ANALYSING THE IMPACT OF GREEN FINANCE POLICY AND DIGITAL TRANSFORMATION ON REGIONAL ENERGY CARBON EMISSIONS UNDER LOW-CARBON DEVELOPMENT

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Abstract. Amid escalating climate challenges, the persistent rise in energy carbon emissions (ECE) poses a critical challenge for China’s sustainable development. The concurrent advancement of digital transformation and green finance has fundamentally restructured manufacturing systems, offering novel pathways for emission mitigation. This study investigates the synergistic effects of green finance and digitalization on ECE reduction, yielding three principal findings: (1) Both green finance and digital transformation demonstrate statistically significant direct and spatial spillover effects, with the spillover effect of digitalization substantially exceeding its direct impact; (2) A comprehensive analysis reveals that green finance exerts significant inhibitory influences through direct, indirect, and total effects on ECE, while digital transformation manifests consistent negative coefficients across all effect dimensions; (3) Regional heterogeneity analysis indicates that eastern China exhibits robust significance in both contemporaneous and lagged green finance effects, whereas central and western regions show diminishing temporal significance. Digitalization significantly curbs local ECE in eastern and central regions, but displays non-significant positive correlation in western areas. These findings advance the digital-environmental research paradigm and provide empirical support for achieving China’s dual carbon objectives.
Keywords: *sustainable development, circular economy, green development, carbon reduction, climate change*

Introduction

With the rapid development of China’s economy, the country’s carbon emissions will still be under great pressure to increase in the future. In September 2020, “China will strive to achieve carbon peak by 2030 and carbon neutrality by 2060”, the focus of realizing the “double carbon” goal is to reduce carbon emissions. China has entered a critical period in which carbon reduction is the key strategic direction and the green transformation of economy and society is promoted, and finding ways to reduce the carbon emission of the whole society has become an important issue of great concern. Low-carbon economy refers to a form of economic development in which economic and social development and ecological and environmental protection can reach win-win situations through technological innovation, institutional innovation, industrial transformation, new energy development and other means minimizing the consumption of high-carbon energy sources, such as coal and oil, and reducing greenhouse gas emissions under the guidance of the concept of sustainable development. Under the severe challenge of global climate change, low carbon economy has become the focus of attention of governments and enterprises (Ahmed et al., 2024; Abbasi et al., 2024; Zhang et al., 2023). China bears the major task of global emission reduction (Burrington, 2024; Akalpler, 2024), since its carbon emissions in the energy sector also occupy an important share of the global total. Therefore, finding ways to reduce energy carbon emissions (ECE) while maintaining sustained economic growth is particularly urgent.

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Digitalization is becoming one of the main drivers of business innovation and green transformation. Digital technology and artificial intelligence, represented by big data, have optimized and integrated the combination of innovation factors, crossed the information gap, reduced transaction costs, and significantly improved the independent innovation capability of enterprises. As the main body of energy saving and emission reduction, enterprises are also important platforms for the extensive use of digital technology, taking the initiative to adjust their development strategy and business direction to comply with the digitalization, greening and high-end transformation are beneficial for them (Wang et al., 2024a; Luo et al., 2025). Digital technology through the digital monitoring and transformation of the energy production process, enhances the efficiency of resource allocation, green productivity and energy efficiency of high-carbon industries (Miao et al.,2022; Zeng et al.,2024). Although, the use of digital technology can improve energy efficiency and effectively reduce carbon emissions, it may stimulate the industry to invest in more energy under certain circumstances. There is a rebound effect in transition of high-carbon industries to low-carbon emission, since high-carbon industries need to reduce overdependence on traditional energy sources, and the use of digital technology is a key factor in the development of the industry. The use of digital technology in the energy sector can promote the cleanliness of fossil energy sources, the industrialization of clean energy sources, and promote the development of low-carbon development.

Green finance as a key driver in modern economic development, is widely recognized as an important tool for green low-carbon transformation (Zavii, 2024). Green finance is a financial system that supports environmentally friendly and low-carbon projects and activities, mainly through green bonds, green funds, green loans and other forms of financial support for clean energy, environmental protection etc. China attaches great importance to the issue of energy carbon emissions and actively explores the role of green financial policies in promoting this issue, green financial policies have been improved, and mechanisms have emerged, promoting low-carbon economy (Mertzanis et al., 2025). Green finance accelerates green transformation by providing financial support and policy incentives to promote enterprises and projects to invest in environmentally friendly projects.

However, current research on how green finance and digital transformation specifically affect regional ECE in China is still relatively scarce. The energy consumption patterns and carbon emission characteristics of different regions vary widely, which makes the strategies and measures of these regions dealing with the challenges of energy and carbon emissions diverse. Therefore, studying green finance and digital transformation effects in different regional contexts is important for regionalized low-carbon policies and strategies.

The possible marginal contributions of this paper are the followings: on one hand, in the context of digital economy, digital transformation and “dual-carbon” goal, incorporating green finance, digital transformation and energy carbon emissions into the same analytical framework, and clarifying the role of digital transformation and green finance in the process of influencing energy carbon emissions; on the other hand, exploring the spatial effects of green finance and digital transformation on the intensity of energy carbon emissions, and providing reference for the adoption of localized and linked governance policies among regions, and also solid theoretical support and practical experience for China’s carbon emission reduction target.

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Literature review

Mitigation of climate change and reduction of ECE have become important goals on a global scale. Chinese government has put forward the strategic goals of "carbon peaking", which provide impetus for low-carbon development in the energy sector. Green finance and digital transformation, as two emerging driving forces, have gradually become important means to address this issue. Green finance guides low-carbon investment through capital allocation, and digital transformation improves energy utilization efficiency through technological innovation, and the synergy between the two is an important way to promote the reduction of regional ECE. This paper presents the existing research results to reveal the influence mechanism of the two on ECE, and provide theoretical support for subsequent research.

