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Does digital economy development reduce carbon emission intensity?

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Carbon emissions from human activities are the main cause of climate warming. Under the background of economic and social digital transformation, accurately assessing the carbon emission reduction effect of the development of the digital economy is of great significance for countries to deal with climate warming in the post-COVID-19 era. This paper constructs a dynamic evaluation model of orthogonal projection to measure the level of digital economy development at the provincial level in China from 2007 to 2019. On this basis, the panel fixed effects model and mediation model are used to empirically test the impact of digital economy development on carbon emission intensity and its mechanism. The results indicate that: (1) The development of China's digital economy is unbalanced among regions, showing a geospatial pattern of decreasing from east to west. (2) China's carbon emission intensity has a trend of decreasing year by year, and there are geospatial differences of "high in the west and low in the east" and "high in the north and low in the south." (3) The digital economy development can effectively reduce regional carbon emission intensity through industrial structure optimization effect and resource allocation effect, and the industrial structure optimization effect can suppress carbon emission intensity more obviously. (4) The development of digital economy in different regions has different degrees of reducing carbon emission intensity. The development of digital economy in the eastern region has a stronger inhibitory effect on carbon emission intensity than that in the middle and western regions, and the development of digital economy in economically developed regions can suppress carbon emission intensity more. This paper provides enlightenment for policy makers to deal with climate warming.

KEYWORDS

carbon emission intensity, digital economy, dynamic orthogonal projection, geospatial differences, mediation model

1. Introduction

Global warming has seriously affected the living environment of human beings, and coping with climate warming has become a common issue faced by all countries in the world (Liu et al., 2021). Existing studies have shown that carbon dioxide emitted by human economic activities is the main cause of climate warming (An et al., 2021).

Therefore, controlling carbon dioxide emissions is the main way for countries around the world to cope with climate warming. As the world's second largest economy, China is a major emitter of global carbon dioxide (Yu et al., 2021). According to statistics from the British Petroleum database, China's carbon emissions reached 6.926 billion tons in 2006, surpassing the United States to become the world's largest carbon emitter; and in 2021, China's carbon emissions rose to 10.523 billion tons, accounting for about 33% of global carbon emissions. As a responsible major country, China has taken the initiative to take responsibility for carbon emission reduction. At the seventy-fifth session of the United Nations General Assembly, the Chinese government made it clear: "China strives to achieve carbon peak by 2030 and achieve carbon neutrality by 2060." The proposal of the "dual carbon goal" shows China's determination to cope with climate warming, which is also in line with the green development concept advocated by China (Wang et al., 2023). However, according to the enlightenment brought by the environmental Kuznets curve and the practical experience of the carbon emission reduction process of developed countries, there are multiple challenges in achieving the "dual carbon goal" in China (Shi et al., 2021). Compared with developed countries, China not only faces the pressure of carbon emission growth brought by incremental energy demand, but also needs to improve the low-carbon substitution of stock energy. At the same time, the huge development differences between regions in China also constitute the constraints of achieving the "dual carbon goal" (Guo et al., 2023).

It is worth noting that the systematic promotion stage of the "dual carbon goal" is also the stage of rapid development of the digital economy. At present, digital technology represented by information and communication technology, cloud computing, the Internet and artificial intelligence has made innovative breakthroughs and achieved deep integration with the real economy. According to the White Paper on the Development of China's Digital Economy (2022), the scale of China's digital economy accounted for more than 1/3 of the gross domestic product (GDP) in 2021, and the average annual growth rate was higher than the growth rate of GDP. With the rapid development of the digital economy, the environmental effects of the digital economy have received extensive attention from the academic community. Some scholars believe that the information and communication technology industry and e-commerce industry in the digital economy, as environmentally friendly industries, can optimize the industrial structure by squeezing out industries with high energy consumption and high emissions, thus promoting economic and social low-carbon development (Zhang W. et al., 2022; Lyu et al., 2023). Other scholars believe that the wide application of digital technology increases electricity consumption and thus has a negative impact on the environment (Salahuddin and Alam, 2015; Lin and Huang, 2023). So, what is the impact of digital economy development on carbon emission intensity? What is its impact mechanism? Clarifying this issue not only helps to accurately assess the carbon emission reduction effect of the digital economy, but also provides useful suggestions for China to achieve the "dual carbon goal."

Based on this, this paper measures the carbon emission intensity of Chinese provinces in 2007–2019 under the IPCC sectoral accounting algorithm. In addition, a framework for measuring the development level of digital economy development at the provincial level in China was constructed, and a dynamic evaluation method based on orthogonal projection was used to measure the development level of digital economy in 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China. On the basis of examining the evolution trend of China's regional carbon emission intensity and digital economy development level, the panel fixed effects model and mediation model were used to empirically test the impact and mechanism of digital economy development on carbon emission intensity.

The possible contributions of this paper are as follows: First, this paper incorporates the digital economy and carbon emission intensity into the same analytical framework, and divides the development of the digital economy into the digital industrialization dimension and the industrial digitization dimension, and respectively examines their impact on carbon emission intensity. Second, this paper constructs the index system of digital economy development level at the provincial level, and uses the dynamic evaluation method based on orthogonal projection to measure the digital economy development level of each province in China, which enriches the research content of existing digital economy measurement. Third, this paper further examines the impact mechanism of digital economy development on carbon emission intensity, and finds that digital economy reduces carbon emission intensity through industrial structure optimization effect and resource allocation effect.

