	Total CO_2 Emissions / Regional GDP
Control Variables	Economic Development Level	Real GDP per capita
	Urbanization Rate	Urban Permanent Population / Total Permanent Population
	Level of Industrialization	Value Added of Secondary Industry / Real GDP
	Degree of Openness	Actual Utilization of Foreign Investment / Real GDP
	Greening Level	Urban Green Coverage Rate
Mediating Variable	Energy Consumption Intensity	10,000 Tons of Standard Coal / Real GDP

5. Digital economy and carbon emission intensity: spatiotemporal evolution characteristics

5.1. *Dynamic evolution characteristics*

To investigate the dynamic evolution characteristics of China's Digital Economy Development Index and Carbon Emission Intensity, this study employs kernel density estimation to analyze the variables. Using MATLAB software, three-dimensional kernel density surface plots are constructed for both variables. Fig. 2 and Fig. 3 illustrate the kernel density estimates of China's carbon emission intensity and DEDI, respectively, from 2011 to 2021.

As shown in Fig. 2, the distribution of carbon emission intensity in China underwent significant changes during the study period. First, regarding the distribution pattern, the curve exhibits a left-skewed unimodal shape, indicating that most cities have achieved relatively low carbon emission intensity, reflecting substantial progress in low-carbon development. However, a small number of cities still maintain higher carbon emission intensity. Second, from a temporal perspective, the kernel density curves for carbon emission intensity shifted leftward from 2011 to 2021, accompanied by a reduction in peak values. This trend suggests a continuous decline in carbon emission intensity across cities over time, with the overall average level decreasing, indicating significant improvements in the carbon efficiency of economic output at the urban level. Furthermore, the widening of the kernel density curve suggests that inter-city disparities in carbon emission intensity have increased, reflecting heterogeneous progress in economic growth models, industrial restructuring, and the adoption of low-carbon technologies among cities.

Fig. 3 reveals that China's digital economy development demonstrates a coexistence of overall advancement and uneven regional progress. First, in terms of distribution characteristics, the kernel density curves consistently exhibit a unimodal pattern across all years, with most cities concentrated in the moderate range of digital economy development. No significant distributional bifurcation is observed, but a "polarization" trend among leading cities has become increasingly prominent. Second, from a temporal perspective, the rightward tail of the kernel density curves for DEDI gradually lengthens from 2011 to 2021, indicating substantial nationwide improvements in digital economy development over time. This reflects the sustained momentum of digital technology innovation, policy support, and the construction of digital infrastructure in recent years.

5.2. *Spatiotemporal differentiation characteristics*

To further study the spatiotemporal differentiation characteristics of China's digital economy and carbon emission intensity, this paper uses ArcGIS 10.8 software, based on the 2023 Survey Map No GS(2023)2765, to generate spatial distribution comparison maps for the digital economy development index and carbon emission intensity in Chinese cities

Table 3
Descriptive statistics for each variable.

Variant	Variable Meaning	Observed value	Average value	Standard error	Minimum value	Maximum values
Cei	Carbon intensity	3058	1.149	0.549	0.123	3.151
Dig	Digital Economy Index	3058	0.470	0.015	0.456	0.682
Pgdp	The level of economic development	3058	10.741	0.561	8.773	12.456
Urb	Urbanization rate	3058	−0.621	0.266	−1.706	0.000
Decy	Industrialization	3058	3.781	0.290	2.250	4.444
Fdi	Degree of openness to the outside world	3058	0.016	0.017	0.000	0.181
Lhcd	Degree of greenery	3058	3.670	0.276	−0.942	4.557
Pegh	Energy intensity	3058	0.129	0.129	0.000	2.283

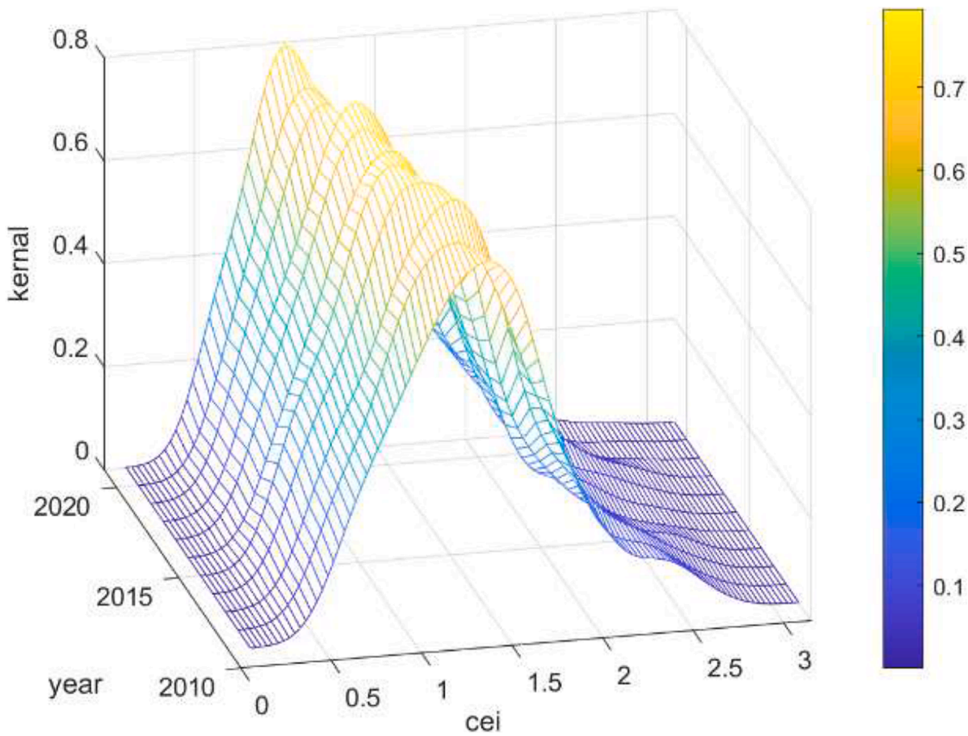

Fig. 2. (a) Kernel density curve of CEI.

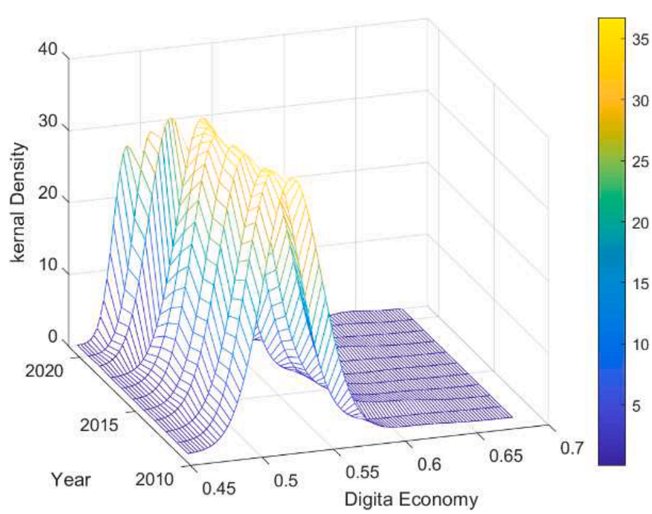

Fig. 3. (b) Kernel density curve of Dig.

for the years 2011, 2016, and 2021, as shown in Fig. 4. In these maps, the digital economy development is represented in green, while carbon emission intensity is represented in red. The varying shades of color reflect the level of digital economy development and the magnitude of carbon emission intensity.