Green finance impact on regional ECE

Green finance constitutes a strategic economic mechanism that directs capital flows toward climate-aligned initiatives through specialized financial instruments. Its operational framework prioritizes three core objectives: (1) funding allocation for sustainable infrastructure development, (2) acceleration of clean energy transitions, and (3) systemic integration of environmental externalities into financial decision-making. This market-driven approach facilitates low-carbon economic restructuring while ensuring optimal resource distribution aligned with ESG (Environmental, Social, Governance) criteria.

Connotation of green finance

The concept of green finance was first proposed by the World Bank, and accepted by financial institutions, governments and enterprises worldwide. Green finance in China started relatively late, but with the increasing attention to environmental pollution, green finance in China has gradually received policy support and industrial recognition. At the beginning of its research, some foreign scholars defined it as financial policy, and then began to focus on its connotation from industrial ties and interdisciplinary perspective; thereafter, with the emergence of concepts such as goodwill assets and reputational risk, there may be a potential impact of environmental performance on financial performance, and hence it is argued that green finance can improve environmental quality and reduce the risk of environmental damage (Soundarrajan and Vivek, 2016; Wright, 2024). The establishment of China's modern green finance framework was catalyzed by the 2016 Guiding Opinions on Green Finance Development, which institutionalized three operational mechanisms: (1) Financing Optimization: Through concessional lending instruments (Chen and Xiong, 2024), green finance reduces capital costs for renewable energy sectors, thereby stimulating green-tech innovation; (2) Market Reorientation: Strategic capital reallocation mechanisms toward climate-aligned projects accelerate phase-out of carbon-intensive industries; (3) Ecosystem Development: Policy incentives including ESG disclosure mandates and green bond tax benefits elevate sustainable assets in capital markets, concurrently enhancing public environmental literacy (Wang et al., 2024b).

Impact of green finance on regional ECE

Finance is an important pillar for promoting green development, and vigorously developing green finance is an important guarantee for achieving carbon neutrality. For

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example, ICBC's ESG report for the past three years found that the balance of green credit was nearly 5.4 trillion yuan, an increase of about 35.7% year-on-year, and the scale ranked first among the six major banks. The equivalent emission reduction of carbon dioxide equivalent from green credit-supported projects has increased steadily over three years, and the amount of standard coal saved has risen year on year. In terms of carbon emission reduction loans, the bank's 2023 ESG report disclosed that a total of 1,496 projects were financed since the launch of the carbon emission reduction support tool, with a loan amount of 20,422 million, and a weighted average lending interest rate of 3.09%, leading to an annual carbon emission reduction of 51,457,200 tons of carbon dioxide equivalent (Zhang and; Zhou, 2024). It is recognized that green finance can stimulate the growth of clean energy and sustainable industries by improving capital allocation, thereby curbing energy consumption and emissions (Shahbaz et al., 2013). Studies by Shen and Li (2025) have shown that the expansion of green finance notably decreases corporate carbon emissions; factoring in environmental protection taxes, the reduction in carbon emissions through green finance becomes more evident. Research by Wei et al. (2024) indicates that green finance can substantially lower regional carbon emissions, although the spillover effect is not sufficiently pronounced. Dogan and Seker (2016) discovered that energy structures heavily rely on non-renewable sources like traditional fuels; the higher the financial development level, the greater the carbon dioxide production, and the more severe the carbon emission issue. Some scholars propose that the impact of financial development on carbon emissions follows an inverted U-shaped relationship. Liu (2023) examined the influence of financial development on carbon dioxide across Chinese provinces, uncovering an inverted U-shaped relationship, which empirically supports the environmental Kuznets curve theory. Chen and Wang (2024) observed that the effect of green finance on carbon emission efficiency in the eastern region exhibited an inverted U-shaped relationship, whereas in the central and western regions, the effects were not significant.

Impact of digital transformation on regional ECE in China

The integration of advanced digital technologies accelerates cross-domain modernization by optimizing resource allocation through intelligent systems, where energy sector innovations leverage smart grid architectures and cognitive computing frameworks to streamline production, distribution, and utilization processes, effectively mitigating energy waste while supporting carbon emission regulation through adaptive energy-carbon-economic system governance mechanisms (Zeng and Zhang, 2024; Cheng, 2023). By improving the intelligence level of the energy system, digital technology can reduce energy waste, and thus lower carbon emissions, for example, Huawei's energy Internet technology, developed in cooperation with Tsinghua University and other universities, has increased energy utilization efficiency by more than 20%. In the production chain, through the digital twin technology, steel companies have realized the refined management of the production process, reduced energy consumption by 8% and carbon emissions by 10%. The application of digital technology in renewable energy grid connection, scheduling, and energy storage has enabled China's installed capacity of renewable energy to grow from 380 million kilowatts (kW) in 2013 to 1.16 billion kW in 2022, with an average annual growth rate of 13.2% (Lin, 2024; Du and Li, 2024). Liu and Song (2023) found that digital transformation can promote energy utilization efficiency. The smart grid technology makes the energy delivery process more efficient, reduces energy loss, and also promotes the larger-scale application of renewable energy (Deer,

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2023). In addition, artificial intelligence provides accurate decision support for energy management, helping companies minimize energy waste. Digital transformation has also increased transparency through the popularization of energy monitoring systems (Xue et al., 2022). Consumers and businesses can monitor energy consumption data in real time and thus take effective energy saving measures (Chen and Wang, 2024). Jiang and Xu (2023) showed that in regions where digital management was implemented, the energy consumption structure gradually transformed to clean and efficient energy utilization, and carbon emission levels were effectively controlled.

Summary and outlook

In summary, green finance and digital transformation impact on ECE in China has attracted extensive attention. Many research studies have shown that green finance promotes the development of clean energy and green industries, while digital transformation reduces energy waste by improving the intelligence of energy management. The synergistic effect of the two helps to promote green transformation in the energy sector. However, current research mainly focuses on policy analysis and technology application at the macro level, and it needs analysis of the synergies between green finance and digital transformation in different regions and industrial contexts. Future research can further explore green finance and digital transformation effects in different regions, analyze their specific impact mechanisms on regional ECE, and propose regionalized policy recommendations.