2. Literature review and theoretical hypothesis

2.1. Digital economy development and carbon emission intensity

With the increasing prominence of global warming, carbon emission reduction has received continuous attention from the academic community (Liu et al., 2021; Yi et al., 2022). Among them, the influencing factors of carbon emissions are the focus of scholars' research (Liu et al., 2022). Domestic and foreign scholars have discussed the influencing factors of carbon emissions with different methods and from different angles (Cai et al., 2021; He et al., 2022). Scholars mainly use Kaya identity (Ma and Cai, 2018; Eskander and Nitschke, 2021), Divisia index method (Ma and Cai, 2018; Eskander and Nitschke, 2021), and Laspeyres index decomposition method (González and Martínez, 2012; Chen et al., 2021) decompose the influencing factors of carbon emissions. Although the conclusions of different methods are different, it is generally believed that technological innovation (Zhang G. et al., 2022), energy structure (Pui and Othman, 2019), industrial structure (Han and Jiang, 2022), and economic growth (Xiao and Peng, 2023) are the main factors affecting carbon emissions.

With the development of the digital economy, scholars have begun to pay attention to the relationship between the digital economy and carbon emissions (Yang et al., 2022). The relationship between digital economy development and carbon emissions is complex. The development of digital economy has both positive and negative effects on the environment (Moyer and Hughes, 2012; Dong et al., 2022). Although the application of digital technology improves the efficiency of energy conservation and emission reduction and reduces the loss in the production process, the expansion of production scale increases energy demand and may lead to an increase in total carbon emissions (Zhou et al., 2019; Wang et al., 2022b). Andrae and Edler (2015) found that the rapid development of information and communication technology (ICT) has been accompanied by an exponential increase in total carbon emissions. Salahuddin and Alam (2015) argued that the wide application of digital technology has increased data generation, transmission and processing, resulting in an increase in demand for electricity, which in turn increases carbon emissions.

Other scholars believe that the industrial linkage emission reduction effect produced by the development of the digital economy plays a greater role than the incremental effect of energy consumption (Koomey et al., 2013; Yi et al., 2022). Yi et al. (2022) used provincial panel data to evaluate the relationship between digital economy and carbon emissions, and found that the development of digital economy has significant carbon emission reduction effects. The research of Niu et al. (2022) shows that digital investment improves energy efficiency, which in turn reduces carbon emissions in the production process. Zhang W. et al. (2022) believes that the development of the digital economy has produced more new clean industries, which has a crowding-out effect on industries with high energy consumption and high emissions, thereby reducing carbon emissions. Han and Jiang (2022) further examined the relationship between digital economy and carbon production efficiency, and found that the digital economy development reduced energy consumption per unit of GDP and improved carbon productivity. Based on the differences in the existing research conclusions, this paper further examines the environmental effects of the development of digital economy. Different from the existing research, this paper examines the impact and mechanism of digital economy development on carbon emission intensity from the regional level, and further considers the heterogeneity of geospatial differences and economic development differences. Based on the above literature conclusions, this paper proposes hypothesis 1.

> **H1:** The digital economy development has positive and negative effects on carbon emissions, but an inhibitory effect on regional carbon emission intensity.

2.2. Impact mechanism of digital economy development on carbon emission intensity

As a new economic form, digital economy has become a new driving force for the upgrading of industrial structure (Chen et al., 2022). Existing research shows that the digital economy promotes the upgrading of industrial structure through industrial integration effect and technology diffusion effect (Hao et al., 2023). The internal logic of industrial upgrading shows that the emergence of new industries and new models will gradually replace traditional industries and traditional economic models, and drive the upgrading of traditional industries through input-output linkages, thus realizing the comprehensive optimization of industrial structure. In the digital age, the speed of technology diffusion and change is faster than ever before, which provides favorable conditions for industrial organization innovation, but also enhances the competition mechanism and promotes the continuous optimization of industrial organization (Tang and Li, 2022). Industrial digitalization will also accelerate the elimination of inefficient enterprises, thereby improving the overall production efficiency of the industry and realizing the optimization of the industrial structure. The optimization of industrial structure improves the efficiency of energy utilization, which has a positive impact on reducing carbon emission intensity (Hao et al., 2023). Based on this, hypothesis 2 is proposed.

> **H2:** The digital economy development reduces carbon emission intensity by optimizing industrial structure.

The internal structure of economic form determines the efficiency of resource allocation, and the allocation and combination mode of various production factors is the main factor affecting carbon emission intensity (Wang et al., 2021). Under the digital economic form, economic entities can obtain more adequate market information, and the matching between supply and demand is more accurate, which can improve the resource search efficiency of market entities (Wu et al., 2022). At the same time, the application of digital technology can improve the utilization efficiency of production factors by optimizing the production process (Zhang Z. et al., 2022). Intelligent production process reduces energy waste, and improves energy utilization. Digital economy improves resource allocation by improving resource search and resource utilization efficiency, which helps to reduce undesired output in the production process and reduce carbon emission intensity (Chen, 2022). Based on this, hypothesis 3 is proposed.

> **H3:** The digital economy development reduces carbon emission intensity by improving resource allocation.

Digital industrialization and industrial digitization provide a collaborative environment for innovation activities and accelerate the progress of carbon emission reduction technology (Yin and Yu, 2022). The improvement of innovation efficiency depends on the efficient interconnection of information (Niu et al., 2023). The digital economy based on information and communication technology provides an efficient way for innovation subjects to obtain information and enriches the information resource elements needed for innovation (Kohli and Melville, 2019). In addition, the improvement of innovation efficiency requires efficient collaboration between innovation subjects (Zhuo and Chen, 2023). Compared with the traditional economic form, the digital economy makes the innovation subjects more closely linked and more likely to produce collaborative innovation effects (Li et al., 2023). The application of digital innovation achievements in traditional production methods has an indirect impact on improving efficiency and reducing pollution (Gao et al., 2022). Based on this, hypothesis 4 is proposed.

