The Impact of the Digital Economy on Carbon Emissions: Evidence From Machine Learning, Graph Neural Networks, and the EKC Hypothesis

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Abstract

This study utilizes panel data from 30 Chinese provinces spanning 2007 to 2023 and integrates machine learning and graph neural network (GNN) approaches to examine the spatial dynamics of carbon emissions. It aims to systematically evaluate the impact pathways of the digital economy on carbon intensity and to uncover its spatial diffusion patterns and regional heterogeneity. The empirical findings are threefold. First, the digital economy significantly reduces carbon intensity, consistent with the Environmental Kuznets Curve (EKC) hypothesis, and this effect exhibits clear heterogeneity across economic development levels and regions. Second, due to the existence of spatial spillover effects, GNN models outperform traditional machine learning methods in carbon emission prediction tasks. Third, carbon intensity displays strong temporal inertia and negative spatial spillovers across regions. Notably, spatial diffusion capacity and sensitivity to the digital economy vary substantially: central and western regions exhibit stronger spillover effects, northeastern provinces show more pronounced internal feedback mechanisms, while eastern coastal areas demonstrate relatively weaker effects. Overall, this study expands the analytical perspective on the digital economy's role in carbon mitigation and provides theoretical and empirical support for the design of differentiated emission reduction policies and coordinated regional governance.

Keywords: digital economy, carbon emissions, machine learning, GNN, spatial spillover effects

1. Introduction

As global climate change and environmental pollution intensify, the transition toward a low-carbon economy has become a pressing concern for the international community. In China in particular, rapid economic growth has been accompanied by mounting energy consumption and carbon emissions, raising the critical question of how to balance economic development with environmental protection. In response, classical theories—especially the Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman and Krueger (1991)—suggest that the relationship between economic growth and environmental degradation follows an inverted U-shape, providing a valuable theoretical framework for exploring sustainable development paths. Against this backdrop, the emerging digital economy offers a promising mechanism for reducing carbon emissions through industrial upgrading, improved resource allocation efficiency, and the diffusion of green technological innovation.

However, despite a growing body of empirical evidence supporting the emission-reduction potential of the digital economy, notable gaps remain. First, existing studies are largely based on aggregate analyses and often overlook differences across regions and levels of economic development. Second, research methods to date have not fully integrated traditional machine learning techniques with more recent approaches such as Graph Neural Networks (GNN), limiting the ability to capture the spatial diffusion and networked interdependence of regional carbon emissions. Third, there remains a lack of systematic analysis of the spatial transmission mechanisms and regional heterogeneity underlying carbon emission patterns. Addressing these gaps is not only critical to advancing theoretical understanding of the digital economy's environmental impacts, but also essential for designing differentiated and effective green transition policies.

Considering this, this study sets out three key objectives. First, it extends the traditional EKC model by incorporating digital economy variables to test the validity of the EKC hypothesis and explore the carbon mitigation effects of digital development. Second, it compares the predictive performance of traditional machine learning models with

GNN-based approaches to assess the suitability and accuracy of different methodologies. Third, it combines spatial econometric models with GNN-based visual analyses to investigate the spatial spillover effects of the digital economy on carbon emissions and uncover the underlying mechanisms and heterogeneity of spatial transmission.

This study contributes to the existing literature in several ways. Theoretically, it enriches the EKC framework by offering new insights into the digital economy–carbon emissions nexus. Methodologically, it introduces an innovative integration of econometric modeling and GNN techniques to analyze spatial spillovers and regional disparities more effectively. Practically, it provides a robust empirical foundation for formulating differentiated digital economy strategies and promoting coordinated regional carbon mitigation efforts.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and formulates the research hypotheses. Section 3 presents the data and variable definitions. Section 4 outlines the model specification. Section 5 reports the empirical results. Section 6 conducts robustness checks, and Section 7 concludes.

2. Literature Reviews and Hypotheses

2.1 Literature Reviews

The Environmental Kuznets Curve hypothesis, first proposed by Grossman and Krueger (1991), posits an inverted U-shaped relationship between economic development and environmental pollution—pollution levels initially rise with income growth, but decline once income surpasses a certain threshold. Although the EKC hypothesis has been widely tested and extended in subsequent studies, its validity remains contested across different pollutants, countries, and stages of development (Alper & Onur, 2016). Meanwhile, the digital economy, as an emerging economic paradigm centered on information technologies and data-driven activities, has attracted growing scholarly interest. Recent studies have explored how the digital economy can influence environmental outcomes through innovation-driven growth, industrial transformation, and more efficient resource allocation (2022). Internationally, Li et al. (2021) found that digitalization significantly reduces carbon emissions, though its effects vary across countries. Further, Muhammad et al (2024) focusing on OECD nations, demonstrated that digital technologies enhance environmental governance and substantially mitigate greenhouse gas emissions. In the Chinese context, Feng et al (2023) suggested that while the digital economy contributes to high-quality economic growth, its emission reduction impact exhibits substantial regional heterogeneity.

As theoretical work has advanced, empirical approaches have also evolved to more accurately capture the complex dynamics between digital economy development and carbon emissions. Traditional machine learning models, such as Random Forest and XGBoost, have been widely adopted in carbon emission forecasting and have shown promising predictive performance (Luo et al., 2024). Meanwhile, spatial econometric methods have proven essential in analyzing the spatial dependence of carbon emissions across regions (Sun et al., 2023). More recently, advanced models such as Dynamic Spatial Panel Models (DSPM) and GNN have emerged as powerful tools, capable of capturing spatial correlations and network structures (Zhang et al., 2022), thereby offering deeper insights into the dynamic and spatial diffusion processes of carbon emissions.

Despite these advances, several gaps remain in the literature. First, most studies are confined to aggregate or single-region perspectives, overlooking the heterogeneity across economic development stages and regional characteristics. Second, existing empirical work predominantly relies on traditional econometric techniques, with limited integration of cutting-edge methods such as machine learning—and particularly graph-based models like GNN—that are better suited to capturing spatial interactions and nonlinearities. Third, there is a notable lack of systematic research on the spatial diffusion pathways of carbon emissions and the heterogeneity of these effects across regions. To address these shortcomings, it is imperative to broaden theoretical perspectives and adopt a more integrated methodological framework for examining the relationship between the digital economy and carbon emissions.

2.2 Hypotheses

Existing studies have found that the digital economy contributes to systematic reductions in carbon emissions through mechanisms such as the green transformation of industrial structures, the efficient allocation of production factors, and innovation-driven low-carbon technological change. Specifically, this is reflected in three pathways: First, industrial structure optimization. The digital economy facilitates the upgrading of traditional industries toward higher value-added and lower-carbon forms, thereby reducing the proportion of high-emission sectors (Guo et al. 2024).Second, enhanced resource allocation efficiency. Digital technologies—such as big data and platform-based economic models—improve the precision of factor matching, effectively reducing emissions (Chen, 2022).Third, technological innovation and diffusion. The digital economy encourages firms to increase investment in green technologies and accelerates their widespread adoption, thereby strengthening long-term decarbonization mechanisms (Yan & Zhang, 2023).Based on these insights, the following hypothesis is proposed:

Hypothesis 1a: Under the EKC framework, the digital economy has a significant mitigating effect on carbon emission intensity.