Based on the spatiotemporal evolution of China's Digital Economy Development Index shown in the first row of Fig. 4, the following observations can be made. From a temporal perspective, the regions with high levels of digital economy development have expanded over time. The spatial distribution pattern has transitioned from a point-like structure centered on pilot cities to a more clustered pattern, with the overall color intensity deepening each year, indicating a continuous improvement in digital economy development across the country. From a spatial perspective, the distribution of digital economy development across Chinese cities exhibits significant heterogeneity and spatial agglomeration. Coastal regions generally demonstrate higher levels of digital economy development and display clustered spatial patterns, indicating that some high-performing areas exert a driving effect on the development of neighboring regions. This suggests a notable degree of spatial correlation in the development of the digital economy.

Regarding the spatiotemporal evolution of carbon emission intensity in Chinese cities, from a temporal perspective, carbon emission intensity has steadily declined over time. This indicates a reduction in the amount of carbon dioxide emitted per unit of GDP, further reflecting a gradual improvement in carbon emission efficiency. From a spatial perspective, carbon emission intensity also demonstrates notable heterogeneity and clustering effects. This phenomenon can be attributed to two primary

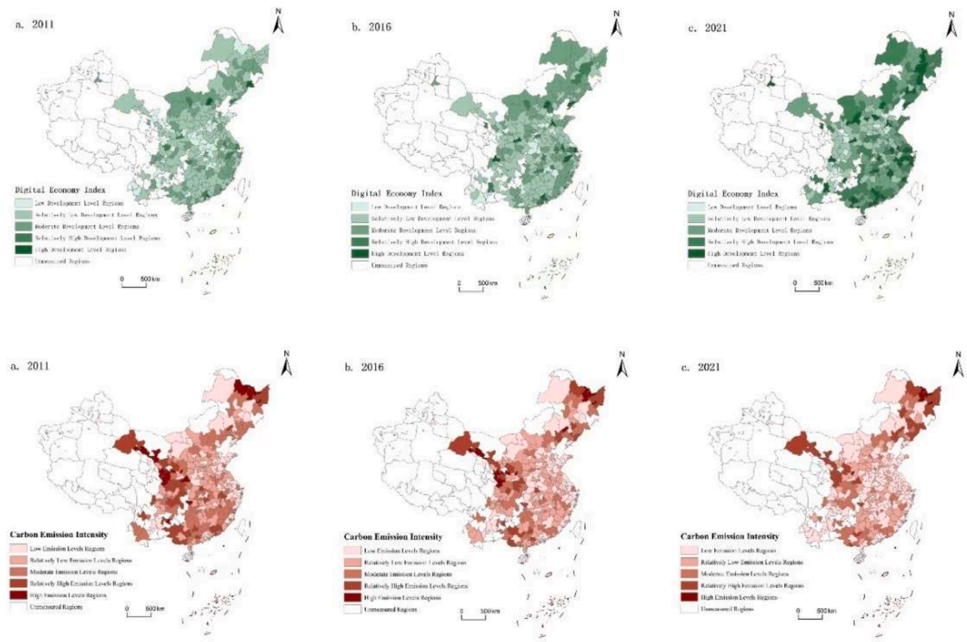

Fig. 4. Characteristics of the temporal and spatial evolution of China's digital economy index and carbon emission intensity in 2011, 2016 and 2021.

factors: the strong spatial mobility of carbon dioxide as a gas, and the imitation effects and comparative behaviors among neighboring cities regarding GDP metrics. These factors contribute to a spatially clustered pattern of carbon emission intensity.

A longitudinal comparative analysis from 2011 to 2021 reveals that while the overall level of digital economy development in China has steadily increased, carbon emission intensity has decreased year by year. This inverse relationship is most pronounced in the eastern and south-eastern coastal regions. Combined with the kernel density estimation results in Section 5.1, it can be preliminarily inferred that the development of the digital economy contributes to the reduction of urban carbon emission intensity.

6. Analysis of empirical results

6.1. Analysis of baseline regression results

To test **H1**, we conduct a baseline regression using fixed effects for panel data in Model (1), which is specified as follows:

$$Cei_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2\ Dig_{it}^2 + \sum \alpha_3 Controls_{it} + \mu_i + \vartheta_t + \varepsilon_{it}$$

Where i and t denote the prefecture level city and year respectively, μ_i and ϑ_t denote individual and time fixed effects respectively, and ε_{it} denotes the perturbation term; Cei_{it} denotes the carbon emission intensity of the ith prefecture-level city in year t; Dig_{it} denotes the digital economy development index of the ith prefecture-level city in year t; $\sum Controls_{it}$ denotes each control variable in year t of prefecture-level city i.

As shown in the regression results of Table 4, the coefficients of the

Table 4
Benchmark regression results.

Variables	(1) Cei	(2) Cei	(3) Cei	(4) Cei	(5) Cei	(6) Cei
Dig	7.205**	12.553***	11.713***	11.897***	11.457***	11.782***
	(2.49)	(5.02)	(4.71)	(4.85)	(4.72)	(4.89)
Dig2	−4.339**	−7.304***	−6.904***	−6.974***	−6.761***	−6.965***
	(−2.43)	(−4.73)	(−4.50)	(−4.60)	(−4.51)	(−4.68)
Pgdp		−0.061***	−0.062***	−0.058***	−0.057***	−0.057***
		(−30.90)	(−31.51)	(−29.06)	(−28.67)	(−28.91)
Urb			−0.149***	−0.140***	−0.127***	−0.111***
			(−6.31)	(−5.99)	(−5.47)	(−4.81)
Decy				−0.143***	−0.146***	−0.152***
				(−8.75)	(−9.04)	(−9.44)
Fdi					−1.473***	−1.454***
					(−7.71)	(−7.67)
Lhcd						−0.054***
						(−6.63)
Constant	−0.744	−2.108***	−1.947***	−1.457**	−1.271*	−1.132*
	(−0.92)	(−3.01)	(−2.80)	(−2.12)	(−1.86)	(−1.67)
Observations	3058	3058	3058	3058	3058	3058
R-squared	0.312	0.488	0.495	0.509	0.519	0.527
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, values in parentheses are standard errors, column (1) is the result without control variables, columns (2)-(6) are the results of adding the control variables of economic development level, greening, industrialization, financial development level, and openness to the outside world respectively.

core explanatory variable—the digital economy index—and its squared term are **−19.517** and **11.013**, respectively, both statistically significant at the 1 % level. After sequentially adding control variables, the signs and significance of the coefficients remain robust, providing preliminary evidence for an "inverted U-shaped" relationship between the digital economy and urban carbon emission intensity. This finding supports Hypothesis 1: the digital economy does not significantly contribute to carbon reduction in its early stage of development; instead, it initially intensifies carbon emissions. However, its emission reduction effect gradually emerges in later stages. Two primary reasons may explain this pattern:

1. In the early stages of development, the digital economy's high demand for digital technologies and equipment significantly increases electricity consumption in China, further exacerbating CO_2 emissions [54]. Meanwhile, the advancement of the "dual carbon" goals has encouraged a large number of heavy manufacturing enterprises to undergo digital transformation. Yet, in the initial phase of this transition, technological constraints and financing limitations have led to excessive resource input and energy consumption, thereby increasing carbon emissions [73, 74].
(2) As the digital economy continues to mature and technologies such as big data and artificial intelligence become more deeply integrated, the emergence of intelligent products and digital industries has significantly enhanced green economic efficiency [75], thus reducing urban carbon emissions.