> **H4:** The digital economy development reduces carbon emission intensity by improving innovation efficiency.

3. Materials and methods

3.1. Measurement of level of digital economy development

3.1.1. Method

In order to ensure the objectivity and accuracy of the measurement results, and consider the degree of difference of the evaluation index values, this paper uses a dynamic evaluation method based on orthogonal projection to measure the digital economy development level of 30 provinces in China.

It is assumed that the digital economy development level of $v_1, v_2, \ldots, v_n$ in a period of time should be measured. Therefore, it is necessary to collect the original data of all the evaluated objects, which includes m indicators during $t_1, t_2, \ldots, t_N$. Based on this, the panel data matrix $x_{ij}(t_k)$ $(i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m;\ k = 1, 2, \ldots, N)$ can be obtained. Since the dimensions are different between the data, the original data needs to be adjusted to dimensionless. This paper uses a globally improved normalization method to process the data, which results in a standardized matrix $Y(t_k) = y_{ij}(t_k)$. In the process of calculating the weighted normalization matrix, this paper first uses the entropy value method to determine the index weight, and then determines the ideal solution and the negative ideal solution. In all periods and all evaluated objects, the maximum value of the j -item indicator is called the ideal solution of the indicator, while the minimum value is called the negative ideal solution of the indicator. Finally, the "vertical" distance $P_i(t_k)$ of the ideal solution of each region is calculated. For each evaluated object, the distance between the negative ideal solution and the ideal solution is constant, so there are:

$$P_i(t_k) = \left|(a - b) \cdot (a - V_i(t_k))\right| \tag{1}$$

where a represents the ideal solution F^+ after translation, that is, $\vec{0}$ vector, and b represents the negative ideal solution F^- after translation. Further simplifying Equation 1, we can get:

$$P_i(t_k) = \left|F^- \cdot V_i(t_k)\right| = \sum_{j=1}^{m} f_j^- v_{ij}(t_k) \tag{2}$$

where $P_i(t_k)$ values are smaller, the better. The $P_i(t_k)$ is standardized to obtain the final evaluation value. After standardization $P_i(t_k)$ becomes $P_i^*(t_k)$, as follows:

$$P_i^*(t_k) = \frac{max_{1 \le i \le n} P_i(t_k) - P_i(t_k)}{max_{1 \le i \le n} P_i(t_k)} \tag{3}$$

where $P_i^*(t_k)$ is the dynamic evaluation score of the evaluated object i in period t_k. Further, $P_i^*(t_k)$ pairs are weighted twice to calculate the comprehensive evaluation score P_i^* of the evaluated object i in the period from t_1 to t_N. Based on the research of Zhu and Lei (2012), the time weight (w_k) is calculated by using the idea of "thick today and thin ancient". That is, within the time period $[t_1, t_N]$, the weight of the t_k period is as follows:

$$w_k = k / \sum_{k=1}^{N} k \ (k = 1, 2, \cdots, N) \tag{4}$$

where, $\sum_{k=1}^{N} w_k = 1$ and $w_k > 0$. According to the Equation 4, the weight values at different times can be calculated, and then the secondary weighted weight value can be obtained. Therefore, the total evaluation value s_i of i in the time period $[t_1, t_N]$ is:

$$P_i^* = \sum_{k=1}^{N} w_k P_i^*(t_k) \tag{5}$$

where, w_k represents the time weight value at time t_k; $P_i^*(t_k)$ represents the evaluation value of evaluation object i at the t_k moment, and its size and ranking can be calculated by Equation 3. The evaluation value P_i^* and total ranking of the ith evaluation object in the time period $[t_1, t_N]$ can be calculated by Equation 5.

3.1.2. Indicators

Based on the consideration of the comprehensiveness, representativeness and availability of evaluation indicators, and combined with relevant literature (Chen et al., 2022; Wang et al., 2022a; Zhang L. et al., 2022), this paper constructs the measurement system of digital economy development in various provinces in China around digital industrialization

TABLE 1 Evaluation index system of digital economy development.

First-level index	Second-level index	Third-level index	Weight
Digital industrialization	Industry scale	Number of employees in information service industry	0.0543
		Total amount of the telecommunication service	0.0555
	Communications capability and service level	Internet penetration rate	0.0662
		Long-distance optical cable line length	0.0638
		Number of Internet broadband access ports	0.0566
		Mobile telephone switch capacity	0.0622
		Mobile subscription	0.0664
Industrial digitalization	Agriculture	Agricultural added value	0.0610
		Rural electricity consumption	0.0487
	Industry	Industrial added value	0.0582
		Proportion of patents granted	0.0609
		Proportion of revenue from new product sales	0.0650
	Service industry	The added value of the tertiary industry	0.0582
		Per capita insurance premium income	0.0611
		Number of mobile Internet users	0.0612
		Total retail sales of consumer goods per capita	0.0634
		Per capita express delivery volume	0.0371

and industrial digitalization, and the specific indicators are shown in Table 1. The data comes from the "China Statistical Yearbook," "China Information Yearbook," and CSMAR digital economy database.