As economic development progresses, heterogeneity in regional resource endowments, technological capacity, and institutional environments may cause the carbon-reducing effects of the digital economy to vary with development level. Specifically, Chen et al (2023) found that regions with higher levels of economic development tend to have more advanced digital infrastructure, greater energy efficiency, and stronger innovation capabilities—factors that enhance the digital economy's ability to reduce carbon emissions. Conversely, less developed regions may face constraints such as weak infrastructure, talent shortages, and limited innovation capacity, which hinder the full realization of digital decarbonization potential. Based on this, the following hypothesis is proposed:

Hypothesis 1b: The carbon-reducing effect of the digital economy increases with the level of economic development.

Moreover, disparities in economic fundamentals, industrial composition, and resource endowments across regions create considerable variation in the conditions for digital economy development. This uneven spatial development may lead to significant regional heterogeneity in how the digital economy affects carbon emissions. For instance, Sun & Chen (2023) found that the emission-reducing effect of the digital economy is more pronounced in highly developed eastern coastal regions of China, while the impact is relatively weaker in central, western, and resource-dependent areas—indicating spatial heterogeneity in digital decarbonization outcomes. Based on this, the following hypothesis is proposed:

Hypothesis 1c: The carbon-reducing effect of the digital economy exhibits significant regional heterogeneity.

As economic and environmental systems increasingly exhibit regional integration and policy coordination, carbon emission activities naturally display strong spatial dependence and spillover effects. Liu & Liu (2019) empirically demonstrated that carbon emissions are significantly spatially correlated across regions, meaning that the emission levels of neighboring areas mutually influence one another. Consequently, traditional machine learning models—if they fail to account for such complex spatial interdependencies—may struggle to capture the dynamic diffusion characteristics of carbon emissions. Building on this, Gong et al (2024) argue that static or non-spatial models have clear limitations in forecasting multi-regional carbon emissions, as they are unable to simulate dynamic propagation paths and spatial feedback mechanisms. Therefore, effectively identifying and modeling interregional spatial linkages, and incorporating these into prediction frameworks, has become a key prerequisite and breakthrough point in carbon emission modeling. Based on this, the following hypothesis is proposed:

Hypothesis 2: Due to the existence of spatial spillover effects, GNN outperform traditional machine learning models in predicting carbon emissions.

The spatiotemporal patterns of carbon emissions are shaped not only by internal factors such as regional economic development stages and industrial restructuring but also by interregional dynamics, including policy coordination, industrial relocation, and similarities in energy structures. On the one hand, Sun et al (2023) identify significant spatial clustering in carbon intensity across regions, suggesting the presence of positive spatial correlations and spillover effects that facilitate the diffusion of emission patterns through spatial transmission mechanisms. On the other hand, Chen and Xu et al (2017) reveal that with the ongoing industrial relocation and regional coordination, energy-intensive industries tend to move from more developed to less developed areas, resulting in a redistribution of carbon emissions and reinforcing the interregional connectivity and dynamic evolution of carbon emission patterns. Based on this, the following hypothesis is proposed:

Hypothesis 3a: Carbon emission intensity exhibits significant temporal inertia and spatial spillover effects.

Furthermore, the spatial diffusion of carbon emissions is not homogeneous but is influenced by both internal structural characteristics and external connectivity. As noted by Chen and Xu et al. (2017), the convergence of industrial structures, energy dependencies, and policy coordination within a region can lead to reinforced internal feedback loops of carbon emissions. In contrast, disparities in economic foundations, governance capacities, and development stages across regions can give rise to asymmetric transmission of spatial spillovers, resulting in distinct and uneven diffusion patterns. Accordingly, we propose the following hypothesis:

Hypothesis 3b: The spatial spillover effects of carbon emissions not only exhibit significant regional heterogeneity but also reflect internal feedback mechanisms and asymmetric diffusion patterns across regions.

3. Data and Variables

Table 1 provides a detailed overview of the dependent variable, key explanatory variables, control variables, and the specification of the spatial weight matrices, along with their respective data sources. Based on these, a comprehensive panel dataset covering 30 Chinese provinces from 2007 to 2023 was constructed. To mitigate potential issues of non-normality, the core explanatory variables—digital economy development level and per capita GDP—were log-transformed. The construction of the digital economy indicator draws on the methodology proposed by Wang et al. (2021), the measurement of technological innovation follows the approach of Xingan (2021), and the low-carbon energy structure index is based on the work of Yaqin et al. (2022). Table 2 presents the descriptive statistics for the main variables.

Table 1. Variable definition and source

Variable	Definition	Source
Dependent Variable		
Carbon intensity	CO_2 emissions (10,000 tons) / GDP (billion RMB)	China Statistical Yearbook; China Energy Statistical Yearbook
Independent Variable		
Digital economy	Level of digital economy development	China Statistical and Electronic Information Industry Yearbook
Economy level	Per capita GDP	Provincial Statistical Yearbooks
Control Variable		
Urbanization	Ratio of urban permanent residents to total population	Statistical Bulletin on National Economic and Social Development of China
Technology	Total number of green patent applications	Green Patent Database from CNRDS
Energy structure	Low-carbon index of energy consumption structure	China Statistical Yearbook; China Energy Statistical Yearbook
Industry structure	Ratio of secondary industry value added to gross output value	Provincial Statistical Yearbooks
New energy	New energy power generation (hydro, wind, solar, nuclear) / total power generation	China Statistical Yearbook
Matrix		
Spatial geographic matrix	Normalized and standardized geographic distance between province capitals	
Spatial economic matrix	Normalized and standardized differences in per capita GDP between provinces	China Statistical Yearbook
Geo-economic matrix	A combined matrix incorporating geographic and economic weights, determined through data-driven optimal weighting based on model fitting results	Computed via data-driven weighting; weights adjusted according to model fit to reflect spatial and economic interdependence

Note: The calculation of carbon emissions follows the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Data on the ratio of new energy generation to total electricity generation is only fully available starting from 2013; for earlier years, some provinces have missing values. This study addresses the issue by applying interpolation methods to fill in the missing data.

Table 2. Variable statistics

Variable	Mean	Std.Dev	Min	P50	Max
Carbon intensity	2.615	2.053	0.140	1.968	11.231
Digital economy	0.113	0.111	0.008	0.081	0.747
Economy level	52862.51	32669.15	7778	45720.5	200278
Urbanization	0.581	0.133	0.282	0.571	0.896
Technology	7.626	1.566	2.708	7.765	10.937
Energy structure	5.659	0.421	4.998	4.998	7.145
Industry structure	0.423	0.088	0.159	0.431	0.620
New energy	0.268	0.336	0	0.182	5.447

4. Models

4.1 Baseline Regression Model

$$\mathrm{ln\_}carbon_{\mathrm{it}} = \beta_0 + \beta_1\mathrm{Digitaleco}_{\mathrm{it}} + \beta_2\mathrm{perGDP}_{\mathrm{it}} + \beta_3{\mathrm{perGDP}^2}_{\mathrm{it}} + \beta_{\mathrm{n}}\mathrm{X}_{\mathrm{it}} + \gamma_1\mathrm{Region}_{\mathrm{i}} + \gamma_2\mathrm{Year}_{\mathrm{t}} + \mathrm{u}_{\mathrm{i}} + \epsilon_{\mathrm{it}}$$

In this study, $\mathrm{ln_}carbon_{\mathrm{it}}$represents the logarithm of carbon emissions intensity, while $\mathrm{perGDP}_{\mathrm{it}}$ and ${\mathrm{perGDP}^2}_{\mathrm{it}}$ denote the level and squared term of per capita GDP, respectively. The variable $\mathrm{Digitaleco}_{\mathrm{it}}$ represents the level of digital economy development and X_{it} represents control variables including urbanization, technology, energy structure, industry structure, and new energy. ϵ_{it} is the residual term capturing unobserved heterogeneity. $\mathrm{Region}_{\mathrm{i}}$ and $\mathrm{Year}_{\mathrm{t}}$ indicate region- and year-fixed effects, respectively.