It is worth noting that while many existing studies suggest that the development of the digital economy directly promotes carbon reduction [76,77], others argue that it may increase emissions [78]. Most of these studies are conducted at the provincial level in China. In contrast, this study focuses on city-level data, and the results reveal a nonlinear relationship between the digital economy and urban carbon emissions that first rises and then declines—a finding consistent with Li et al. [54].

6.2. Robustness tests

To test the robustness of the regression model in this study, we employed three methods: replacing the dependent variable, excluding municipalities directly under the central government, and conducting an endogeneity test. The specific regression results are presented in Columns (1) to (3) of Table 5. For the endogeneity issue, we used the two-stage least squares (2SLS) instrumental variable method for testing.

6.2.1. Substitution of the dependent variable

Considering the uneven economic development levels across cities, which may impact the regression results, we replace the dependent variable, carbon emission intensity, with the logarithm of total CO_2 emissions. The output results, shown in Column (1) of Table 5, indicate that after replacing the dependent variable, the coefficients of the core explanatory variable, the Digital Economy Index, and its quadratic term remain significant at the 1 % level, with positive and negative signs, respectively. This suggests that the digital economy indeed exerts a nonlinear effect on carbon emissions, first exacerbating and then suppressing them.

6.2.2. Excluding municipalities directly under the central government

Due to the significant differences in economic development and carbon emissions between China's municipalities directly under the central government and other prefecture-level cities, such differences may cause errors in the regression results. Therefore, we re-estimate the model after excluding the data for China's four municipalities—Beijing, Shanghai, Tianjin, and Chongqing—from the sample. The results, shown in Column (2) of Table 5, remain unchanged, with all variables still significant at the 1 % level, passing the robustness test.

6.2.3. Endogeneity test

Considering the potential endogeneity issue arising from the mutual causality between the digital economy and carbon emission intensity, we validate the reliability of the estimation results by using the number

Table 5
Robustness test results.

Variables	Substitution of the Dependent Variable	Excluding municipalities	Endogeneity test	
	(1)	(2)	(3)	
	Co2	Cei	First-Stage	Second-Stage
Dig	6.472***	11.892***		94.577***
	(2.79)	(4.89)		(5.37)
Dig2	−3.489**	−7.052***		−57.946***
	(−2.43)	(−4.69)		(−5.34)
Pgdp	0.025***	−0.057***	0.001***	−0.061***
	(16.12)	(−28.08)	(3.00)	(−24.38)
Urb	0.273***	−0.109***	−0.015***	−0.068**
	(14.55)	(−4.66)	(−6.63)	(−2.36)
Decy	−0.180***	−0.152***	0.002	−0.157***
	(−13.84)	(−9.35)	(1.25)	(−8.18)
Fdi	−0.641***	−1.511***	−0.053***	−1.298***
	(−3.47)	(−7.75)	(−2.83)	(−5.69)
Lhcd	0.007	−0.054***	0.001	−0.060***
	(0.85)	(−6.59)	(0.92)	(−6.11)
Lniv1			−0.034***	
			(−11.15)	
Lniv2			0.038***	
			(12.09)	
Constant	6.815***	−1.165*	0.545***	
	(10.43)	(−1.70)	(44.84)	
Under identification test			73.725***	73.725***
Weak identification test			37.622	37.622
			(19.93)	(19.93)
Observations	3058	3014	3058	3058
R-squared	0.452	0.521	0.289	0.325
F statistics	326.8	174.3	66.02	127.5

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, the values in parentheses are standard errors, column (1) is the regression result replacing the explained variable, column (2) is the regression excluding municipalities, and column (3) is the regression result of 2sls.

of post offices per 100 people and the number of fixed telephones per 100 people in 1984 as instrumental variables, following the approach by Huang et al. [70]. The regression results in Column (3) show that the instrumental variables pass both the over-identification test and the weak instrument test, indicating a sufficiently strong correlation with the endogenous variables, thus confirming their validity as instruments for the endogeneity test. Further regression using the instrumental variables method reveals that the first and second-order terms of the core explanatory variable, the Digital Economy Index, remain significantly positive and negative at the 1 % confidence level, respectively. This suggests that even after addressing the endogeneity issue, there still exists a nonlinear relationship between the development of the digital economy and carbon emission intensity in Chinese cities.

6.3. Mechanism analysis

To verify the mediating effect of energy consumption intensity in this study, a stepwise regression analysis was conducted based on Model 2, with the regression results presented in Table 6. In line with the aforementioned hypothesis, this paper extends the baseline mediation model by incorporating the squared term of energy consumption intensity, in order to examine whether energy consumption intensity serves as the primary mechanism underlying the nonlinear relationship between the digital economy and carbon emission intensity. The specific model is formulated as follows:

$$
\begin{aligned}
Cei_{it} &= \alpha_0 + \alpha_1 Dig_{it} + \alpha_2\ Dig_{it}^2 + \sum \alpha_3 Controls_{it} + \mu_i + \vartheta_t + \varepsilon_{it} Pegh_{it} \\
&= \beta_0 + \beta_1 Dig_{it} + \beta_2\ (Dig)_{it}^2 + \sum \beta_3 Controls_{it} + \mu_i + \vartheta_t + \varepsilon_{it} Lncei_{it} \\
&= \beta_0 + \beta_1 Dig_{it} + \beta_2\ (Dig)_{it}^2 + \beta_3 Pegh_{it} + \beta_4 (Pegh)_{it}^2 + \sum \beta_5 Controls_{it} \\
&\quad + \mu_i + \vartheta_t + \varepsilon_{it}
\end{aligned}
$$

where i and t denote the prefecture-level city and year, respectively; μ_i and ϑ_t denote individual and time fixed effects respectively, and ε_{it} denotes the perturbation term; $Pegh_{it}$ represents the energy consumption intensity for the i th prefecture-level city in year t; Cei_{it} denotes the carbon emission intensity of the i th prefecture-level city in year t; Dig_{it} denotes the digital economy development index of the i th prefecture-level city in year t; $\sum Controls_{it}$ denotes each control variable in year t of prefecture-level city i.

Table 6
Mediation effect regression results.

Variables	(1) Cei	(2) Cei	(3) Cei
Dig	11.782***	3.558**	12.289***
	(4.89)	(2.53)	(5.12)
Dig2	−6.965***	−2.149**	−7.229***
	(−4.68)	(−2.46)	(−4.88)
Pegh			0.353***
			(4.89)
Pegh2			−0.342***
			(−5.45)
Pgdp	−0.057***	−0.001	−0.055***
	(−28.91)	(−1.43)	(−27.00)
Urb	−0.111***	0.179***	−0.123***
	(−4.81)	(15.76)	(−5.27)
Decy	−0.152***	−0.083***	−0.152***
	(−9.44)	(−10.52)	(−9.52)
Fdi	−1.454***	−0.437***	−1.458***
	(−7.67)	(−3.91)	(−7.73)
Lhcd	−0.054***	0.002	−0.055***
	(−6.63)	(0.40)	(−6.77)
Constant	−1.132*	−0.463	−1.326**
	(−1.67)	(−1.17)	(−1.97)
Observations	3058	3058	3058
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, Values in parentheses are standard errors, Column (1) is the result without the mediating variable, Column (2) is the regression result between the mediating variable and the explanatory variable, and Column (3) is the regression result of the mediating effect.