3.1.3. Results

Table 2 shows the score of digital economy development level of 30 provinces in China from 2007 to 2019. The results show that the score of digital economy development level in each province has an obvious growth trend in 2007–2019. From the perspective of time nodes, 2007–2015 is the initial period of digital economy development. This period is the stage of rapid integration of digital technology and real economy, and the growth rate of digital economy is slow. 2016–2019 is the stage of rapid development of the digital economy, which is mainly due to the government's strong investment in digital construction.

In order to show the differences in the development level of digital economy among different regions, ArcGis software was used to draw the spatial pattern distribution map of digital economy development in each province of China in 2007, 2013, and 2019. It can be seen from Figure 1 that the development of China's digital economy is uneven among regions, showing a geographical spatial pattern of decreasing in the east, middle and west, and obvious differences between the east and the west. From the time dimension, the development level of digital economy in the east, middle and west regions have a trend of increasing year by year. This reflects the phenomenon of "digital divide" caused by the imbalance of development between regions in the era of digital economy, and advanced regions have more advantages in the development of digital economy than backward regions.

3.2. Measurement of carbon emission intensity

3.2.1. Method

To study the impact of the digital economy on carbon emissions under the "dual carbon goal", we must first measure the carbon emissions. In this paper, the carbon emission coefficient method is used to measure China's interprovincial carbon emissions. The required data are the amount of energy consumption in each province and city and the corresponding carbon emission factor. Among them, the main types of energy consumption that cause carbon emissions are coal, gasoline, kerosene, crude oil, coke, diesel, fuel oil and natural gas. Among them, the carbon emission factors of various energy sources need to be estimated. In this paper, the carbon emissions of each province are measured under the IPCC sectoral accounting algorithm. The calculation formula is as follows:

$$C_{it} = \sum (E_{ijt} \times \delta_j \times \eta_j) \tag{6}$$

among them, C_{it} represents the estimated carbon emissions of province i in t year; E_{ijt} represents j energy consumption of province i in t year; δ_j is the average low calorific value of j energy; η_j is the carbon emission coefficient of j energy, and the relevant values are shown in Table 3.

Carbon emission intensity is the CO_2 emission per unit of real GDP, and its calculation formula is as follows:

$$CI_{it} = \frac{C_{it}}{GDP_{it}} \tag{7}$$

among them, CI_{it} is the carbon emission intensity of i province in t year; C_{it} represents the carbon emissions of province i in t year; GDP_{it} represents the real GDP of province i in t year.

3.2.2. Results

According to the calculated carbon emission intensity data of each province, the spatial distribution map of carbon emission intensity of each province in China in 2007, 2013, and 2019 is drawn. As shown in Figure 2, China's carbon emission intensity shows the geographical spatial differences of "high in the west and low in the east" and "high in the north and low in the south." Resource-based provinces bear more carbon emissions, and the carbon emission intensity in economically developed regions is lower, indicating that there is a "profit and loss deviation" phenomenon in China's carbon emissions. From the time dimension, the carbon emission intensity in various regions of China has a trend of decreasing year by year. This shows that since the 18th CPC National Congress, the concept of low-carbon development advocated by China has been well implemented.

3.3. Research design

3.3.1. Model design

This paper constructs the following panel fixed effects model to study the impact of digital economy development on carbon emission intensity:

$$CI_{it} = \beta_0 + \beta_1 digital_{it} + \rho X_{it} + \delta_t + \zeta_i + \varepsilon_{it} \tag{8}$$

In Equation 8, i, t represent province and year, respectively; CI_{it} is the dependent variable, namely carbon emission intensity. The independent variable $digital_{it}$ is the level of digital economic development. X_{it} is the control variable; β_0 is the intercept term; δ_t is the year-fixed effects; ζ_i is the individual (province)-fixed effects; ε_{it} is the random disturbance term. The research goal of this paper is to test the impact of digital economy development on carbon emission intensity at the provincial level in China, so it focuses on the significance, direction and size of the coefficient β_1.

3.3.2. Variables and data sources

The dependent variable is carbon emission intensity (*CI*). The independent variable is the level of digital economic development (*digital*). Mechanism variables include: Industrial structure optimization (*indust*). Industrial structure optimization is represented by the ratio of the tertiary industry to the secondary industry (Zhao and Xi, 2022). Resource allocation (*tfp*). Resource allocation is measured by total factor productivity of each province (Xi and Mei, 2022). Innovation efficiency (*innov*). Innovation efficiency is measured by DEA method (Li et al., 2018). According to the existing research conclusions, this paper selects the following control variables: Energy structure (*es*). Energy structure is an important factor affecting the carbon emission intensity of region.

TABLE 2 Score of digital economy development level.