*4.2 Traditional Machine Learning Models for Carbon Emissions Predic*tion

4.2.1 XGBoost

$$\widehat{y_t} = \sum_{m=1}^{M} f_m(x_t),\ \ L = \sum_{t=1}^{T}(\widehat{y_t} - y_t)^2 + \lambda\sum_{m=1}^{M} |\, f_m|^2$$

Here, $\widehat{y_t}$ is the predicted value of carbon emissions intensity at time t, and y_t is the observed value. $\boldsymbol{x_t}$ is the feature vector, including the digital economy, per capita GDP and its squared term (as core explanatory variables), as well as control variables. $f_m(\boldsymbol{x_t})$ represents the output of the m -th decision tree, and M is the number of trees. The loss function L includes a mean squared error term and a regularization term λ, which helps prevent overfitting and controls model complexity.

4.2.2 Random Forest

$$\widehat{y_t} = \frac{1}{M}\sum_{m=1}^{M} f_m(\mathbf{x_t})$$

This formula shares the same structure as XGBoost. In constructing the random forest model, the digital economy, per capita GDP, and its squared term are set as the core explanatory variables. Control variables such as industry structure, urbanization, and energy structure are incorporated as additional inputs to capture temporal trends in carbon emissions intensity and to compare results across models.

4.2.3 LSTM

$$\mathbf{i_t} = \sigma(W_i\mathbf{x_t} + U_i\mathbf{h_{t-1}} + b_i)$$

$$\mathbf{f_t} = \sigma\left(W_f\mathbf{x_t} + U_f\mathbf{h_{t-1}} + b_f\right)$$

$$\mathbf{o_t} = \sigma(W_o\mathbf{x_t} + U_o\mathbf{h_{t-1}} + b_o)$$

$$\mathbf{c_t} = \mathbf{f_t} \cdot \mathbf{c_{t-1}} + \mathbf{i_t} \cdot \tanh(W_c \mathbf{x_t} + U_c \mathbf{h_{t-1}} + b_c)$$

$$\mathbf{h_t} = \mathbf{o_t} \cdot \tanh(\mathbf{c_t})$$

x_t is the input feature vector, including variables such as the digital economy, per capita GDP and its square (the core explanatory variables), as well as control variables such as industrial structure. $\mathrm{h_{t-1}}$ represents the hidden state (model memory), and $\mathbf{c_t}$ is the cell state that stores long-term memory. W_i, W_f, W_o, W_c are weight matrices controlling input, forget, and output gates. σ is the Sigmoid activation function, and $\tanh$ is the hyperbolic tangent function.

4.2.4 Transformer

$$\mathrm{Attention}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{QK^T}}{\sqrt{d_k}}\right)\mathrm{V}$$

$$\mathrm{Multi\ Head}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)\mathrm{W^O}$$

In the Transformer self-attention mechanism, $(\mathrm{Q}, \mathrm{K}, \mathrm{V})$, Q, K, V refer to the query, key, and value matrices, respectively, which are derived via linear transformation from the input feature vectors (including explanatory and control variables).d_k denotes the dimensionality of the key vector. The softmax function is used to normalize the attention weights. In the multi-head attention mechanism $\mathrm{Multi\ Head}(\mathrm{Q}, \mathrm{K}, \mathrm{V})$, each head_h corresponds to an independent attention module, $\mathrm{W^O}$ represents the output projection weight matrix.

4.3 Carbon Emission Prediction Models From the Perspective of GNN

Traditional machine learning models often overlook the implicit spatial dependencies between regions, making it difficult to effectively capture spatial spillover effects. To address this, we further introduce GNN models to better reflect the spatial characteristics and transmission mechanisms of carbon emissions. In this section, we compare the performance of GCN, GAT, and GraphSAGE models—not merely to conduct carbon emission prediction, but more importantly, to identify the most suitable GNN method for analyzing the spatial spillover effects of the digital economy. This also lays the foundation for the in-depth analysis in the following sections. The specific model settings are as follows:

4.3.1 GCN

$$H^{(l+1)} = \sigma\left(\hat{A} H^{(l)} W^{(l)}\right)$$

Where $H^{(l)}$ represents the node feature matrix at layer l, including explanatory and control variables panel data features at the provincial level. $\hat{A}$ is the normalized adjacency matrix, constructed based on a geo-economic nested weight matrix, which captures spatial linkages and economic spillover pathways across regions. $W^{(l)}$ is the trainable weight matrix of layer l, and σ is the activation function.

4.3.2 GAT

$$h_i' = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} W\, h_j\right)$$

Where $\boldsymbol{h_i'}$ is the updated feature representation of node i, and $\mathcal{N}(i)$ represents the set of its neighboring nodes. The attention coefficient α_{ij}between node i and node j is computed as:

$$\alpha_{ij} = \frac{exp(LeakyReLU(a^T[\boldsymbol{W h}_i||\boldsymbol{W h_j}]))}{\sum_{k \in \mathcal{N}(i)} exp(LeakyReLU(a^T[\boldsymbol{W h}_i||\boldsymbol{W h_j}]))}$$

Here, a is the learnable weight vector, $\boldsymbol{W}$ is the weight matrix for node features, and $||$ denotes concatenation. In this study, the GAT model can adaptively learn the spatial influence weights α_{ij} based on carbon emission correlations and geo-economic similarities between provinces. This allows for a more accurate modeling of spatially heterogeneous carbon spillover paths—particularly in cases where "strong-weak" transmission patterns exist between regions—thus significantly enhancing prediction accuracy and structural interpretability.

4.3.3 GraphSAGE

$$h_i' = \sigma\left(W_1 h_i + W_2 \cdot \text{AGGREGATE}\big(\{h_j, j \in \mathcal{N}(i)\}\big)\right)$$

In this equation, h_i' is the updated feature representation of node i, and the AGGREGATE function refers to a neighborhood feature aggregation function (e.g., mean, max, or LSTM-based methods). W_1 and W_2 are learnable weight matrices. In this study, GraphSAGE aggregates spatial and digital economy characteristics of neighboring regions to model the spatial diffusion of carbon emissions. Its flexible aggregation mechanism makes it particularly suitable for large-scale regional datasets and scalable implementation.

4.4 Spatial Spillover Effects Under Traditional Econometric Models

To further investigate the spatial transmission mechanism of how the digital economy affects carbon emissions, this study introduces traditional spatial econometric models. By comparing various models, we select the most appropriate one to identify and quantify the spillover effects of carbon emissions across regions, providing a benchmark and theoretical foundation for the construction of GNN-based spatial models.