Column (2) of Table 6 reports the regression results between the mediating variable and the explanatory variable. The results show that the coefficients of both the linear and quadratic terms of the digital economy index are statistically significant at the 5 % confidence level, with values of **4.440** and **−2.705**, respectively. This indicates that the relationship between the development of the digital economy and energy consumption intensity also exhibits a nonlinear "inverted U-shape".

Further regression results from the mediation model reveal that, even after including energy consumption intensity and its squared term as mediators, the relationship between the digital economy and carbon emission intensity remains an inverted U-shape and is statistically significant at the 1 % level. Specifically, the coefficients of energy consumption intensity and its squared term are **0.234** and **−0.174**, respectively, both significant at the 1 % level. These findings suggest that energy consumption intensity constitutes the primary mechanism underlying the nonlinear relationship between the digital economy and carbon emission intensity. In other words, the digital economy influences urban carbon emissions through first increasing and then decreasing energy consumption intensity.

Furthermore, to rigorously examine the mediating role of energy consumption intensity, this study conducts a Bootstrap test on the mediating variable, with the results presented in Table 7. As shown, the indirect effect of energy consumption intensity is statistically significant at the 5 % level, and the 95 % confidence interval does not include zero, indicating the presence of a significant mediating effect. This confirms that energy consumption intensity serves as an effective mediating variable.

It is worth noting that Li et al. [79] argue that the digital economy functions as a moderating variable between energy structure and carbon emissions. In contrast, this study investigates the nonlinear relationship between the digital economy and carbon emissions, incorporating economic factors into the measurement of the energy consumption structure and employing energy consumption intensity as a mediating variable. The findings reveal that energy consumption intensity is the primary mechanism through which the digital economy exhibits an "inverted U-shaped" impact on carbon emissions. This conclusion is consistent with the studies of Yi et al. [80] and Wang [81], thereby confirming the validity of H2.

6.4. Spatial effect regression analysis

Based on the inverse distance matrix (W1) and economic geography matrix (W2) constructed in this study, global Moran's I statistics for both the dependent and independent variables were computed and tested. Table 8 presents the results.

Based on the above test results, it is evident that both the inverse distance matrix and the economic geography matrix show Moran's I indices for carbon emission intensity and digital economy index that are significantly greater than zero at the 1 % confidence level. This indicates a positive spatial correlation between carbon emissions and the development of the digital economy. Therefore, spatial effects should be considered when investigating the relationship between these two variables.

After conducting the Moran's I test, this study follows the approach of Elhorst [82] for model selection, employing both the

Table 7
Bootstrap test results.

	Observed coefficient	Bootstrap std. err.	Z -score	P > |Z|	Normal-based [95 % conf. interva]	
Ind_eff	−0.085498	0.0388996	−2.20	0.028	−0.1617	−0.00926
Dir_eff	−0.905116	0.5812778	−1.56	0.119	−2.0444	0.234167

Table 8
Moran's index test results.

Year	Inverse Distance Weight Matrix (W1)		Economic Geography Weight Matrix (W2)	
	Lncei	Lndigzcf	Lncei	Lndigzcf
2011	0.064***	0.031***	0.210***	0.109***
2012	0.059***	0.023***	0.197***	0.111***
2013	0.056***	0.011***	0.187***	0.119***
2014	0.061***	0.017***	0.201***	0.150***
2015	0.059***	0.016***	0.199***	0.170***
2016	0.068***	0.017***	0.175***	0.189***
2017	0.071***	0.010***	0.182***	0.189***
2018	0.072***	0.007**	0.163***	0.187***
2019	0.090***	0.059***	0.145***	0.160***
2020	0.091***	0.070***	0.149***	0.197***
2021	0.098***	0.066***	0.144***	0.166***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

"specific-to-general" and "general-to-specific" testing strategies. The results are shown in Table 9. First, due to the inherent heterogeneity of geographical locations and the influence of local policy changes, the fixed effects model is identified as the optimal choice. The Hausman test results in Table 9 reject the use of the random effects model at the 1 % significance level. Therefore, the fixed effects model is selected for further analysis. Additionally, the joint significance test for spatial and temporal effects indicates the presence of both spatial and temporal fixed effects, suggesting the adoption of an individual-time double-fixed effects model.

Furthermore, according to the "specific-to-general" testing approach, the LM test results reject the null hypothesis of the absence of both Spatial Autoregressive (SAR) and Spatial Error Models (SEM) effects, indicating the existence of spatial dependence. Given that neither the SAR nor SEM models can be excluded, a "general-to-specific" approach is subsequently employed to assess the applicability of the Spatial Durbin Model (SDM). The results of both the Likelihood Ratio (LR) test and the Wald test reject the null hypotheses that the SDM can be simplified to either the SAR or SEM model at the 1 % significance level. These findings confirm that the SDM is the most appropriate specification for capturing the spatial characteristics of the data.

Finally, based on the series of tests mentioned above, this study selects the double-fixed effects SDM for spatial econometric analysis, specifically Model (3), as shown below:

$$\begin{aligned} Cei_{it} = \ & \alpha_0 + \rho WCei_{it} + \alpha_1 Dig_{it} + \alpha_2 Dig_{it}^2 + \sum \alpha_3 Controls_{it} + \gamma_1 WDig_{it} \\ & + \gamma_2 WDig_{it}^2 + \sum \gamma_3 WControls_{it} + \sigma_i + \varphi_t + \varepsilon_{it} \end{aligned}$$

In this model, α_0 represents the intercept term, W denotes the spatial weight matrix, and σ_i, φ_t, ε_{it} represent the spatial effects, temporal effects, and disturbance term, respectively. The meanings of the independent and dependent variables remain as previously defined. Based on Model (3), this study employs the maximum likelihood estimation (MLE) method for estimation, with the results presented in Table 10.

Table 9
Model selection test results.

From specific to general	Statistic	*P*-value
LM-lag	324.121	0.000
R-LM-lag	211.380	0.000
LM-err	113.679	0.000
R-LM-err	0.938	0.333
From general to specific	**Statistic**	***P*-value**
LR test for SAR	38.01	0.000
Wald test for SAR	35.77	0.000
LR test for SEM	102.90	0.000
Wald test for SEM	153.88	0.000
Fixed-effects test		
Hausman test	76.288	0.000
LR joint statistics test	**LR statistic**	***P*-value**
Time effect	62.50	0.000
Spatial effect	11,225.84	0.000

According to the results presented in Table 10, the estimated coefficients of the endogenous interaction terms $WDig_{it}$ and $WDig_{it}^2$ under both spatial weight matrices are significantly positive and negative, respectively, at the 5 % significance level. This indicates that the digital economy exhibits significant spatial interaction effects—namely, the development of the digital economy in one city exerts a measurable impact on the carbon emission intensity of neighboring cities. Moreover, the nature of this spatial spillover effect also follows an inverted-U shaped pattern, suggesting that the digital economy initially intensifies, and subsequently mitigates, regional carbon emission intensity.