Methodology

Calculation method of energy carbon emission

More than 90% of CO_2 emissions from human activities come from energy use. Therefore, at this stage, many scholars regard the CO_2 emissions from energy consumption in a certain region as the actual total CO_2 emissions of the region. Based on types of energy and the carbon emission coefficients proposed by IPCC (Intergovernmental Panel on Climate Change) Guidelines for National Greenhouse Gas Inventories, the specific calculation is given in *Equation 1*:

$$C_t = \sum_{i=1}^{n} E_i S_i E_f \quad \text{(Eq.1)}$$

where *Ct* represents the cumulative CO_2 emissions; *Ei* signifies the consumption of a specific energy type; *Si* indicates the conversion factor of that energy type to a standard coal equivalent; *Ef* represents the carbon emission factor (as defined by the IPCC, the carbon emission factor refers to the CO_2 emission coefficient), and *i* denotes energy source type to be counted. Due to the different actual situation in different regions, the methods used to calculate carbon emissions are also different.

In this paper, the total energy consumption (standard coal) is chosen as the research data, and the IPCC coefficient is used which is relatively more accurate (Yan and Li, 2023), and the specific calculation is given in *Equation 2*.

$$C_p = \sum E_p F_p \frac{44}{12} \quad \text{(Eq.2)}$$

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where *Cp* stands for the aggregate CO_2 emissions; *Ep* signifies the total energy consumption measured in standard coal units; *Fp* denotes the carbon emission factor associated with energy; and 44/12 represents that the molecular weight of carbon (C) changes from 12 to 44 when it is oxidized to carbon dioxide (CO_2), i.e., 1 t of carbon can produce about 3.67 t of carbon dioxide when it is burnt in oxygen.

Spatial measurement modeling

It has been shown that with the passage of time and economic development, the boundaries between regions are gradually blurred, the mutual flow of production factors between regions becomes more frequent, and inter-regional ties are gradually strengthened. Various economic variables may have spatial spillover effects, which test is of great significance.

(1) Spatial weighting matrix

Commonly used spatial weight matrices are based on geographic, or on economic and social characteristics,, among which, the spatial weight matrix based on geographic characteristics mainly has geographic neighboring and geographic distance spatial weight matrix, and the spatial weight matrix based on economic and social characteristics mainly has the economic distance spatial weight matrix with income, employment, human capital, etc., as economic variables (Cheng et al., 2014). Generally, the spatial linkage of ECE reflected by geographic location differences can only measure the influence of geographic proximity characteristics, but the spatial spillover effect of ECE is also influenced by many non-geographic proximity factors. Thus, it needs to construct other types of spatial weight matrices so as to measure the spatial effects objectively and accurately (Xu, 2012). Based on this, considering data availability, this paper takes the per capita gross domestic product in the sample period as the economic variable, combines the geographic distance weights with the economic distance weights as *Equation 3*:

$$W = W_{ij} diag\left(\overline{Y_1}\big/_{\overline{Y}},\ \ \overline{Y_2}\big/_{\overline{Y}},\ \ \cdots,\ \ \overline{Y_n}\big/_{\overline{Y}}\right) \quad \text{(Eq.3)}$$

where W_{ij} is the geographic distance spatial weight matrix; $\overline{Y} = \frac{1}{t_0 - t_1 + 1}\sum_{t=1}^{n} Y_i, \overline{Y_i} = \frac{1}{n(t_0 - t_1 + 1)}\sum_{i=1}^{n}\sum_{t_0}^{t_1} Y_{it}$.

$\overline{Y_i}$ denotes the average real GDP (Gross Domestic Product) per capita across all spatial units over the observed timeframe, $\overline{Y}$ represents the overall average real GDP per capita for the entire period, and Y_{it} indicates the real GDP per capita for the i-th spatial unit in year t within the timeframe.

(2) Spatial autocorrelation test

The global Moran'I index is selected to test spatial autocorrelation of ECE in each province, and the global spatial correlation tests the degree of spatial correlation between regions. Drawing on the global Moran's index proposed by Moran (1950), is calculated as shown in *Equation 4*:

$$\text{Moran'I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad \text{(Eq.4)}$$

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where I denotes the global Moran's index, *Xi* and *Xj* denote the ECE of regions *i* and *j*, $\bar{X}$ is ECE average, W_{ij} means spatial weight matrix, and *n* are all provinces. Moran'I takes the value of [- 1, 1], when I = 0, it indicates that the intensity of ECE is spatially randomly distributed; when I is above 0, a positive correlation is shown, the larger value showing that the characteristics of agglomeration are stronger; when I is below 0, it means negative correlation, the smaller value showing that the dispersion is more apparent.

(3) Spatial measurement model setting

Spatial econometric models incorporate spatial elements to capture the interdependencies among geographical units (Liam, 2003; Huang et al., 2024). Three principal types of spatial panel models include the spatial autoregressive (SAR), spatial lag (SLM), and spatial Durbin (SDM) models.

Spatial lag model (SLM). The spatial lag model accounts for the spatial correlation in the dependent variable, indicating that neighboring areas' explanatory variables impact the dependent variables in a given area. The fundamental structure of this model is:

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + x_{it}\beta + \varepsilon_{it} \tag{Eq.5}$$

Here, ρ denotes the coefficient for spatial dependence, W represents the matrix of spatial weights, y_{it} signifies the dependent variable, x_{it} indicates the set of independent variables, β is the coefficient vector for the independent variables, and ϵit stands for the error term.

Spatial error model (SEM). The spatial error model acknowledges the spatial autocorrelation present within the model's stochastic component, meaning that the error term of one region is influenced by the errors of adjacent regions (Yu et al., 2020). Essentially, the model's fundamental structure is as follows:

$$y_{it} = x_{it}\beta + \varepsilon_{it}; \varepsilon_{it} = \lambda \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \mu_{it} \tag{Eq.6}$$

In the spatial error model, λ represents the coefficient that captures the spatial correlation in the model's error term, μ_{it} denotes the idiosyncratic error term, with the remaining elements being consistent with the previously mentioned.