Year	2007	2009	2011	2013	2015	2017	2019
Beijing	0.1707	0.1997	0.2400	0.3009	0.3869	0.4833	0.5709
Tianjin	0.0793	0.0825	0.0856	0.1056	0.1267	0.1749	0.2111
Hebei	0.0715	0.1103	0.1242	0.1636	0.1911	0.2405	0.3645
Shanxi	0.0372	0.0572	0.0637	0.0867	0.0953	0.1231	0.1823
Inner Mongolia	0.0298	0.0495	0.0616	0.0817	0.0960	0.1287	0.1817
Liaoning	0.0727	0.1003	0.1135	0.1478	0.1820	0.2092	0.2560
Jilin	0.0565	0.0977	0.0739	0.0643	0.0837	0.1208	0.1844
Heilongjiang	0.0414	0.0633	0.0673	0.0870	0.1041	0.1415	0.1821
Shanghai	0.1293	0.1622	0.1759	0.2662	0.3371	0.4602	0.5371
Jiangsu	0.1674	0.2148	0.2650	0.3520	0.4301	0.5145	0.7241
Zhejiang	0.1553	0.1883	0.2186	0.2923	0.4012	0.5405	0.7868
Anhui	0.0531	0.0759	0.0987	0.1258	0.1685	0.2212	0.3261
Fujian	0.0758	0.0993	0.1185	0.1568	0.1993	0.2503	0.3538
Jiangxi	0.0320	0.0410	0.0493	0.0743	0.1052	0.1494	0.2339
Shandong	0.1205	0.1648	0.1866	0.2369	0.2755	0.3363	0.4628
Henan	0.0754	0.1101	0.1181	0.1574	0.2015	0.2558	0.4093
Hubei	0.0753	0.0915	0.1068	0.1412	0.1850	0.2352	0.3479
Hunan	0.0764	0.4410	0.1017	0.1444	0.1758	0.2132	0.3152
Guangdong	0.2461	0.3083	0.3219	0.4132	0.5148	0.6731	1.0000
Guangxi	0.0515	0.0672	0.0679	0.0892	0.1063	0.1452	0.2268
Hainan	0.0095	0.0074	0.0359	0.0420	0.0437	0.0609	0.0866
Chongqing	0.0956	0.0936	0.1014	0.1029	0.1424	0.1736	0.2307
Sichuan	0.0898	0.1238	0.1224	0.1733	0.2213	0.2738	0.4157
Guizhou	0.0228	0.0330	0.0488	0.0568	0.0764	0.1090	0.1974
Yunnan	0.0329	0.0501	0.0582	0.0827	0.1041	0.1362	0.2258
Shaanxi	0.0427	0.0658	0.0785	0.0979	0.1216	0.1602	0.2523
Gansu	0.0164	0.0272	0.0357	0.0517	0.0614	0.0791	0.1303
Qinghai	0.0001	0.0069	0.0048	0.0169	0.0293	0.0534	0.0723
Ningxia	0.0000	0.0112	0.0175	0.0339	0.0464	0.0657	0.0913
Xinjiang	0.0236	0.0376	0.0514	0.0751	0.0928	0.1094	0.1753

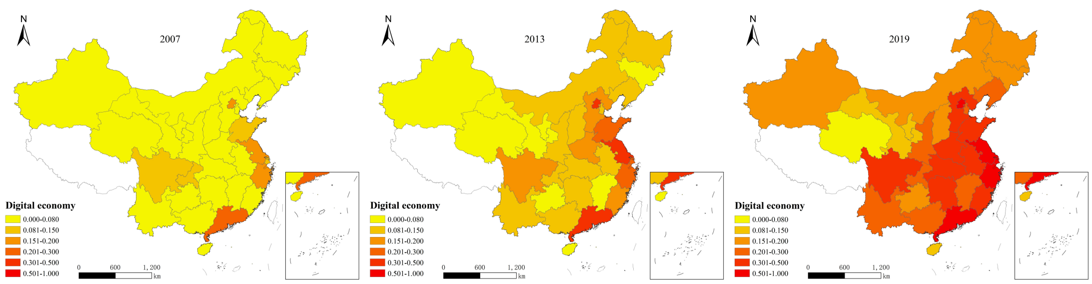

FIGURE 1
Spatial distribution of China's digital economy development level in 2007, 2013, and 2019.

The energy structure with too high proportion of coal often has higher carbon emission intensity. Therefore, it is expressed by the ratio of coal consumption to total energy consumption (Guan et al., 2023). Population density (*popu*). Regions with higher population density have greater demand for energy consumption and more frequent socio-economic activities (He et al., 2023), which are more

TABLE 3 Average low calorific value and carbon emission coefficient of various energy sources.

Type	Raw coal	Coke	Gasoline	Diesel oil	Kerosene	Crude oil	Fuel oil	Natural gas
δ_j (kj/kg)	20,908	28,435	43,070	42,652	43,070	41,800	41,816	38,931
ς_j (kg/TJ)	95,333	107,000	70,000	74,100	71,500	73,000	77,400	56,100

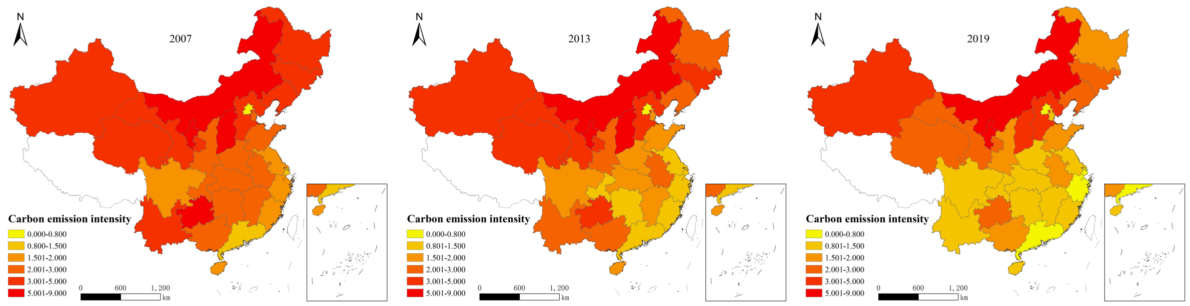

FIGURE 2
Spatial distribution of China's carbon emission intensity in 2007, 2013, and 2019.

likely to affect carbon emission intensity. Foreign direct investment (*fdi*). Foreign direct investment is expressed by the ratio of foreign direct investment to real GDP. Openness to the outside (*open*). Openness to the outside is expressed by the ratio of total import and export to real GDP (Tiba and Belaid, 2020). Environmental regulation (*er*). Environmental regulation is expressed by the proportion of environmental pollution control investment in real GDP.