This finding is consistent with the spatial distribution patterns illustrated in Fig. 4, where cities with high carbon emission intensity are often surrounded by cities with similarly high emissions, and regions with more advanced digital economy development tend to cluster spatially. These results collectively confirm the existence of spatial spillover effects for both carbon emission intensity and digital economy development, highlighting the presence of pronounced regional transmission mechanisms.

Furthermore, drawing on the methodological contributions of LeSage, [83], a change in a specific explanatory variable in a given city not only affects the carbon emission intensity of that city itself but also alters the emission levels of neighboring cities. These changes, through feedback effects among cities, can in turn influence the originating city, thereby creating a network of spatial interdependencies. This phenomenon closely aligns with the regional transmission effects examined in this study.

Building upon the results presented in Table 10, this paper further conducts a partial derivative decomposition of the spatial regression estimates—including control variables—to quantify the direct, indirect (spillover), and total effects of each explanatory variable. The detailed results of this decomposition are reported in Table 11.

Based on the effect decomposition results in Table 11, the following conclusions can be drawn:

Table 10
Spatial panel regression results.

	Inverse Distance Matrix W1 (1)		Economic Geography Matrix W2 (2)	
	Main	Wx	Main	Wx
Dig	5.7228***	89.3778***	3.5160	23.70**
	(2.79)	(4.08)	(1.42)	(3.28)
Dig2	−3.1350**	−56.7360***	−2.1440	−14.26**
	(−2.46)	(−4.16)	(−1.36)	(−3.09)
Pgdp	−0.0326***	−0.0362***	−0.0628***	0.0324***
	(−16.04)	(−2.99)	(−32.20)	(7.56)
Urb	−0.1071***	−0.2819	−0.0537*	−0.0241
	(−5.34)	(−1.59)	(−2.56)	(−0.50)
Decy	−0.1375***	−0.5541***	−0.1540***	0.0198
	(−10.33)	(−3.60)	(−11.08)	(0.50)
Fdi	−0.1120	−12.0397***	−0.6960***	−3.7790***
	(−0.67)	(−7.50)	(−4.14)	(−7.72)
Lhcd	−0.0335***	−0.5336***	−0.0397***	−0.1120***
	(−5.02)	(−5.39)	(−5.65)	(−4.77)
Time FE	YES	YES	YES	YES
Spatial FE	YES	YES	YES	YES
N	3058	3058	3058	3058
Spatial rho	0.8722*** (23.98)		0.4750*** (17.22)	
Variance sigma2 e	0.0063*** (38.60)		0.0057*** (38.95)	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The values in parentheses represent the t-statistics. Column (1) presents the results of the main regression and interaction effects using the inverse distance matrix for the spatial panel model. Column (2) presents the results of the main regression and interaction effects using the economic distance matrix for the spatial panel model.

Table 11
Partial derivative regression results.

	Inverse Distance Matrix W1 (1)			Economic Geography Matrix W2 (2)		
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
Dig	8.6279***	789.3302**	797.958**	5.278*	44.35***	49.63***
	(3.72)	(2.40)	(2.42)	(2.23)	(4.40)	(5.03)
Dig2	−4.9788***	−498.1326**	−503.1114**	−3.216*	−26.67***	−29.89***
	(−3.44)	(−2.41	(−2.42)	(−2.16)	(−4.25)	(−4.93)
Pgdp	−0.0346***	−0.5683***	−0.6028***	−0.0625***	0.00567	−0.0569***
	(−16.15)	(−2.29)	(−2.43)	(−31.90)	(0.88)	(−8.60)
Urb	−0.1181***	−3.3821	−3.5003	−0.0559*	−0.0893	−0.145
	(−5.36)	(−1.25)	(−1.29)	(−2.41)	(−0.92)	(−1.40)
Decy	−0.1621***	−5.9501**	−6.1122**	−0.157***	−0.0980	−0.255**
	(−8.43)	(−1.94)	(−1.98)	(−10.09)	(−1.26)	(−3.05)
Fdi	−0.5053**	−108.8594**	−109.3647**	−1.030***	−7.606***	−8.636***
	(−2.27)	(−2.30)	(−2.30)	(−5.06)	(−7.42)	(−7.84)
Lhcd	−0.0513***	−4.8646	−4.9159	−0.0491***	−0.244***	−0.293***
	(−4.81)	(−2.16)	(−2.18)	(−6.81)	(−6.33)	(−7.00)
R-square	0.1883			0.333		
Time FE	YES			YES		
Spatial FE	YES			YES		
N	3058			3058		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The values in parentheses represent the t-statistics. Column (1) presents the regression results for the direct, indirect, and total effects using the inverse distance matrix. Column (2) presents the regression results for the direct, indirect, and total effects using the economic distance matrix.

(1) Direct Effects: First, the regression results for the direct effects show that, regardless of the weight matrix used (inverse distance or economic distance), the coefficients for the first and second-order terms of the digital economy's direct effects are both significantly positive and negative at the 10 % significance level. This indicates that, in the absence of interaction effects, the development of the digital economy has a nonlinear impact on local carbon emission intensity, with an initial positive effect followed by a negative effect. This is consistent with the previous analysis, suggesting that the digital economy exacerbates carbon emissions in its early stages, with the carbon reduction effect becoming more significant in later stages of development.

(2) Indirect Effects: Further analysis of the indirect effects reveals that the regression coefficients for the first and second-order terms of the core explanatory variable are significant at the 5 % level for both weight matrices, with coefficients also exhibiting an initial positive and then negative pattern. This suggests that the local development of the digital economy has spatial spillover effects on carbon emission intensity, with the spillover effects following a similar pattern. This implies that the development of the digital economy in a local city influences the carbon emission intensity of surrounding regions. The likely reason is that when the digital economy in a local city advances, neighboring cities, driven by a "demonstration effect", also strengthen their digital economy, which further impacts their carbon emission intensity.

In summary, the digital economy exhibits significant spatial spillover effects. Core cities with more advanced digital economic development exert positive externalities on surrounding areas, influencing not only their own carbon emission intensity but also that of neighboring cities. This finding is consistent with existing literature. For instance, Bai et al. [84], focusing on the Yangtze River Delta Urban Agglomeration, demonstrated that the development of the digital economy in core cities such as Shanghai and Hangzhou generated positive spatial spillovers to surrounding cities like Jiaxing and Huzhou, thereby enhancing the overall level of regional green innovation.

Notably, the results of this study further reveal that the spatial spillover effect of the digital economy on urban carbon emission intensity also follows an "inverted U-shaped" pattern. In the early stages of digital economic development, the construction of digital infrastructure led to increased carbon emissions both locally and in adjacent regions, indicating a strong regional transmission effect. As digital technologies further mature, the carbon-reduction benefits of the digital economy begin to take effect, fostering spatial linkages and facilitating collaborative carbon mitigation across regions. These findings provide empirical support for **H3** of this study.