4.4.1 Static Spatial Spillover Models

$$y = \rho W y + X\beta + \epsilon \tag{1}$$

$$y = \rho W y + X\beta + WX\theta + \epsilon \tag{2}$$

$$y = X\beta + \lambda W\epsilon + \epsilon \tag{3}$$

According to established theoretical frameworks, equations (1), (2), and (3) correspond to the Spatial Autoregressive Model (SAR), Spatial Durbin Model (SDM), and Spatial Error Model (SEM), respectively.

In these models, $\boldsymbol{y}$ denotes carbon emission intensity, ρ is the spatial autoregressive coefficient, indicating the strength of spatial dependence. W is the spatial weight matrix representing adjacency between units. X and β denote the matrix of explanatory variables and their coefficients. θ represents the spatial spillover coefficients of explanatory variables, capturing the spatial diffusion effect. λ is the spatial error coefficient, and ϵ is the error term assumed to be independently and identically distributed.

4.4.2 Dynamic Spatial Panel Model

$$y_{it} = \rho W y_{it} + X_{it}\beta + \lambda y_{i(t-1)} + \epsilon_{it}$$

Here, $\boldsymbol{y}_{it}$ and $\boldsymbol{y}_{i(t-1)}$ denote the carbon emission intensity of region i at time t and $t-1$, respectively. W is the spatial weight matrix, ρ is the spatial autoregressive coefficient, X_{it} is the vector of explanatory variables for region i at time t, β represents the coefficients of the explanatory variables, and λ is the lag effect coefficient, capturing the impact of past emissions on current carbon emissions. ϵ_{it} is the error term.

5. Results

5.1 Baseline Regression Model Results

As shown in column 1 of Table 3, the coefficient of the digital economy development level is −0.333 and is statistically significant at the 1% level, indicating that the digital economy significantly reduces carbon emission intensity. Specifically, a one-unit increase in the digital economy index is associated with a 0.333-unit reduction in carbon intensity. In addition, per capita GDP is positively correlated with carbon intensity at the 10% significance level, while its squared term is negative and significant at the 1% level, suggesting a pronounced inverted U-shaped relationship between carbon intensity and economic development. This finding confirms the EKC hypothesis.

Table 3. Baseline and Economic heterogeneity results

	Baseline	Low-digital	Mid-digital	High-digital
	(1)	(2)	(3)	(4)
Digitaleco_{it}	-0.333***	-0.125*	-0.094	-0.353***
	(0.053)	(0.227)	(0.180)	(0.040)
perGDP_{it}	0.808*	-0.921	14.897	2.689
	(0.483)	(1.035)	(14.865)	(1.299)
${\text{perGDP}^2}_{it}$	-0.104***	0.019	-0.767	-0.171**
	(0.022)	(0.050)	(0.727)	(0.048)
Industry_structure	0.798	1.127	0.959	0.952
	(0.456)	(1.117)	(0.645)	(0.657)
Urbanization	0.028***	0.001	0.012	0.027*
	(0.005)	(0.014)	(0.006)	(0.010)
Technology	-0.103*	-0.089	-0.111	-0.035
	(0.056)	(0.059)	(0.061)	(0.043)
Energy_structure	-0.291***	-0.099*	-0.157	-0.274***
	(0.069)	(0.033)	(0.093)	(0.056)
New_energy	-0.053*	-0.628*	-0.952**	-0.033
	(0.024)	(0.164)	(0.245)	(0.024)
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	510	70	48	392
R-squared	0.551	0.463	0.477	0.558

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$(Unless otherwise specified, all tables in this paper represent this meaning).

The underlying mechanisms can be explained as follows: First, in the early stages of economic development, rapid industrialization and urbanization tend to rely heavily on energy-intensive industries and fossil fuels, leading to increased emissions alongside GDP growth (Jing et al. 2023). Second, once per capita income reaches a certain threshold, enhanced fiscal capacity enables governments to invest in environmental infrastructure and promote low-carbon industrial transformation (Hu et al. 2024). At this stage, technological advancement and green innovation become key drivers of growth, with economic activities shifting toward services and digital sectors, contributing to lower emissions per unit of output (Chen et al. 2023). These results are consistent with Hypothesis H1a.

Regarding the control variables, urbanization has a significantly negative effect on carbon intensity, with a coefficient of −0.028. This may be attributed to two factors: first, urbanization improves the efficiency of green infrastructure and public services, contributing to lower emissions per unit of GDP; second, it promotes a shift in industrial structure toward the service sector, reducing the share of secondary industry, particularly energy-intensive manufacturing, thereby decreasing overall carbon intensity (Tang et al. 2020). Additionally, industrial structure has a positive coefficient of 0.798, which, although statistically insignificant, suggests that a higher share of secondary industry may be associated with increased emissions—a trend that warrants attention.

Technological innovation, energy structure, and the share of renewable energy generation all exhibit significant negative effects on carbon intensity, with coefficients of −0.103, −0.291, and −0.053, respectively. The rationale is as follows: first, innovation enhances green technologies and energy efficiency, thereby reducing emissions (2021); second, coal-dominated energy structures are major contributors to high carbon intensity, while structural optimization—namely reducing coal dependency and increasing the share of cleaner energy sources—leads to lower emissions (Yin, Ding & Fan, 2021); third, a higher share of renewables in the energy mix facilitates low-carbon transformation and reduces reliance on fossil fuels, contributing to effective carbon mitigation (Liu et al. 2023).

5.2 Heterogeneity Results

5.2.1 Economic Heterogeneity

Columns (2), (3), and (4) of the Table 3 present the effects of the digital economy on carbon intensity across regions with low, medium, and high levels of economic development. The estimated coefficients are −0.125, −0.094, and −0.353, respectively. Among them, the reduction effect is most significant in regions with high economic development, significant at the 1% level. Although the coefficient for the low-development group is also statistically significant at the 10% level, the magnitude of the reduction effect is relatively weak. In contrast, the result for the medium-development group is statistically insignificant, suggesting that the emission-reduction mechanism may be unstable or underdeveloped in such regions. These findings partially support Hypothesis H1b.

Several factors may explain these results. First, high-income regions typically possess more advanced digital infrastructure and stronger technological absorption capacity, enabling more efficient application of digital tools in energy conservation and emissions reduction (Wu, 2022). Second, in regions with lower levels of economic development, carbon reduction mechanisms are still in the early stages. Although the digital economy is beginning to take effect, it has not yet brought about deep transformation in energy-intensive industries, leading to relatively limited reduction effects (Yan & Zhang, 2023). Third, medium-development regions are generally in a “technological integration phase,” where a mismatch exists between digital infrastructure and the degree of industrial digitization. As a result, digital technologies have not yet penetrated deeply into high-emission sectors, and the emission-reduction mechanism remains immature or unstable (Liu, 2023).

5.2.2 Regional Heterogeneity

Table 4 presents the results of the regression analysis examining the impact of the digital economy on carbon intensity across different regions. The estimated coefficients for the eastern, central, western, and northeastern regions are −0.093, 1.642, −0.626, and −0.189, respectively. Specifically, the coefficient for the central region is significantly positive at the 1% level, indicating a counterintuitive positive correlation between the digital economy and carbon emissions in that region. In contrast, the coefficient for the western region is significantly negative at the 1% level, suggesting a strong emission-reduction effect. For the eastern and northeastern regions, the coefficients are statistically insignificant, indicating that the digital economy has not yet shown a clear impact on carbon intensity in these areas. Overall, these findings are consistent with Hypothesis H1c.