Spatial Durbin Model (SDM). The Spatial Durbin model is recognized for its extensive use and comprehensive nature. It considers spatial dependencies in both the dependent and independent variables, meaning that the independent variables in each area are influenced not only by their own set of variables but also by those in surrounding areas. The fundamental structure of the SDM is outlined as follows:

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + x_{it}\beta + \theta \sum_{j=1}^{n} w_{ij} x_{it} + \varepsilon_{it} \tag{Eq.7}$$

where θ denotes the regression coefficient, and the rest as above.

Furthermore, within the spatial econometric framework, alterations in the independent variables of one area have a dual impact: they exert a direct influence on the dependent variables within the same area and may also have an indirect influence on those in other areas. This study employs the partial differentiation approach of Lesage and Pace (2009) to dissect the spatial econometric model, with the decomposition model presented as follows.

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$$\begin{bmatrix} \frac{\partial Y_1}{\partial X_1} \cdots \frac{\partial Y_1}{\partial X_n} \\ \vdots \vdots \vdots \\ \frac{\partial Y_n}{\partial X_1} \cdots \frac{\partial Y_n}{\partial X_n} \end{bmatrix} = (1-\rho W)^{-1} \cdot \begin{bmatrix} \beta_k \; \omega_{12}\theta_k \; \cdots \; \omega_{1n}\theta_k \\ \omega_{21}\theta_k \; \beta_k \; \cdots \; \omega_{2n}\theta_k \\ \vdots \vdots \vdots \vdots \\ \omega_{n1}\theta_k \; \omega_{n2}\theta_k \; \cdots \; \beta_k \end{bmatrix} \quad \text{(Eq.8)}$$

where direct and indirect effects are represented by diagonal and non-diagonal element means, respectively.

Variable selection and data sources

Explained variables

Energy Carbon Emission (ECE): the CO_2 emission from energy consumption in a region is regarded as the total actual CO_2 emission in the region, and the specific calculation method is described above.

Explanatory variables

(1) Green finance (GF)

This paper’s central explanatory variable is green finance. In accordance with the work of Zeng and Zhang (2024), Cai and Song (2024), and other relevant studies, and considering the comprehensiveness of the indicator system and data availability, green finance is categorized into five dimensions based on its definition and service type: green credit, green securities, green investment, green insurance, and carbon finance. Each of these dimensions are further divided into five sub-indicators. A comprehensive index of green financial development is determined using principal component analysis, and the resulting indicator system is detailed in *Table 1*.

(2) Digital transformation (DT)

In this paper, the data of 30 Chinese regions from 2010-2023 are selected as the research sample in measuring digital transformation. The reason for setting the use of provincial data is mainly due to data availability, since many of the indicators are only available at the provincial level, without data at the more subdivided prefecture level. This paper selects these data to measure the digital transformation index as shown in *Table 2*.

Control variables

Economic development (LPGDP): The per capita gross regional product serves as a pivotal metric for gauging the economic development level within a region, effectively indicating the region’s economic affluence (Zhou et al., 2024). This paper has chosen to use the logarithm of regional GDP per capita as a control variable, aiming to eliminate the potential interference that different regions may have on the results of the study due to differences in economic levels.

Urbanization (UR), the expansion of urbanization will bring the accumulation of human capital, which will bring a variety of green technologies, green technology has promoted the improvement of energy efficiency, which is conducive to reducing carbon emissions. However, the advancement of urbanization may increase residents' income,

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thereby stimulate residents' consumption and increase energy consumption, which in turn increases carbon emissions. Therefore, the impact of the level of urbanization on energy carbon emissions is uncertain (Xuan, 2024). This paper uses the ratio of urban population to the total population to represent the level of urbanization.

Table 1. *Green finance indicator system*

<table>
<tr><th></th><th>Level 1 indicators</th><th>Level 2 indicators</th></tr>
<tr><td rowspan="9">Green finance</td><td rowspan="2">Green credit</td><td>Interest on energy-consuming industrial industries/Interest on industrial industries</td></tr>
<tr><td>Energy-saving and environmental protection loans/gross regional product</td></tr>
<tr><td rowspan="2">Green securities</td><td>Total market capitalization of environmental protection enterprises/A-share total market capitalization</td></tr>
<tr><td>Total market capitalization of six major energy-consuming industries/A-share total market capitalization</td></tr>
<tr><td rowspan="2">Green insurance</td><td>Agricultural insurance payout/agricultural property premium income</td></tr>
<tr><td>Agricultural insurance income/gross agricultural output value</td></tr>
<tr><td rowspan="2">Green investment</td><td>Total investment in environmental pollution control/GDP</td></tr>
<tr><td>Total fiscal expenditures on energy-saving and environmental protection industries/total fiscal expenditures</td></tr>
<tr><td>Carbon finance</td><td>Carbon emissions/GDP</td></tr>
</table>

Table 2. *Digital transformation index system*

<table>
<tr><th></th><th>Level 1 indicators</th><th>Level 2 indicators</th></tr>
<tr><td rowspan="13">Digital transformation</td><td rowspan="7">Digital foundations</td><td>Number of employees in the software industry/total regional employment</td></tr>
<tr><td>Number of computers per 100 people in industrial enterprises</td></tr>
<tr><td>Number of software enterprises/total number of enterprises in the region</td></tr>
<tr><td>Optical fiber lines</td></tr>
<tr><td>Number of international Internet users</td></tr>
<tr><td>Electricity consumption of the whole society</td></tr>
<tr><td>Number of cell phone subscribers</td></tr>
<tr><td rowspan="6">Industrial innovation and transformation</td><td>Investment in R&D</td></tr>
<tr><td>Turnover of technology contracts</td></tr>
<tr><td>Number of digital technology-related patent applications</td></tr>
<tr><td>Sales revenue of new products of industrial enterprises</td></tr>
<tr><td>E-commerce sales</td></tr>
<tr><td>Software business revenue/GDP</td></tr>
</table>

The level of fiscal expenditure (FIS), as a part of the government's macro policy is important in influencing economic development, since the development of a region

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cannot be separated from governmental support (Zhang et al., 2024). The government's financial investment, will increase the effectiveness of technological research and development of local industries, local industries through the transformation of energy utilization affect ECE, this paper selects the proportion of government fiscal expenditure in the regional gross domestic product to indicate.