7. Research conclusions and policy implications

This paper investigates the nonlinear relationship and underlying mechanisms between the development of the digital economy and urban carbon reduction, with a particular focus on energy consumption intensity. Based on a series of empirical analyses and robustness tests, the following conclusions are drawn:

(1) Nonlinear Relationship between Digital Economy Development and Carbon Emission Intensity. The relationship between the development of the digital economy and carbon emission intensity exhibits an "inverted U-shape" nonlinear pattern. In the early stages of digital economy development, it tends to exacerbate carbon emissions to some extent. However, as digital technologies mature, the energy-saving and carbon-reduction effects of the digital economy gradually emerge, thereby mitigating carbon emissions and fostering urban carbon reduction.

(2) Spatial Spillover Effects. Local carbon emission intensity is influenced not only by the development of the local digital economy but also by the factors in neighboring cities. The direction of this influence also follows an "inverted U-shape" pattern. Additionally, the development of the digital economy exhibits spatial spillover effects: the advancement of the digital economy in one city not only promotes local carbon reduction but also stimulates the digital economy in surrounding cities, thereby influencing their carbon emission intensities.

(3) Mechanism of the Nonlinear Relationship. The primary mechanism underlying the nonlinear relationship between digital economy development and carbon emission intensity is energy consumption intensity. The digital economy influences urban carbon emissions through its nonlinear interaction with energy consumption intensity, thereby establishing the "inverted U-shape" relationship between the two.

Based on the above findings and in light of the characteristics of urban development in China, the following policy recommendations are proposed:

(1) Fully leverage the carbon reduction potential of the digital economy and promote differentiated low-carbon transition strategies based on the stage of digital development. For cities with a mature digital economy (e.g., first-tier cities and provincial capitals in eastern coastal regions), the focus should be on greening digital infrastructure and accelerating the substitution of clean energy. This can be achieved by constructing green data centers and integrating AI computing with carbon budgeting systems to embed carbon neutrality into digital infrastructure. In contrast, cities in the early stages of digitalization (e.g., prefecture-level cities in central and western China) should prioritize the coordinated planning of digital infrastructure while guiding the development of low-carbon-oriented digital industries, thereby avoiding the "high energy consumption trap" of digital infrastructure.
(2) Strengthen the embedded design of energy efficiency mechanisms. Improving energy efficiency is essential to unlocking the carbon mitigation potential of the digital economy. It is recommended to promote a dual mechanism of “digital empowerment + energy efficiency constraints”, incorporating energy efficiency as a key criterion for project approval, fiscal support, and performance evaluation in digital economy investments. On one hand, the government should enhance environmental regulations and encourage enterprises to engage in digital transformation to reduce energy consumption during production. On the other hand, the deep integration of the digital economy with clean energy should be accelerated by using digital technologies to lower the development costs of clean energy and reduce dependence on coal-based power. A "carbon intensity elasticity regulatory mechanism" should be introduced, allowing for a flexible carbon intensity control range based on the level of digital economy development. This would involve tolerating higher energy consumption in early stages while imposing stricter constraints in later stages.
(3) Harness the spatial spillover effects of the digital economy and establish regional coordination mechanisms for collaborative carbon reduction. Given the spatial coupling between digital economy development and carbon mitigation, a coordinated governance mechanism should be established, linking core cities with surrounding node cities in a digitally driven low-carbon framework. Regional data, technology, and energy resources should be jointly allocated to promote synergetic development. Moreover, regionally integrated carbon reduction incentive policies should be designed, such as implementing carbon reduction performance-sharing mechanisms within urban agglomerations. This would allow digitally advanced cities to transfer part of their carbon reduction benefits to surrounding cities through carbon accounts, creating a redistribution mechanism of digital technologies and carbon efficiency across the region.

8. Limitations and future directions

Although this study systematically analyzes the nonlinear impact mechanism of the digital economy on carbon emission intensity and its spatial spillover effects based on panel data from 278 prefecture-level cities in China, several limitations should be acknowledged:

First, there are constraints related to the availability and consistency of city-level data. Due to the lack of a unified carbon emission accounting system at the city level, the carbon emission data used in this study are primarily estimated based on energy consumption and industrial activity intensity, which may introduce some degree of estimation error. Additionally, data for a few cities are missing. Although linear interpolation and other methods were employed to address these gaps, systematic bias may still be introduced. Furthermore, while the indicators used to measure digital economy development attempt to balance comprehensiveness and data availability, their construction relies on China-specific statistical systems (e.g., the Digital Inclusive Finance Index), which may lead to inconsistencies in statistical definitions across different cities.

Second, the generalizability of the findings is limited. The inverted U-shaped relationship between the digital economy and carbon emissions, as well as the identified spatial spillover effects, are derived from China’s specific stage of development, institutional context, and policy environment. These relationships may not hold in other countries or regions—particularly those with underdeveloped digital infrastructure, weak regional coordination mechanisms, or less stringent environmental regulations. Therefore, the international applicability of the conclusions should be considered with caution.

In light of these limitations, future research could be expanded in the following directions:

(1) Incorporating higher-resolution micro-level data, such as firm-level carbon emissions or satellite-based remote sensing data, to improve estimation accuracy;
(2) Conducting cross-country comparative studies to explore how the impact of the digital economy on carbon emissions varies under different institutional settings, thereby testing the robustness and universality of the conclusions;
(3) Integrating qualitative case studies to further uncover the behavioral mechanisms and institutional foundations through which the digital economy affects carbon emissions, thus enriching both the depth and breadth of existing research.

CRediT authorship contribution statement

Haiwen Sun: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chunling Tang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis. **Ping Gao:** Writing – review & editing, Validation, Supervision, Formal analysis. **Guoxiong Zhou:** Writing – review & editing, Validation, Resources.

Declaration of competing interest

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

Acknowledgements

This study was supported by the Project of Social Science Foundation of Hunan Province in 2022 (22YBA107).

Data availability

Data will be made available on request.

References

[1] B. Lin, China’s high-quality economic growth in the process of carbon neutrality, China Financ. Econ. Rev. 11 (2022) 3–22.
[2] Z. Zhang, Deepening reforms to transition from an extensive economic growth model, Econ. Res. J. 11 (2005) 4–9.
[3] Y. Xin, X. Chang, J. Zhu, How does the digital economy affect energy efficiency? Empirical; research on Chinese cities, Energy Environ.-UK 35 (2024) 1703–1728.
[4] Y. Xue, C. Tang, H. Wu, J. Liu, Y. Hao, The emerging driving force of energy consumption in China: does digital; economy development matter? Energy Policy 165 (2022).
[5] Q. Wang, Y. Li, R. Li, Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI), Human. Soc. Sci. Commun. 11 (2024) 1–18.
[6] C. Huang, B. Lin, Digital economy solutions towards carbon neutrality: the critical role; of energy efficiency and energy structure transformation, Energy 306 (2024).