Table 4. Regional heterogeneity results

	East	Mid	West	Northeast
	(1)	(2)	(3)	(4)
$\mathrm{Digitaleco}_{it}$	-0.093	1.642***	-0.626***	-0.189
	(0.095)	(0.449)	(0.114)	(0.264)
perGDP_{it}	2.359**	6.151	0.355	5.248
	(0.874)	(8.464)	(0.927)	(3.907)
$\mathrm{perGDP}^2{}_{it}$	-0.137***	-0.419	-0.140**	-0.288
	(0.038)	(0.381)	(0.047)	(0.198)
Industry structure	-0.456	6.995***	1.431***	0.233
	(0.454)	(1.784)	(0.371)	(0.498)
Urbanization	0.026***	0.149***	0.034**	0.071***
	(0.005)	(0.024)	(0.011)	(0.012)
Technology	-0.108*	-0.239	0.098*	-0.065
	(0.052)	(0.234)	(0.044)	(0.072)
Energy_structure	-0.239***	-0.475	-0.394***	-0.351**
	(0.064)	(0.409)	(0.100)	(0.118)
New_energy	-0.019	-0.736*	-0.816***	0.322
	(0.022)	(0.307)	(0.162)	(0.545)

Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	170	102	187	51
R-squared	0.409	0.804	0.482	0.882

Several factors may explain these regional disparities. First, in the central region, the development of the digital economy tends to be “virtual-oriented,” with a bias toward consumer internet and digital finance, rather than real-sector applications. This structural imbalance limits its capacity to promote green transformation, and may even increase energy consumption through data centers, logistics, and other infrastructure—ultimately raising carbon intensity (Guo et al. 2024). Second, the western region, as a national pilot zone for green development, has benefited from preferential policies supporting digital infrastructure. The digital economy in this context has been more effectively applied to improving energy efficiency and advancing green energy, thereby significantly reducing carbon emissions (Hu et al. 2024). Third, both the eastern and northeastern regions are approaching “digital saturation,” where marginal effects diminish. Although the eastern region has a well-established digital foundation, digital integration into high-carbon industries has plateaued, weakening its additional mitigation effect. In the northeast, industrial inertia and deep-rooted reliance on traditional heavy industries hinder the effective deployment of digital technologies, making it difficult to observe emission reductions in the short term (Lyu et al. 2023).

5.3 Machine Learning Models

5.3.1 Comparison of Traditional Machine Learning Models

As shown in Figure 1, compared to Random Forest, LSTM, and Transformer, the residuals from the XGBoost model are more evenly distributed around zero, suggesting that the model demonstrates the most stable performance in carbon emission prediction. The lack of systematic bias and low prediction error further highlight its robustness and high predictive accuracy.

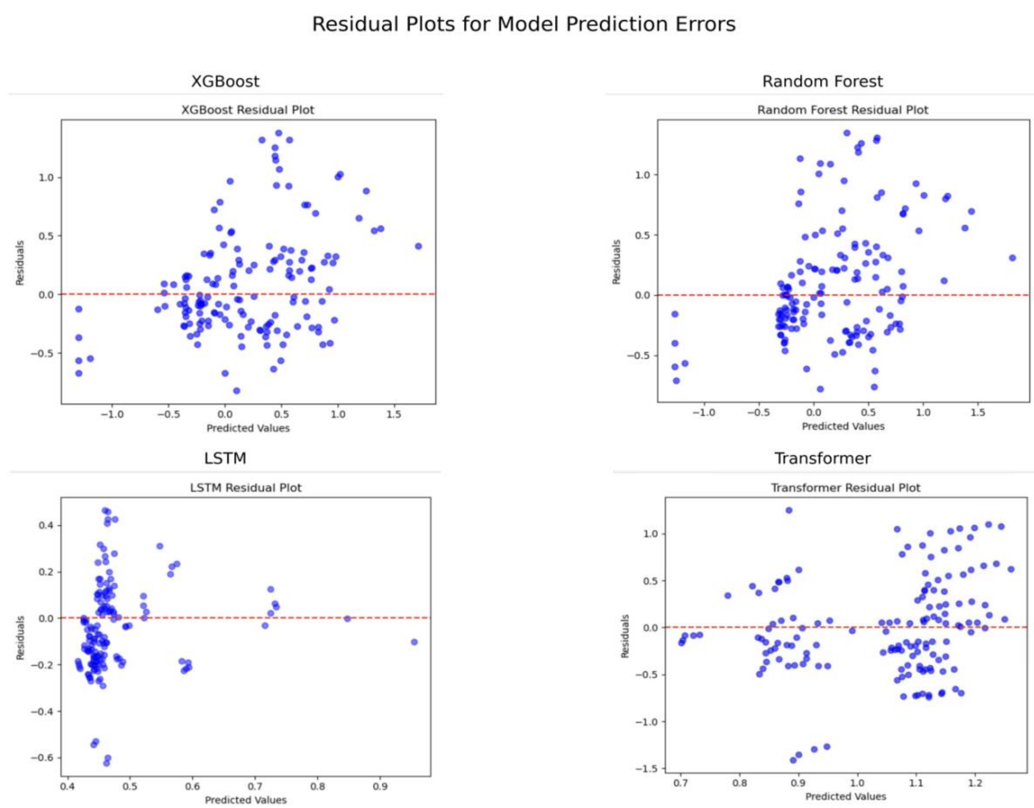


Figure 1. Residual analysis chart

From Figure 2, it can be observed that the residual distributions of XGBoost and Random Forest are clearly symmetric and centered around zero, in contrast to LSTM and Transformer. This indicates that XGBoost and Random Forest models provide better fitting performance with smaller and more balanced prediction errors in carbon emissions forecasting.