Human capital is measured by years of education per capita (EDU). Referring to the study of Wang (2010), the education level is divided into five tiers, namely, illiteracy, elementary school, junior high school, senior high school and middle school, junior college and bachelor's degree or above (in which secondary vocational education is equivalent to middle and senior high school qualifications, and higher vocational education is equivalent to junior college qualifications, the corresponding years of education are 1, 6, 9, 12 and 16, respectively, which results in the per capita number of years of schooling, that is calculated as follows: (the number of illiterate people * 1 + the number of people with elementary school qualifications * 6 + number of people with junior high school education * 9 + number of people with high school and junior college education * 12 + number of people with college and bachelor's degree or above * 16) / total population over 6-year-old. Usually, the improvement of human capital level means that the development of new and efficient environmental protection technologies improves providing obvious technical support for emission reduction, which is conducive to the upgrading of emission reduction technologies of the state and enterprises. The improvement of human capital will also help to raise the public's attention to the issue of carbon emission, thus improving the efficiency of low carbon emission initiatives. The data in this paper are mainly obtained from China Statistical Yearbook, China Industrial Statistical Yearbook, China Energy Statistical Yearbook, as well as the Statistical Yearbook of each province, autonomous region and city, and the website of the National Bureau of Statistics, etc. A few missing values are made up by linear interpolation. The descriptive statistics of each variable are shown in *Table 3*.

Table 3. *Results of descriptive statistics*

Variables	Mean	Standard deviation	Minimum	Maximum
ECE	2.009	1.459	0.128	8.635
GF	0.355	0.127	0.089	0.739
DT	0.786	0.538	0.073	2.573
LPGDP	10.256	0.558	8.127	13.142
FIS	0.248	0.117	0.096	0.752
EDU	9.882	0.962	5.935	14.332
UR	0.514	0.158	0.009	0.998

Results

Spatial autocorrelation test results

Focusing on provincial-level energy carbon emissions across 30 Chinese administrative regions, this study employs spatial autocorrelation methodologies to quantify geographic clustering dynamics through Moran's index computations in the period of 2010-2023, with analytical outcomes revealing significant spatial dependency patterns in emission distributions, results are shown in *Table 4*.

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Table 4. *Spatial autocorrelation test results*

Year	ECE		
	Moran	**Z-value**	**P-value**
2010	0.3122	3.3111	0.0001
2011	0.3126	3.3252	0.0002
2012	0.3265	3.3456	0.0001
2013	0.3301	3.3532	0.0010
2014	0.3412	3.3564	0.0000
2015	0.3521	3.3763	0.0001
2016	0.3634	3.3788	0.0000
2017	0.3677	3.3811	0.0000
2018	0.3698	3.3821	0.0000
2019	0.3722	3.3826	0.0000
2020	0.3832	3.3865	0.0004
2021	0.3875	3.3875	0.0000
2022	0.3943	3.3892	0.0000
2023	0.4122	3.3923	0.0001

Statistical analysis reveals consistently significant Moran's index coefficients ($p < 0.01$) for China's provincial ECE during 2010-2023, demonstrating strong spatial convergence patterns where emission behaviors exhibit positive autocorrelation tendencies influenced by neighboring jurisdictions, thereby confirming the necessity to incorporate spatial interdependence mechanisms through rigorous econometric modeling frameworks.

Multicollinearity test

Given that the study data are panel data, multicollinearity test is carried out to avoid multicollinearity between variables, which may cause bias in the measurement results. *Table 5* reports the variance inflation factor (VIF) of each variable, and the findings indicate that the Variance Inflation Factor (VIF) for each variable is below 5, with an overall average of 2.45, signifying the absence of multicollinearity among the variables. Thus, the next step of data analysis can be carried out.

Table 5. *Results of multicollinearity test*

	ECE	DT	GF	LPGDP	UR	FIS	EDU	Mean
VIF	3.3	1.22	2.25	3.48	1.99	2.36	2.54	2.45
1/VIF	0.30	0.82	0.44	0.29	0.50	0.42	0.39	0.45

Spatial econometric model selection test

In advancing spatial econometric methodologies, the pre-estimation phase demands scrupulous adherence to hierarchical diagnostic sequencing as prescribed by seminal econometric theory (Lin and Guan, 2020), where preliminary Lagrange Multiplier (LM) tests serve as critical gatekeepers by detecting statistically significant thresholds ($p < 0.01$) between competing spatial autoregressive (SAR) and spatial error correction

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(SEM) model typologies—a diagnostic impasse that necessitates rigorous application of heteroskedasticity-robust R-LM testing protocols to disentangle model selection indeterminacy, thereby empirically substantiating the co-existence of both spatial spillover propagation mechanisms (via dependent variable interactions) and latent structural error clustering phenomena. This methodological conundrum acquires heightened theoretical salience when contextualized within macroeconomic dynamics characterized by non-Markovian temporal persistence, wherein intertemporal dependency structures systematically propagate historical emission trajectories into contemporary outcomes through path-dependent institutional lock-ins and technological inertia—a stylized fact that axiomatically necessitates adoption of spatial Durbin model (SDM) parameterizations capable of holistically capturing both endogenous interaction effects (through spatially lagged dependent variables) and exogenous spillover conduits (via geographically weighted independent variable matrices). After SDM specification, iterative application of Wald's quadratic form evaluation and Likelihood Ratio (LR) non-nested hypothesis testing procedures categorically refuted any mathematical reducibility of the SDM framework into constrained SAR/SEM functional forms, thereby statistically ratifying the SDM's superior capacity to model complex spatial feedback loops. Parallel to these diagnostics, Hausman's seminal specification test — operationalizing a systematic comparison of fixed-effects versus random-effects covariance structures — yielded decisive evidence favoring fixed-effects estimators through dual evidentiary channels: ontologically, by recognizing the non-stochastic nature of observational units drawn exhaustively from population-level administrative jurisdictions rather than probabilistic subsamples; statistically, through resounding rejection of the random-effects orthogonality assumption. Synthesizing these multidimensional analytical insights, the research architecture strategically converges upon a doubly fixed-effect SDM specification that simultaneously disciplines temporal non-stationarity through period-specific intercept adjustments and neutralizes unobserved cross-sectional heterogeneity via entity-demeaning transformations, thus engineering an estimator robust to both chronologically evolving policy regimes and spatially stratified institutional configurations — a methodological imperative particularly acute in decarbonization studies where provincial emission trajectories are inexorably shaped by both localized path dependencies and interprovincial technological diffusion asymmetries (*Table 6*).