[7] S. Shao, K. Zhang, J. Dou, Effects of economic agglomeration on energy saving and emission reduction: theory and empirical evidence from China, Manag. World 35 (2019) 24–42.
[8] W. Pan, Z. He, H. Pan, Research on spatiotemporal evolution and distribution dynamics of digital economy development in China, China Soft Sci. 10 (2021) 137–147.
[9] X. Zhou, Y. Liu, L. Peng, Development of digital economy and improvement of green total factor productivity, Shanghai Econ. Res. 12 (2021) 51–63.
[10] L. Wei, Y. Hou, Research on the impact of China's digital economy on urban green development, J. Quant. Tech. Econ. 8 (2022) 60–79.
[11] J. Wen, Z. Yan, Y. Cheng, Digital economy and upgrading regional innovation capacity, Inq. Into Econ. 11 (2019) 112–124.
[12] M. Chen, X. Zhang, The scale measurement and productivity analysis of China's digital economy, J. Quant. Technol. Econ. 39 (2022) 3–27.
[13] X. Wan, Y. Luo, Measurement of the development level of digital economy and its impact effect on total factor productivity, Reform (2022) 101–118.
[14] W. Li, W. Cui, P. Yi, Digital economy evaluation, regional differences and spatio-temporal; evolution: case study of Yangtze River economic belt in China, Sustain. Cities Soc. 113 (2024) 105685.
[15] D. Bai, M. Li, Y. Wang, S. Mallek, U. Shahzad, Impact mechanisms and spatial and temporal evolution of digital economy; and green innovation: a perspective based on regional collaboration; within urban agglomerations, Technol. Forecast. Soc. 207 (2024) 123613.
[16] H. Yu, Study on spatial correlation of digital economy and its driving factors in China, 2021, pp. 23–34.
[17] S. Cai, C. Gu, Z. Zhang, Research on temporal and spatial characteristics and influencing factors of China's provincial digital economy, East China Econ. Manag. 36 (2022) 1–9.
[18] J. Liu, Y. Yang, S. Zhang, Research on the measurement and driving factors of China's digital economy, Shanghai J. Econ. 6 (2020) 81–96.
[19] M. Ge, X. Fang, S. Zhao, Research progress of digital economy evaluation system: empowerment mechanism and driving factors, J. Xi'an Univ. Financ. Econ. 35 (2022) 5–16.
[20] Y. Miao, Y. Li, Y. Wu, Digital economy and economic competitive pressure on local governments: evidence from China, Econ. Model. 140 (2024) 106859.
[21] W. He, J. Hou, The impact of digital economy development on residents' consumption: empirical evidence from cities panel data, Reform (2023) 41–53.
[22] C. Jian, Z. Hong, Z. Junying, The impact of digital economy on the spatial-temporal pattern of residents' consumption upgrading in China, Econ. Geogr. 42 (2022) 129–137.
[23] H. Cai, Z. Wang, Y. Ji, L. Xu, Digitalization and innovation: how does the digital economy drive technology transfer in China? Econ. Model. 136 (2024) 106758.
[24] G. Tian, X. Zhang, Digital economy, non-agricultural employment, and division of labor, Manag. World 38 (2022) 72–84. +311.
[25] X. Chen, X. Yang, The impact of digital economic development on the upgrading of industrial structure: based on the research of grey relational entropy and dissipative structure theory, Reform 3 (2021) 26–39.
[26] Y. Fan, H. Xu, L. Ma, Characteristics and mechanism analysis of the influence of digital economy on the income gap between urban and rural residents, China Soft Sci. 37 (2022) 181–192.
[27] Q. Huang, T. Pan, P. Shi, The impact of digital economy on the income gap between urban and rural residents and its impact mechanism, Reform 4 (2023) 53–69.
[28] P. Bai, Y. Zhang, Digital economy, declining demographic dividends and the rights and interests of low-and medium-skilled labor, Econ. Res. J. 56 (2021) 91–108.
[29] Z. Tao, Z. Zhang, L. Shangkun, Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China, Front. Econ. China 17 (2022) 393.
[30] B. Ren, H. He, Empowerment of digital economy to high-quality development: theoretical logic, path choices and policy orientation, Financ. Econ. (2022) 61–75.
[31] B. Guo, Y. Wang, H. Zhang, C. Liang, Y. Feng, F. Hu, Impact of the digital economy on high-quality urban economic; development: evidence from Chinese cities, Econ. Model. 120 (2023).
[32] Y. Zhong, The Chinese provincial regional differences and space-time evolution characteristics of energy consumption carbon emissions, Ecol. Econ. 34 (2018) 30–33.
[33] M. Han, W. Liu, Y. Xie, W. Jiang, Regional disparity and decoupling evolution of China's carbon emissions by province, Resour. Sci. 43 (2021) 710–721.
[34] J. Cong, X. Liu, X. Zhao, Demarcation problems and the corresponding measurement methods of the urban carbon accounting, China Popul., Resourc. Environ. 24 (2014) 19–26.
[35] J. Wu, Z. Guo, Research on the convergence of carbon dioxide emissions in China: a continuous dynamic distribution approach, Stat. Res. 33 (2016) 54–60.
[36] S. Wang, S. Gao, Y. Huang, C. Shi, Spatio-temporal evolution and trend prediction of urban carbon emission performance in China based on super-efficiency, SBM Model. 75 (2020) 1316–1330.
[37] H. Liu, M. Shao, Y. Ji, The spatial pattern and distribution dynamic evolution of carbon emissions in China: empirical study based on county carbon emission data, Sci. Geogr. Sin. 41 (2021) 1917–1924.
[38] Y. Li, S. Zhang, Spatio-temporal evolution of urban carbon emission intensity and spatiotemporal heterogeneity of influencing factors in China, China Environ. Sci. 43 (2023) 3244–3254.
[39] Q. Yang, H. Liu, Regional difference decomposition and influence factors of China's carbon dioxide emissions, J. Quant. Tech. Econ. 29 (2012) 36–49.
[40] H. Zhu, L. Duan, Y. Guo, K. Yu, The effects of FDI, economic growth and energy consumption on carbon; emissions in ASEAN-5: evidence from panel quantile regression, Econ. Model. 58 (2016) 237–248.
[41] B. Lin, X. Liu, China's carbon dioxide emissions under the urbanization process: influence factors and abatement policies, Econ. Res. J. 8 (2010) 66–78.
[42] W. Wang, Q. Xiang, Adjustment of industrial structure and the potential assessment of energy saving and carbon reduction, China Ind. Econ. 310 (2014) 44–56.
[43] Z. Chen, S. Wu, W. Ma, X. Liu, B. Cai, J. Liu, X. Jia, M. Zhang, Y. Chen, L. Xu, Driving forces of carbon dioxide emission for China's cities: empirical analysis based on extended STIRPAT Model, China Popul. Resour. Environ. 28 (2018) 45–54.
[44] M. Zhang, Y. Liu, Influence of digital finance and green technology innovation on China's carbon emission efficiency: empirical analysis based on spatial metrology, Sci. Total Environ. 838 (2022) 156463.
[45] Y. Chen, Z. Yao, K. Zhong, Do environmental regulations of carbon emissions and air pollution; foster green technology innovation: evidence from China's; prefecture-level cities, J. Clean. Prod. 350 (2022) 131537.
[46] M. Liu, L. Chen, X. Sheng, Y. Xu, X. Yuan, Q. Wang, Q. Ma, J. Zuo, Zero-waste city pilot and urban green and low-carbon transformation: quasi-experimental evidence from China, Resour. Conserv. Recy. 206 (2024).
[47] G. Yang, Q. Zhang, Z. Zhao, C. Zhou, How does the "Zero-waste City" strategy contribute to carbon footprint; reduction in China? Waste Manag. 156 (2023) 227–235.
[48] Q. Wang, F. Zhang, R. Li, Artificial intelligence and sustainable development during urbanization: perspectives on AI R&D innovation, AI infrastructure, and AI market advantage, Sustain. Dev. 33 (2025) 1136–1156.
[49] Q. Wang, Y. Li, R. Li, Integrating artificial intelligence in energy transition: a comprehensive review, Energy Strategy Rev. 57 (2025) 101600.
[50] C. Miao, Z. Chen, A. Zhang, Green technology innovation and carbon emission efficiency: the; moderating role of environmental uncertainty, Sci. Total Environ. 938 (2024).
[51] K. Du, J. Li, Towards a green world: how do green technology innovations affect; total-factor carbon productivity, Energy Policy 131 (2019) 240–250.
[52] M. Yi, Y. Liu, M.S. Sheng, L. Wen, Effects of digital economy on carbon emission reduction: new evidence from China, Energy Policy 171 (2022) 113271.
[53] X. Yan, Y. Deng, L. Peng, Z. Jiang, Study on the impact of digital economy development on carbon emission intensity of urban agglomerations and its mechanism, Environ. Sci. Pollut. Res. 30 (2023) 33142–33159.
[54] Z. Li, J. Wang, The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China, J. Clean. Prod. 351 (2022) 131570.
[55] L. Bai, T. Guo, W. Xu, Y. Liu, M. Kuang, L. Jiang, Effects of digital economy on carbon emission intensity in Chinese cities: a life-cycle theory and the application of non-linear spatial panel smooth transition threshold model, Energy Policy 183 (2023) 113792.
[56] Z. Yang, W. Gao, Q. Han, L. Qi, Y. Cui, Y. Chen, Digitalization and carbon emissions: how does digital city construction affect China's carbon emission reduction? Sustain. Cities Soc. 87 (2022) 104201.
[57] L. Ge, L. Mo, N. Huang, Development of digital economy, upgrading of industrial structure and urban carbon emission, Mod. Financ. Econ. J. Tianjin Univ. Financ. Econ. 42 (2022) 20–37.
[58] B. Xuejie, S. Xianzhen, Impact of internet development on total factor carbon productivity: induced by cost, innovation, or demand? China Popul. Resourc. Environ. 31 (2021).
[59] X. Wang, J. Li, Heterogeneous effect of digital economy on carbon emission reduction, J. Clean. Prod. 429 (2023) 139560.
[60] Q. Wang, F. Zhang, R. Li, J. Sun, Does artificial intelligence promote energy transition and curb carbon emissions? The role of trade openness, J. Clean. Prod. 447 (2024) 141298.
[61] J. Chen, Z. Guo, Z. Lei, Research on the mechanisms of the digital transformation of manufacturing enterprises for carbon emissions reduction, J. Clean. Prod. 449 (2024) 141817.
[62] S. Zhang, X. Wei, Does information and communication technology reduce enterprise's energy consumption—Evidence from Chinese manufacturing enterprises survey, China Ind. Econ. 2 (2019) 155–173.
[63] E. Williams, Environmental effects of information and communications technologies, Nature 479 (2011) 354–358.
[64] M. Lenzen, D. Moran, K. Kanemoto, B. Foran, L. Lobefaro, A. Geschke, International trade drives biodiversity threats in developing nations, Nature 486 (2012) 109–112.
[65] H. Bathelt, A. Malmberg, P. Maskell, Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, Prog. Hum. Geog. 28 (2004) 31–56.
[66] Z. Zhu, B. Liu, Z. Yu, J. Cao, Effects of the digital economy on carbon emissions: evidence from China, Int. J. Env. Res. Pub. Health 19 (2022) 9450.
[67] F. Lan, C. Jiao, G. Deng, H. Da, Urban agglomeration, housing price, and space–time spillover effect—empirical evidences based on data from hundreds of cities in China, Manag. Decis. Econ. 42 (2021) 898–919.
[68] E. Parzen, On estimation of a probability density function and mode, Ann. Math. Stat. 33 (1962) 1065–1076.
[69] M. Rosenblatt, Remarks on some nonparametric estimates of a density function, Ann. Math. Stat. 27 (1956) 832–837.
[70] Q. Huang, Y. Yu, S. Zhang, Internet development and productivity growth in manufacturing industry: internal mechanism and China experiences, China Ind. Econ. 8 (2019) 5–23.