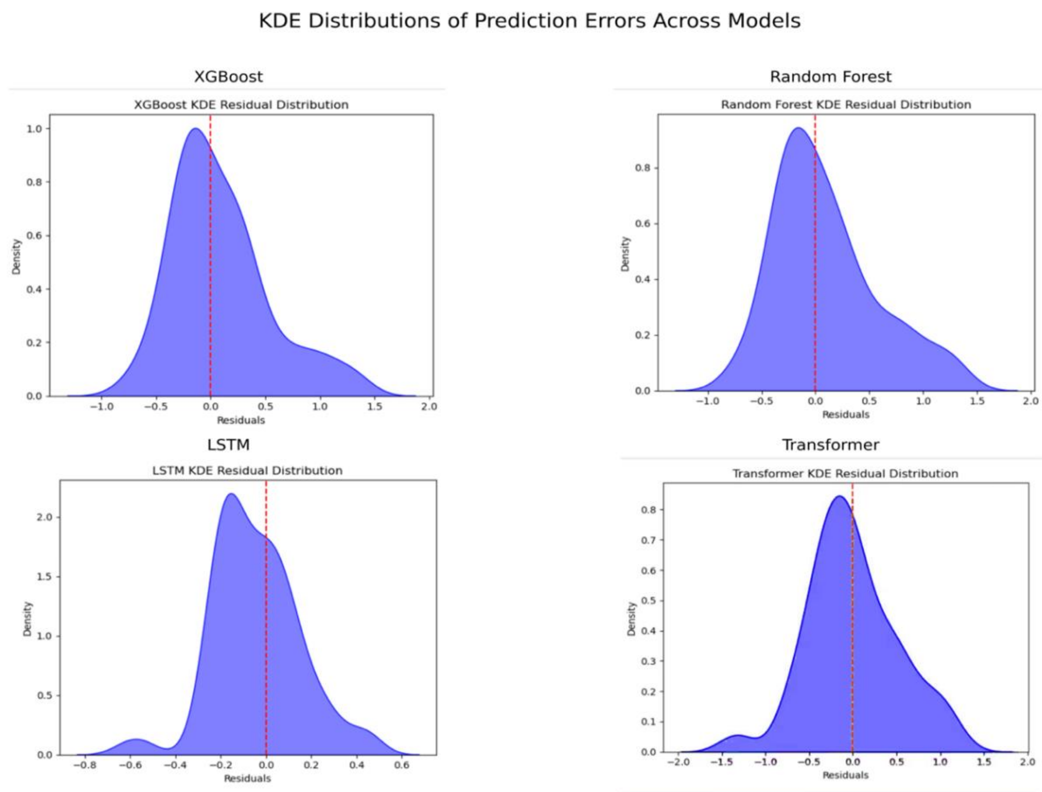


Figure 2. Error density analysis chart

Figure 3 further illustrates that the predicted values of XGBoost and Random Forest align closely with the actual values. The prediction curves almost completely overlap with the observed trends, suggesting strong fitting capability and high accuracy in capturing carbon emission dynamics. In contrast, the prediction curve of LSTM deviates slightly from the actual values, particularly in lower and higher value ranges, indicating less accurate performance at certain data points.

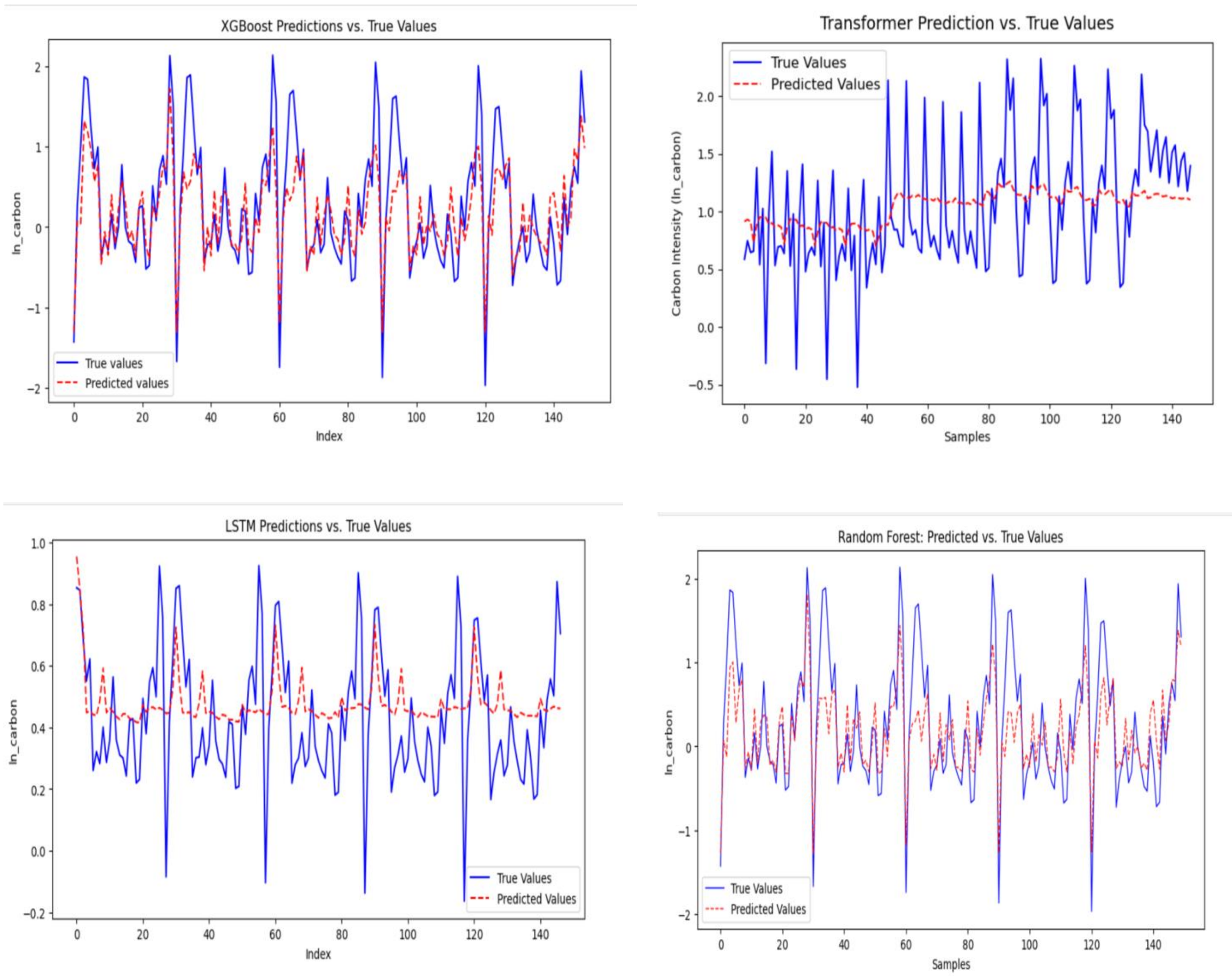


Figure 3. Predictions VS True values

Table 5 compares the prediction results of traditional machine learning models on the 2019–2023 test set. XGBoost, Random Forest, and LSTM all outperform the Transformer model in terms of both MSE and RMSE. According to the R^2 metric, XGBoost achieves the highest explanatory power at 0.6879, outperforming the other three models.

Table 5. Machine learning comparison

	MSE	RMSE	R^2
XGBoost	0.2069	0.4549	0.6879
Random Forest	0.2350	0.4848	0.6454
LSTM	0.2935	0.5418	0.5506
Transformer	0.2644	0.5142	0.1595

Taken together, these findings demonstrate that XGBoost performs exceptionally well in carbon emissions prediction, offering accurate data fitting and low prediction error. Therefore, XGBoost is selected as the baseline model for subsequent forecasting tasks.

5.3.2 XGBoost-Based Further Analysis

Figure 4 presents the feature importance rankings derived from the XGBoost model. The results indicate that technological innovation holds the highest importance among all variables, followed by regional fixed effects and new energy indicators. In contrast, the digital economy variable exhibits relatively low weight in the model, suggesting its marginal contribution to prediction outcomes is limited. However, this does not preclude its potential impact through nonlinear relationships or interaction effects. Therefore, SHAP analysis is further employed to gain deeper insight into its influence.