Table 6. *Identification tests for spatial measurement models*

Testing	p-Value
LM-lag	0.012
LM-error	0.000
R-LM-error	0.030
R-LM-lag	0.012
Wald-lag	0.000
Wald-error	0.011
LR-lag	0.000
LR-error	0.000
Hausman	0.000

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Spatial measurement regression

SDM model regression results

Within this study, the model selection was initially scrutinized, leading to the adoption of a spatial-temporal double fixed effects spatial Durbin model for the empirical examination. The regression outcomes are detailed in *Table 7*.

Table 7. *SDM model regression results*

Variable	Bidirectional fixed effect
DT	-0.255***(-4.43)
GF	-0.335***(-5.33)
PDGP	0.158***(4.77)
UR	-0.098**(-1.99)
FIS	-0.0995***(-3.22)
EDU	-0.124**(2.33)
W* DT	-0.354***(-4.63)
W*GF	-0.569*** (-4.14)
W*LPGDP	0.253*** (5.95)
W*UR	-0.0936 ***(-4.87)
W*FIS	-0.1877**** (-2.97)
W*EDU	-0.278*** (3.99)
ρ	0.3398

The core analytical findings demonstrate statistically significant negative associations between green finance development and ECE, with the composite green finance index exhibiting dual-channel regulatory efficacy. This is similar to the findings of most scholars, who believe that financial institutions are directly linked to the real economy by providing loans to low-pollution projects, directly investing in environmental industries, and helping green enterprises to issue shares, thus contributing to the fulfillment of carbon emission reduction targets (Claessens and Feijen, 2007; Wara., 2007), Its direct effect coefficient (-0.335) quantifies substantial local ECE abatement per unit index enhancement, while the spatially lagged coefficient (-0.569) reveals amplified cross-jurisdictional mitigation impacts, confirming the mechanism's simultaneous operation through both intra-regional decarbonization pathways and interregional spillover diffusion. Specifically, a 1% incremental elevation in the index corresponds to 0.335% endogenous ECE reduction within origin jurisdictions, coupled with 0.569% exogenous diminution in contiguous territories—empirical evidence substantiating green finance's dual capacity as both localized environmental regulator and spatial sustainability propagator in low-carbon transition systems.

Empirical results establish statistically robust dual-directional regulatory impacts ($p < 0.01$) of digital transformation on energy-carbon intensity, manifesting through both endogenous mitigation channels and exogenous spatial interactions. Per unit augmentation in digitalization level generates 0.255-unit localized intensity abatement alongside 0.354-unit cross-jurisdictional attenuation. This finding is in line with most scholars who have concluded that, for example, Xie (2022), Chen et al. (2021) concluded that digital transformation can significantly reduce energy carbon intensity, while other scholars

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proved a non-linear relationship between the two (Mu Lun et al., 2022; Batool et al., 2022), A possible explanation is that different results are obtained at different stages of the development of digital economy. The spatial spillover magnitudes demonstrate statistically significant predominance over direct effects, thereby mechanistically confirm the asymmetric efficacy gradient between cross-regional decarbonization pathways (via technology diffusion networks and data interoperability synergies) and localized mitigation mechanisms (through intelligent process optimization and predictive emission controls). Therefore, when exploring such issues, the diffusion effect and radiation effect should be taken into account, mainly because the digital economy not only strengthens the industrial linkages between various regions and promotes the inter- and multi-regional flow of factors but also expands information spillover borders and strengthens inter-regional exchanges and cooperation, thus realizing a “win-win” situation in terms of carbon emission reduction. While easing the pressure on local ECE, digital transformation also has a significant positive impact on other regions. The reason may be: the carbon emission reduction effect of digital transformation mainly relies on digital technology to empower the production, exchange, distribution and consumption links, using the scale effect, technology effect and structural effect of digital transformation to improve production technology, optimize industrial structures and circulation processes, converge income distribution, and make use of the technological innovations to reduce ECE, alleviate the problem of ECE, and promote the realization of low-carbon goals.

Multivariate analysis reveals statistically significant suppressing effects ($p < 0.10$) of socioeconomic determinants on energy-carbon emissions (ECE), where per capita economic affluence (LPGDP) demonstrates tripartite decarbonization mechanics: its negative marginal effect coefficients across specifications originate from endogenous structural transitions (energy efficiency innovations, industrial upgrading, and clean energy adoption) amplified by cross-jurisdictional spillover dynamics. Regional economic growth synergistically curtails local ECE through technological leapfrogging while neighboring LPGDP elevation triggers spatial knowledge diffusion that further suppresses territorial emission intensities. Concurrently, human capital accumulation manifests transboundary regulatory capacity, with direct and total effect coefficients achieving statistical significance at $\alpha = 0.10$, quantitatively confirming its dual-channel emission governance through both localized green skill deployment and interregional innovation network effects that systematically displace carbon-intensive practices across geographic clusters. Thereby, multi-scale decarbonization pathways are established where human capital operates as both endogenous mitigator and spatial sustainability catalyst in low-carbon transition frameworks. Every percentage increase in human capital level will indirectly reduce the efficiency of ECE in neighboring regions by 0.278 percentage points, indicating that there will be mutual exchanges of talent and learning between talents. Spatial econometric evidence identifies human capital as a cross-regional decarbonization accelerator, where endogenous human capital accumulation stimulates interjurisdictional knowledge spillovers, driving neighboring territories’ technological upgrading through labor mobility networks and R&D collaboration channels, thereby ECE reduction in adjacent regions per standard deviation will increase.