[71] F. Guo, J. Wang, F. Wang, T. Kong, X. Zhang, Z. Cheng, Measuring China's digital financial inclusion: index compilation and spatial characteristics, China Econ. Q. 19 (2020) 1401–1418.
[72] S. Chen, Energy consumption, CO2 emission and sustainable development in Chinese industry, Econ. Res. J. 4 (2009) 1–5.
[73] L. Belkhir, A. Elmeligi, Assessing ICT global emissions footprint: trends to 2040 & recommendations, J. Clean. Prod. 177 (2018) 448–463.
[74] S. Lange, J. Pohl, T. Santarius, Digitalization and energy consumption. Does ICT reduce energy demand? Ecol. Econ. 176 (2020) 106760.
[75] Q. Wang, T. Sun, R. Li, Does Artificial Intelligence (AI) enhance green economy efficiency? The role of green finance, trade openness, and R&D investment, Human. Soc. Sci. Commun. 12 (2025) 1–22.
[76] J. Wang, K. Dong, X. Dong, F. Taghizadeh-Hesary, Assessing the digital economy and its carbon-mitigation effects: the case of China, Energy Econ. 113 (2022) 106198.
[77] H. Chang, Q. Ding, W. Zhao, N. Hou, W. Liu, The digital economy, industrial structure upgrading, and carbon emission intensity——empirical evidence from China's provinces, Energy Strategy Rev. 50 (2023) 101218.
[78] L. Zhang, R. Mu, Y. Zhan, J. Yu, L. Liu, Y. Yu, J. Zhang, Digital economy, energy efficiency, and carbon emissions: evidence from provincial panel data in China, Sci. Total Environ. 852 (2022) 158403.
[79] Y. Li, X. Yang, Q. Ran, H. Wu, M. Irfan, M. Ahmad, Energy structure, digital economy, and carbon emissions: evidence from China, Environ. Sci. Pollut. Res. 28 (2021) 64606–64629.
[80] M. Yi, Y. Liu, M.S. Sheng, L. Wen, Effects of digital economy on carbon emission reduction: new evidence from China, Energy Policy 171 (2022) 113271.
[81] W. Shuailong, Digital economy development for urban carbon emissions: 'accelerator' or 'speed bump'? China Popul. Resourc. Environ. 33 (2023).
[82] J.P. Elhorst, Matlab software for spatial panels, Int. Reg. Sci. Rev. 37 (2014) 389–405.
[83] J.P. LeSage, An introduction to spatial econometrics, Rev. Écon. Ind. 123 (2008) 19–44.
[84] D. Bai, M. Li, Y. Wang, S. Mallek, U. Shahzad, Impact mechanisms and spatial and temporal evolution of digital economy and green innovation: a perspective based on regional collaboration within urban agglomerations, Technol. Forecast. Soc. 207 (2024) 123613.