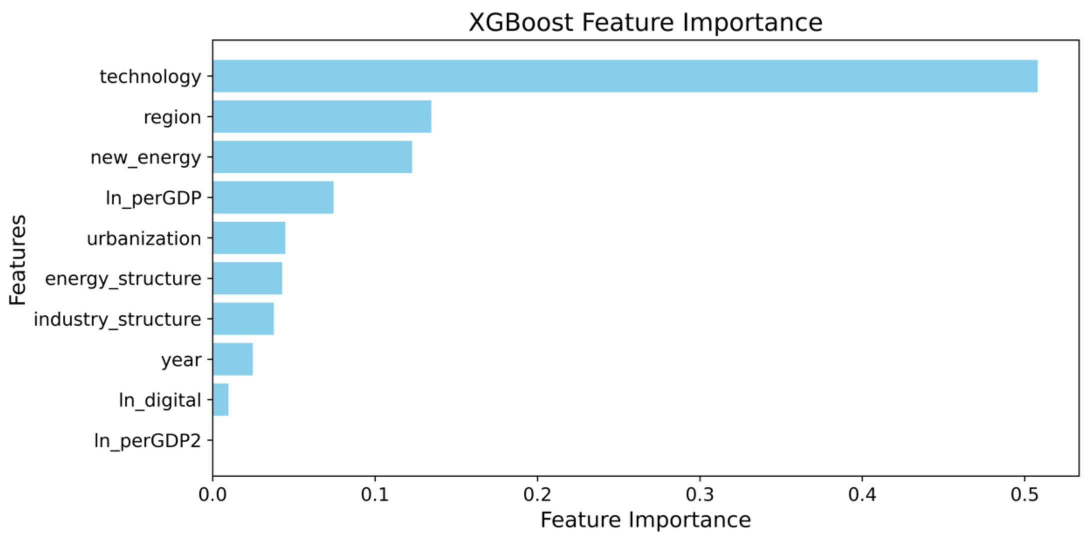
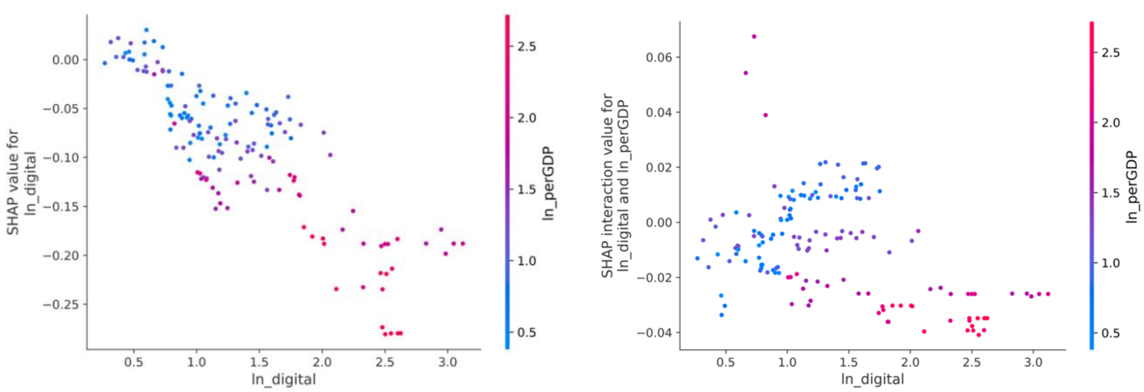


Figure 4. Feature importance

Figure 5(a) displays the SHAP dependence plot for the digital economy variable. The results show a clear downward trend in SHAP values as the level of digital economy increases, indicating a progressively stronger suppressive effect on carbon emissions. Furthermore, the negative marginal effects are more pronounced in high-income regions (represented by red data points), implying that the digital economy more effectively promotes emission reduction in more developed areas—further supporting Hypothesis H1b.



(a) SHAP dependance (b) SHAP interaction

Figure 5. SHAP analysis

Figure 5(b) illustrates the SHAP interaction effect between the digital economy and per capita GDP, revealing whether their combined influence contributes additional explanatory power to carbon emissions prediction. The plot shows that under higher levels of economic development (red dots), the interaction values are predominantly negative, suggesting a significant synergistic effect on emission reduction. In contrast, in lower-income regions (blue dots), the interaction effect weakens and, in some cases, approaches positive values, indicating limited or even absent joint mitigation effects.

Synthesizing the findings from Figures 4 and 5, the XGBoost model identifies technological innovation, new energy, and regional heterogeneity as the most important drivers of carbon emissions, highlighting their critical roles. Although the digital economy variable ranks lower in feature importance, further SHAP-based dependence and interaction analyses reveal that it has a significant marginal suppressive effect at higher levels of development and demonstrates a nonlinear linkage with economic growth. These findings not only reveal the heterogeneous mechanisms underlying the digital economy's environmental impact but also provide empirical support for the Environmental Kuznets Curve (EKC) hypothesis observed in the baseline regressions.

5.3.3 Application of GNN Models in Carbon Emissions Prediction

In this study's carbon emissions prediction task, the performance of three graph neural network (GNN) models—GCN, GAT, and GraphSAGE—is compared using test error (MSE) and training loss curves as the primary evaluation metrics.

As shown in Table 6, the GAT model outperforms GCN and GraphSAGE across all test-set evaluation indicators, including MSE, RMSE, and R^2, indicating its superior generalization ability and predictive accuracy in the carbon emissions prediction task.

Table 6. GNN comparison

	MSE	RMSE	R^2
GCN	0.0236	0.1536	0.9564
GAT	0.0117	0.1082	0.9683
GraphSAGE	0.0172	0.1311	0.9628

According to the loss curves presented in Figure 6, all three GNN models demonstrate strong fitting capabilities during training. Compared to GCN and GraphSAGE, which converge at a moderate pace, the GAT model achieves faster early-stage convergence and maintains the lowest MSE in the later training stages—reflecting its excellent stability and convergence efficiency.

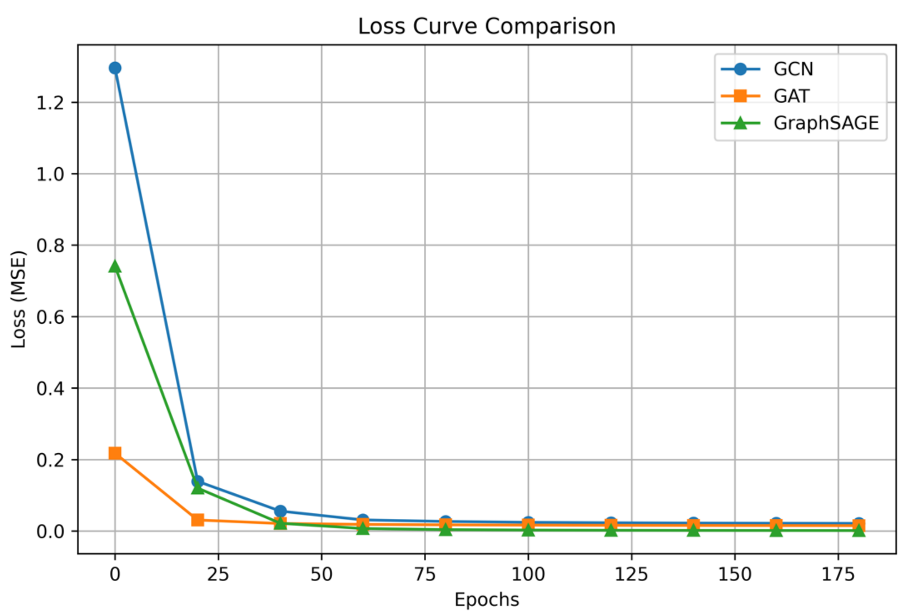


Figure 6. Loss curve

Figure 7 provides a visual representation of the GAT model's performance. The scatter plot (left) shows that the predicted values are closely aligned with the actual values, with data points densely distributed along the diagonal line, suggesting high overall predictive accuracy. The right panel unfolds predicted and actual values along the time series, further demonstrating that the GAT model effectively captures temporal trends in carbon emissions, even under conditions of high volatility.