Concurrently, urbanization manifests bidirectional inhibitory effects, mechanistically rooted in metropolitan carbon governance systems that synergistically integrate smart grid infrastructures with circular economy protocols to disrupt emission lock-in effects, while fiscal expenditure coefficients quantitatively verify the spatial decarbonization premium of green public investment. Intergovernmental fiscal transfers systematically

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reallocate low-carbon assets across regions, creating emission abatement cascades through renewable energy subsidies and carbon pricing policy diffusion. Ultimately, polycentric climate mitigation architectures are configured where human-ecological-financial vectors collaboratively rewrite regional carbon metabolic trajectories, and an increase in the government's fiscal expenditure will lead to more investment in pollution control, so that the government will be able to inhibit the increase of energy and carbon emissions effectively.

Decomposition of spatial spillover effects

To gain a more thorough and precise analysis of spatial disparities, this research employs the partial differentiation approach suggested by Lesage and Pace (2009), to delve into the direct, indirect, and total impacts of green finance and digital transformation on ECE. The outcomes of the spatial spillover effect decomposition are outlined in *Table 8*.

Table 8. *Decomposition results of spatial spillover effect*

Variant	Direct effect	Indirect effect	Aggregate effect
DT	-0.324***	-0.445***	-0.769***
GF	-0.564***	-0.698***	-0.2501***

The spatial effect decomposition results in *Table 8* reveal that the direct, indirect, and total impacts of green finance on ECE are all statistically significant at the 1% level. This suggests that an increment in the green finance index will directly decrease the ECE level in a region by 0.324 percentage points, and indirectly reduce the level of ECE in the neighboring regions by 0.445 percentage points, and the overall regional energy carbon emission level will be reduced by 0.769 percentage points. Also, since the indirect effect of green finance is greater than the direct effect, green finance gathers are spreading to the outside, it has a strong radiating effect, which reduces ECE level of the neighboring regions. Research on green finance and carbon emissions from a spatial perspective is currently focused on green finance and low carbon economy. Yin et al. (2021) concluded that green finance and green economy show a U-shaped relationship of inhibition followed by promotion, so it can be seen that the study of the relationship between green finance and carbon emission efficiency from a spatial perspective in this paper is complementary and in line with existing research.

The influence of digital transformation on ECE through its direct, indirect, and total effects is significantly negative. Specifically, the direct impact coefficient of digital transformation is -0.564, which is significant at the 1% level, indicating that with each unit rise in a province's digital level, ECE is reduced by 0.564%. The indirect effect is also significantly negative at the 1% level, with a coefficient of -0.698, signifying a decrease of approximately 0.698% in the surrounding areas' ECE intensity for each unit increase in digital transformation. Thus, the total effect of digital transformation on ECE is -1.154, indicating a potential ECE reduction of 1.154% per unit increase in digital transformation. The decomposition results indicate that digital transformation not only directly inhibits ECE but also substantially affects the ECE of adjacent regions. Hu et al. (2025) also concludes that in the process of digital transformation of the manufacturing industry, the digital economy not only strengthens industrial linkages between regions

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and promotes the cross-regional and multi-regional flow of factors, but also expands the information spillover boundaries, strengthens inter-regional exchanges and cooperation, and makes the spatial spillover effect of carbon emission reduction better than the direct effect.

Direct effect is reflected in the operation and management of digital technology-enabled industries, and the empowerment of digital technology not only improves production efficiency, but also helps to maximize resource utilization and achieve a low-carbon economy. In contrast, the indirect effect stems from technological and knowledge spillover due to digital transformation, which prompt the development of the digital transformation in the neighboring regions. The digital transformation of these regions will also have a certain inhibition effect on the intensity of ECE in the region. In addition, the indirect effect of digital transformation on the inhibitory nature of ECE is greater than the that of direct effect, which is enough to highlight the importance of the spatial spillover effect brought about by the interprovincial mobility of digital transformation development in promoting the process of carbon reduction.

Heterogeneity analysis

In accordance with the Division of Standards of the National Bureau of Statistics, the 30 provincial-level administrative regions are divided into East, Central and West, the eastern region including 11 provinces (municipalities), namely Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the central region, including 10 provinces (autonomous regions), that are Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi; the western region including 9 provinces (autonomous regions), Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang. From the perspective of data availability (in this paper, Tibet, Hong Kong, Macao and Taiwan are not considered), 30 regions are selected for regression analysis, with the regression outcomes detailed in *Table 9*.

Table 9. *Results of heterogeneity analysis*

Variable	East	Central	West
DT	-0.563***	-0.332***	0.147
W*DT	-0.652***	-0.263***	0.025
GF	-0.356***	-0.125**	0.016
W*GF	-0.448***	-0.063	0.096

The spatial effect coefficients of green finance did not pass the significance test in the central and western regions, indicating that green finance only has a significant impact on the level of ECE in the region, and does not show a significant spatial spillover effect on the neighboring regions. Due to the rapid economic development in the eastern region of China, it can utilize its own green capital and advanced environmental protection technology to spread to the surrounding regions, thus the development of green finance not only affects the local ECE, but also inhibits ECE of the surrounding regions. The rapid rise of green finance in the central region will promote the concentration of capital, labor and other key production resources in the region, which may lead to the loss of development resources and reduced opportunities to a certain degree in the surrounding areas. Although

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the development of green finance in the central region has played an obvious role in curbing ECE, its effect on curbing ECE in neighboring regions is not outstanding. Due to the relative lag in economic development and the undertaking of many high-pollution and high-emission industries, the western region is facing the urgent need for economic structural transformation, so that the development of green finance in the region will not have a significant impact on the neighboring regions either.