The data sources of this paper are "China Statistical Yearbook", "China Social Statistical Yearbook" and statistical yearbooks of various provinces and cities, the website of the National Bureau of Statistics, CNRDS database, CEADs database, and Wind database. Considering the availability of data, the panel data of 30 provinces in China (except Tibet and Hong Kong, Macao, and Taiwan) from 2007 to 2019 are finally selected. Descriptive statistics of variables are shown in Table 4.

4. Results and discussion

4.1. Benchmark regression results

Considering that regional differences and time factors may affect the estimation results, this paper uses the fixed effect model to estimate the parameters, and the results are shown in Table 5. It can be seen from columns (1) and (2) of Table 5 that the regression coefficient of digital economy development (*digital*) is negative at the 1% significance level, indicating that the improvement of digital economy development level in each region can promote the reduction of carbon emission intensity. The core explanatory variables in columns (3) and (4) were digital industrialization, and the core explanatory variables in columns (5) and (6) were industrial digitalization, and the results showed that the regression coefficients of digital industrialization and industrial digitalization were significantly negative, indicating that both inhibited the increase of carbon emission intensity. However, there are differences in the inhibitory effect of the two on carbon emission intensity. The absolute value of the regression coefficient of digital industrialization is greater than that of industrial digitization, indicating that digital industrialization has a greater inhibitory effect on carbon emission intensity. In the integration stage of digital economy and real economy, the process of industrial digitization often lags behind digital industrialization, which is the main reason for the difference in impact.

4.2. Endogenous treatment

Although carbon emission intensity is a relative quantity index, which can alleviate endogenous problems to a certain extent, it cannot rule out endogenous problems caused by missing variables. If the factors that affect both the digital economy and the carbon emission intensity are not controlled, it will lead to endogenous problems, such as relevant policies and technological changes. First, using fixed effects model can alleviate endogenous problems to a certain extent. Second, construct the instrumental variables of digital economy development to reduce endogenous bias. The previous benchmark regression uses fixed effects, which alleviates endogeneity to some extent.

Construct instrumental variables to alleviate endogenous problems. Refer to the practice of Bartik (2006) to construct instrumental variables, that is, the first-order difference ($\Delta digital_{it}$) of the development of the digital economy and the intersection ($digital_{it-1}$) of the lag phase ($\Delta digital_{it} = digital_{it-1}$) of the development of the digital economy are used as instrumental variables. The considerations for constructing the instrumental variable are as follows: Firstly, carbon emission intensity will not affect the development of the digital economy in the previous period. Choosing a lag period can effectively avoid the endogeneity that may be caused by reciprocal causation, which also shows that the instrumental variable satisfies the exogenous hypothesis. Secondly, the level of development of the digital economy in the previous period will affect the current period. Choosing the intersection of the lag phase of the digital economy and the

TABLE 4 Descriptive statistics of variables.

Definition	Variables	Mean	SD	Min	Med	Max
CI	Carbon emission intensity	2.527	1.661	0.343	2.085	10.210
digtial	Digital economy development	0.163	0.142	0.000	0.121	1.000
digtial_1	Digital industrialization	0.140	0.118	0.000	0.102	1.000
digtial_2	Industrial digitalization	0.198	0.172	0.000	0.150	1.000
indust	Industrial structure	1.081	0.622	0.500	0.894	5.169
tfp	Resource allocation	1.518	0.747	0.070	1.443	2.900
innov	Innovation efficiency	0.462	0.231	0.068	0.422	1.000
es	Energy structure	0.574	0.186	0.019	0.601	0.903
popu	Population density	0.282	0.120	0.062	0.263	0.597
fdi	Foreign direct investment	0.401	0.526	0.048	0.206	5.849
lnopen	Openness to the outside	−1.740	0.970	−4.368	−1.964	0.587
er	Environmental regulation	1.403	0.688	0.300	1.245	4.240

TABLE 5 Benchmark regression results[a].

Variables	*CI*					
	(1)	(2)	(3)	(4)	(5)	(6)
digtial	−2.9206***	−1.3632***				
	(−11.5679)	(−4.4021)				
digtial_1			−3.4913***	−1.9186***		
			(−12.5392)	(−5.7179)		
digtial_2					−2.1916***	−0.7683***
					(−9.7948)	(−2.9878)
es		−1.6462***		−1.5772***		−1.7955***
		(−3.2092)		(−3.1376)		(−3.4590)
popu		3.2365***		2.9662***		3.6226***
		(8.0981)		(7.5432)		(9.2847)
fdi		0.0965		0.1143*		0.0736
		(1.4448)		(1.7404)		(1.0925)
lnopen		0.1609*		0.1800**		0.1848**
		(1.8714)		(2.1786)		(2.1016)
er		−0.0066		0.0002		−0.0122
		(−0.1267)		(0.0030)		(−0.2318)
constant	3.0036***	1.6013***	3.0165***	1.7985***	2.9608***	1.4122***
	(63.8766)	(5.0063)	(67.2096)	(5.6432)	(59.0132)	(4.4216)
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.2715	0.3994	0.3046	0.4201	0.2109	0.3821

[a]The t statistics are in parentheses, $^*p < 0.010$, $^{**}p < 0.05$, $^{***}p < 0.01$. FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects. The notes for the following tables are the same.

first-order difference as the instrumental variable can meet the correlation assumption (Lyu et al., 2023). This paper uses the two-stage least squares method of instrumental variables to estimate.