The regression coefficients are significant for the effect of digital transformation on ECE in the eastern and central regions, but not significant in the western region, this means that digital transformation significantly impacts local ECE in both the eastern and central regions, with the eastern region experiencing a more pronounced effect. In the western region, where urbanization and digitalization are still nascent and reliant on traditional high-carbon energy sources, a rise in digital transformation level does not show a significant relationship with ECE reduction. The spatial spillover effect of the western region did not pass the significance test, considering that the western region is less developed compared with the eastern region, and therefore may face difficulties in terms of pollution transfer brought by foreign direct investment, lax environmental control policies, and the lack of scientific industrial planning capacity. These difficulties are reflected in the control variables of this paper, which may offset the effect of the digital transformation on the reduction of energy carbon emission intensity among provinces, resulting in a non-significant spillover effect.

Robustness test

Benchmark regression analysis and spatial effect decomposition have already proved the carbon emission reduction effect of digital transformation to a certain extent; in order to verify the stability and reliability of the model, we replace the explanatory variables (replaced by per capita carbon emissions) to analyze the robustness of the above results again, the findings are displayed in *Table 10*. It is evident that the direct, spatial spillover, and total impacts of green finance and digital transformation align with the conclusions of the previous analysis, confirming the validity of the constructed model's construction.

Table 10. *Robustness test results*

Variable	National	East	Central	West
DT	-0.356***	-0.459***	-0.398***	0.153
*W*DT*	-0.399***	-0.552***	-0.277***	0.098
GF	-0.386***	-0.389***	-0.148**	0.089
*W*GF*	-0.529***	-0.466***	-0.095	0.126

Conclusions and recommendations

Conclusions

Both the direct and spillover effects of green finance and digital transformation pass the significance test, indicating that they can not only reduce the local level of ECE, but also produce spatial spillover effects to reduce the level of ECE in the surrounding regions.

The indirect effect of green finance on ECE is greater than that of the direct effect, indicating that with the development of green finance, the high-quality resources it gathers spread outwards, and to a certain extent, it has a strong spillover effect, which

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reduces the ECE of the neighboring regions. The impact of digital transformation on ECE not only has an obvious direct inhibitory effect, but its inhibitory effect on ECE in neighboring regions is also very significant.

Green finance in the eastern region not only has a significant impact on ECE, but also has a significant spillover effect on ECE in neighboring regions. The coefficients of the spatial effect of green finance in the central region and the western region did not pass the test of significance, which indicates that the green finance in the central and western regions does not show a significant spatial spillover effect on ECE in neighboring regions. The effect of digital transformation on ECE did not pass the significance test in the west, indicating that in the western region, the urbanization and digitalization processes are still in the initial state, and still mainly rely on traditional high-carbon energy sources. As a result, when the level of digital transformation is increased in the western region it does not appear to have a significant inhibitory relationship observed in the eastern and central regions, but rather presents a non-significant positive effect.

Recommendations

Considering the advancement of the digital transformation in the manufacturing sector, it is crucial to focus on the impact of digitalization on reducing carbon emissions. The government should increase support for the digital transformation of the manufacturing industry, incentivize enterprises to adopt and upgrade digital technologies to reduce energy and carbon emissions, and promote the development of low-carbon technologies; strengthen regional policy synergy and cooperation, and also cooperation to jointly formulate and promote the carbon emission reduction policy of digital transformation, responding to the challenge of carbon emission reduction. At the same time, attention must be turned to the management and training of professionals, and the reasonable avoidance of information security issues. On the other hand, the threshold effect of carbon emission reduction of digital transformation should also be considered, along with strengthening the digital awareness and basic capacity building, implementing in-depth production process of carbon emissions grading measurement, constructing digital carbon management big data cornerstone, refining the impact factor level, and implementing targeted development of carbon emission reduction policies.

Digital transformation needs to be based on regional development differences and tailored to local conditions. The results of the heterogeneity analysis show that the digitalization of the manufacturing industry has failed to exert a significant carbon emission reduction effect in the central part of the country. First, policymakers should consider imposing appropriate policy tilts to the central region, such as formulating incentivized tax and proactive fiscal policies to support the digitalization of manufacturing firms in the central region. Furthermore, the government should foster the growth of technology-intensive industries characterized by substantial high-tech digital investments, leveraging their cutting-edge technologies. It should enhance educational funding and prioritize the development of human capital to bolster the diffusion of advanced digital technologies from the eastern region. Additionally, the central region should develop emerging digital sectors, innovate through emulation, and eventually cultivate locally advantageous digital industries to attain sustainable long term energy and carbon emission reductions.

Green financial policies can reduce regional energy and carbon emission intensity, and this effect will continue over time and be further enhanced by promoting green technology innovation and optimizing energy structure. It is important to actively cultivate a sound

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regional green financial infrastructure, increase green financial funding support, establish a green financial technology platform, realize the intelligent identification, evaluation and monitoring of green emerging projects. These measures promote green financial policies to accurately make efforts to achieve results on the ground, and help regional emission reduction and carbon reduction.

The green supply of financial policies can be increased to promote the production and use of clean energy. The development of green finance is characterized by market failures such as externalities, public goods and information asymmetry. Therefore, while insisting on the main role of the market, the government should play a good role in macro-control and increase the supply of green financial infrastructure, so as to minimize the problems caused by externalities and the nature of public goods. At the same time, it is necessary to strengthen the top-level design, increase the punishment of highly polluting enterprises, encourage and support the production of clean and non-polluting new energy enterprises, and improve the transparency of green financial information.

Promoting the green and low-carbon transformation of energy enterprises and the improvement of energy carbon emission efficiency require technological innovation. Energy enterprises should utilize their own advantages to enhance their technological innovation capability to maximize the use of resources. According to the nature and technological innovation ability of different energy enterprises, policymakers should implement differentiated and precise support, scientifically allocate resources, and orderly invest in technological innovation.

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