In order to ensure the reliability of the endogenous test results, this paper also takes the carbon emission intensity measured by the apparent method as the dependent variable for regression. The estimation results are shown in **Table 6**. Columns (1) and (2) are based on the carbon emission intensity calculated by the IPCC sector accounting method as the dependent variable; columns (3) and (4) are based on the carbon emission intensity calculated by the apparent method as the dependent variable. The results show that the instrumental variable has a significant strong correlation with the independent variable. The F statistic in the weak *IV* test is much larger than the judgment value at the 10% level. The instrumental variable satisfies the correlation hypothesis and there is no weak correlation problem. In addition, the digital economy development (*digtial*) is significantly negative at the significance level of 10%, indicating that the results are still robust after controlling endogenous problems.

4.3. Robustness test

Referring to the existing research, the model robustness test was carried out by substituting variables and removing outliers. One is to replace the dependent variable. The carbon emission intensity of each province calculated by the apparent method calculated by the apparent method in the CEADs database was selected as the replacement variable. The second is to eliminate outliers. That is, the values in the carbon intensity data are replaced by values that are 5% below the average and 95% above the average. In Table 7, columns (1), (3), and (5) are listed as the regression results of the dependent variable after tail shrinking. Columns (2), (4), and (6) are the regression results after replacing the dependent variable. After tail shrinking and replacing the dependent variable, the independent variable were still significant, and the direction and magnitude of the coefficients were consistent with the benchmark estimates, indicating that the model estimation had high confidence and proved the robustness of the research conclusions.

4.4. Heterogeneity analysis

4.4.1. Analysis of geospatial differences

In order to examine the regional differences in the impact of digital economy development on carbon emission intensity, this paper divides the sample into eastern, middle and western regions, and still uses the panel fixed effects model for regression. As shown in Table 8, there are significant spatial differences in the impact of digital economy development on carbon emission intensity. Compared with the east, the impact of the development of digital economy in the middle and western regions on reducing carbon emission intensity is more obvious. The reason may be that the eastern regions is economically developed, the carbon emission intensity is much lower than that of the middle and western regions, and the space for reduction is limited, so the role of the digital economy in reducing carbon emissions is not as good as that of the middle and western regions.

4.4.2. Analysis of differences in economic development

Is there a difference in the impact of digital economy on carbon emission intensity under different economic development levels? This paper divides the samples into economically developed regions and economically underdeveloped regions based on the average per capita GDP of each province. The grouping regression results are shown in Table 8. The regression results of developed and underdeveloped regions are significantly negative at the level of 1%, but the absolute value of the regression coefficient in underdeveloped regions is greater than that in developed regions. It shows that the digital economy has a more obvious effect on reducing the carbon emission intensity in underdeveloped regions. The results of heterogeneity analysis provide guidance for policymakers to achieve the "dual carbon goals".

4.5. Mechanism test

According to mechanism analysis, the development of digital economy reduces carbon emissions per unit output through industrial structure optimization effect, resource allocation effect and innovation effect. This section tests the above influence mechanism. The test process is divided into three steps: Firstly, the independent variable are regressed with the mechanism variables, and the regression coefficients represent the impact of the digital economy on the intermediary variables. Secondly, the digital economy and carbon emission intensity are regressed to verify the impact of the digital economy on carbon emission intensity. Finally, the digital economy, intermediary variables and carbon emission intensity are regressed to verify whether the digital economy has an impact on carbon emission intensity through intermediary variables. The mechanism test model is constructed as follows:

$$mechanism_{it} = \alpha_0 + \alpha_1\, digital_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (9)$$

$$CI_{it} = \beta_0 + \beta_1\, digital_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (10)$$

$$CI_{it} = \sigma_0 + \sigma_1 digital_{it} + \sigma_2 mechanism_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (11)$$

among them, $mechanism_{it}$ contains three mechanism variables: $indust_{it}$, tfp_{it} and $innov_{it}$, which verify the industrial structure optimization effect, resource allocation effect and innovation effect, respectively, and the other variables are the same as the Equation 8. Equation 9 is used to verify the impact of the digital economy on the intermediary variables; Equation 10 is used to verify the impact of the digital economy on carbon emission intensity, that is, the benchmark regression; Equation 11 is used to verify the mechanism effect of the digital economy on carbon emission intensity.

Table 9 shows the results of the mechanism test. The results of columns 1, 3, and 5 demonstrate that the development of digital economy can promote the upgrading of industrial structure, improve total factor productivity and improve innovation efficiency. Among them, the impact of digital economy development on promoting industrial structure upgrading and improving total factor productivity has passed the 1% significance level, but the innovation efficiency has not passed the significance test. The results of columns 2 and 4 demonstrate that the industrial structure optimization effect and resource allocation effect have passed the 5% significance level, which proves the existence of intermediary effect. The coefficient of structural optimization effect and resource allocation effect is significantly negative, which verifies the previous theoretical mechanism analysis. This shows that the digital economy suppresses carbon emission intensity through the industrial structure optimization effect and resource allocation effect, which verifies H2 and H3. However, the innovation efficiency does not play an inhibitory role in reducing carbon emission intensity. The possible reason is that China's

TABLE 6 Endogenous test results[a].

Variables	*digtial*	*CI*	*digtial*	*CI_1*
	First stage (1)	Second stage (2)	First stage (3)	Second stage (4)
digtial		−1.1029*		−1.1252***
		(−1.8747)		(−4.2471)
digtial_iv	6.5101***		6.5101***	
	(20.9361)		(20.9361)	
constant	0.2834***	−1.2641***	0.2834***	−0.9470***
	(11.0026)	(−3.3390)	(11.0026)	(−5.5542)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390
R^2	0.6893	0.6435	0.6893	0.6622
Over-identification test	*NO*	/	*NO*	/
Weak IV test	438.14 [16.38]	/	438.14 [16.38]	/

[a]Over-identification test shows that there is no over-identification; the *Cragg − Donald Wald F* statistic is reported in the weak *IV* test, and the judgment value at the 10% level is in the brackets.

TABLE 7 Robustness test results.

Variables	*CI*	*CI_1*	*CI*	*CI_1*	*CI*	*CI_1*
	(1)	(2)	(3)	(4)	(5)	(6)
digtial	−1.2036***	−1.8646***				
	(−4.3338)	(−3.1358)				
digtial_1			−1.7888***	−2.3570***		
			(−5.9724)	(−3.6105)		
digtial_2					−0.6320***	−1.1814**
					(−2.7373)	(−2.4133)
constant	1.4091***	1.6106***	1.6146***	1.7918***	1.2272***	1.3942**
	(4.9126)	(2.6224)	(5.6758)	(2.8899)	(4.2796)	(2.2931)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.4334	0.1178	0.4580	0.1255	0.4157	0.1080

FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects.
[a]The t statistics are in parentheses.
$^{**}p < 0.05$, $^{***}p < 0.01$.

current innovation efficiency mechanism has not yet played a role, even at the expense of the environment.

5. Conclusion

Under the background of global climate change and digital transformation, it is of great practical significance to study the impact of digital economy development on carbon emission intensity. This paper constructs a measurement model of digital economy development level and carbon emission intensity at the provincial level in China, and on this basis, examines the impact and mechanism of digital economy development on carbon emission intensity. The results show that: (1) The development of China's digital economy is unbalanced among regions, showing a geographical spatial pattern of decreasing from east to west. (2) China's carbon emission intensity has a decreasing trend year by year, but there is a spatial difference of "high in the west and low in the east." (3) The development of digital economy can effectively reduce regional carbon emission intensity, but the impact of digital industrialization and industrial digitalization on regional carbon emission intensity is different, and digital industrialization has a more significant effect on reducing regional carbon emission

TABLE 8 Heterogeneity analysis results.

Variables	*CI*				
	East	Middle	West	Developed regions	Underdeveloped regions
digtial	−0.4211**	−2.2333***	−2.1632***	−0.5325***	−3.7053***
	(−2.0299)	(−3.4151)	(−6.0209)	(−3.1814)	(−5.1913)
constant	1.6754***	4.2736***	−0.2583	0.9756***	1.8866***
	(5.8533)	(7.8686)	(−1.3102)	(3.4909)	(4.0849)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	143	117	130	239	151
R^2	0.7021	0.6378	0.7578	0.6802	0.4134

TABLE 9 Mechanism test results.

Variables	Industrial structure optimization effect		Resource allocation effect		Innovation effect	
	indust	*CI*	*tfp*	*CI*	*innov*	*CI*
digtial	1.4446***	−0.5829*	2.0492***	−1.3777***	0.0757	−1.3837***
	(9.1056)	(−1.7605)	(3.6838)	(−4.3599)	(0.5510)	(−4.4923)
indust		−0.5402***				
		(−5.4109)				
tfp				−0.0826**		
				(−2.3874)		
innov						0.2701**
						(2.2691)
constant	0.7760***	2.0205***	0.9867*	1.5943***	0.1462	1.5618***
	(4.7355)	(6.3657)	(1.7174)	(4.9573)	(1.0296)	(4.9040)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.5048	0.4454	0.1018	0.3995	0.0865	0.4080

FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects.
[a]The t statistics are in parentheses.
*$p < 0.010$, **$p < 0.05$, ***$p < 0.01$.

intensity. (4) The digital economy has different effects on reducing carbon emission intensity in different regions. The inhibitory effect of developing digital economy on carbon emission intensity in the middle and western regions is stronger than in the eastern region. Compared with developed regions, the development of digital economy in underdeveloped regions has a greater inhibitory effect on carbon emission intensity. (5) The development of digital economy reduces carbon emission intensity through industrial structure optimization effect and resource allocation effect, and the industrial structure optimization effect suppresses regional carbon emission intensity more obviously, and carbon emission intensity is not reduced through innovation effect at this stage.

Clarifying the relationship between the development of digital economy and carbon emission intensity has important policy implications for the global response to climate change and China's realization of the "dual carbon goal." The development of digital economy is based on digital technology. Promoting digital technology innovation is to lay a solid foundation for the development of digital economy from the "root," and is a long-term and effective strategic measure to promote the role of digital economy in reducing carbon emissions. First, implement relevant policies to support the development of the digital economy, provide differentiated financial and tax support for the development of digital technology innovation enterprises, and focus on supporting the growth of "specialized and new" digital enterprises. Second, promote digital industrialization and industrial digitization, relying on the existing information and communication infrastructure, focusing on the construction of AI industry center, big data center, 5G base station service, industrial Internet service and other digital industry projects to meet the needs of the digital transformation of the real economy. Third, narrow the differences in the development of regional digital economy, formulate digital economy development strategies in accordance with local conditions, and give full play to their own resource advantages, increase the introduction of technology and talents, and create regional characteristic digital economy industries.

Data availability statement

The original contributions presented in this study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YL: conceptualization, methodology, resources, and validation. LZ: data curation, software, writing—original draft preparation, and visualization. DW: writing—reviewing and editing and supervision. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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