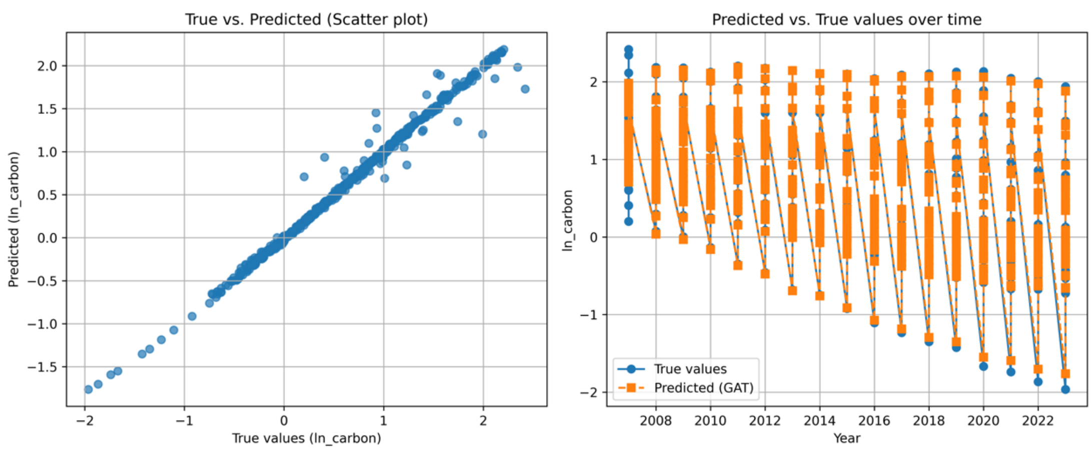


Figure 7. GAT results

Furthermore, in the context of this carbon emissions forecasting task, GAT not only outperforms GCN and GraphSAGE across all metrics but also surpasses traditional machine learning models such as XGBoost, Random Forest, LSTM, and Transformer—thereby supporting Hypothesis H2. Several factors may account for this performance advantage: First, GNN is inherently well-suited to handle spatially structured data, enabling them to capture inter-regional spatial dependencies(Bao et al. 2024), whereas traditional models rely solely on local sample features and fail to account for neighborhood spillovers. Second, GNN is capable of modeling complex geographic adjacency and economic linkages within graph structures, allowing them to fully leverage regional interconnectivity and improve overall predictive performance(Zhang et al. 2023). Third, carbon emissions exhibit notable spatial heterogeneity and diffusion characteristics. Neighboring regions often share commonalities in policy responses, industrial activities, and energy structures (Liao et al. 2024)—all of which can be better represented by GNN, thanks to their stronger expressive power in modeling such mechanisms.

Based on these insights, the following section will adopt both spatial econometric models and graph neural network frameworks to analyze and compare spatial spillover effects, offering complementary perspectives on spatial dynamics.

5.4 Spatial Spillover Effect Results

5.4.1 Model Selection

We ultimately adopt the Dynamic Spatial Panel Model (DSPM) based on a geo-economic nested spatial weight matrix. The rationale is as follows:

First, from an empirical perspective, prior SHAP-based interpretability analysis and subgroup regressions by economic development level and regional heterogeneity reveal that the impact of the digital economy on carbon emissions exhibits significant spatial heterogeneity. Relying solely on traditional non-spatial models may fail to accurately capture these cross-regional influence pathways. By introducing a geo-economic nested spatial weight matrix and adopting the DSPM—which incorporates both spatial spillovers and temporal dynamics—the model achieves not only theoretical consistency but also enhanced explanatory power and empirical suitability.

Second, considering existing literature and model characteristics, carbon emissions—as an environmental variable with strong externalities—are inherently shaped by interregional policy coordination, industrial spillovers, and synchronized energy structures. These spatial interactions align with China's current landscape of regional governance (Song et al. 2020). Compared with traditional static spatial models such as the SAR, the DSPM incorporates lagged dependent variables, thereby capturing the inertia and persistence of carbon emissions over time. This feature enhances both the model's interpretability and its theoretical relevance.

Third, from the perspective of statistical performance, Table 7 provides a comparative evaluation that further supports the DSPM's superiority in modeling spatial spillover effects. Specifically, under the geo-economic nested matrix, the DSPM achieves a Pseudo R^2 of 0.772, with AIC and BIC values of 1355.7 and −1311.94, respectively outperforming all alternative specifications in terms of model fit and explanatory power.

Fourth, from the standpoint of robustness, subsequent sections conduct additional sensitivity tests using alternative spatial weight matrices and variable specifications. These robustness checks are designed to validate the stability of the DSPM results and provide stronger empirical support for the model's validity.

5.4.2 DSPM Model Results Analysis

Table 8 and Figure 8 report the results of the DSPM. The direct effects of per capita GDP and its squared term are 0.1519 and −0.0088, respectively. Although these coefficients are not statistically significant, their signs exhibit a clear inverted U-shaped relationship, in line with the EKC hypothesis. The direct effect of the digital economy variable is 0.0486 and is significant at the 1% level. The indirect effect is −0.0019, and the total effect is 0.0467, both statistically significant at the 1% level.

Table 7. Matrix comparison

Matrix	Spatial geographic matrix				Spatial economic matrix				Geo-economic matrix			
	Pseudo R^2	LogL	AIC	BIC	Pseudo R^2	LogL	AIC	BIC	Pseudo R^2	LogL	AIC	BIC
SAR	0.6404	-333.33	686.68	729.02	0.6712	-310.35	640.71	683.05	0.6401	-333.47	686.94	729.29
SEM	0.6231	-301.61	621.23	665.58	0.6345	-316.38	650.77	695.11	0.6197	-309.86	637.73	605.09
SDM	0.7240	-271.27	578.54	654.76	0.6734	-308.68	653.36	729.58	0.7456	-246.43	528.87	682.08
DSPM	0.6975	669.16	1365.3	-1310.40	0.6944	-674.88	1349.96	-1303.04	0.772	-635.9	1355.7	-1311.94

Table 8. DSPM results

Variable	Direct effect (1)	Indirect effect (2)	Total effect (3)
Digitaleco_{it}	0.0486***	-0.0019	0.0467***
perGDP_{it}	0.1519	-0.0059	0.1460
$\text{perGDP}^2{}_{it}$	-0.0088	0.0003	-0.0085
Industry structure	0.0156	-0.0006	0.0150
Urbanization	0.0007	-0.0000	0.0007
Technology	-0.0191***	0.0007	-0.0184***
Energy structure	-0.0018	0.0001	-0.0017
New energy	-0.0202**	0.0008	-0.0194**
L.ln_carbon	1.0168***	–0.0393	0.9775***
W_ln_carbon	–0.0402**		

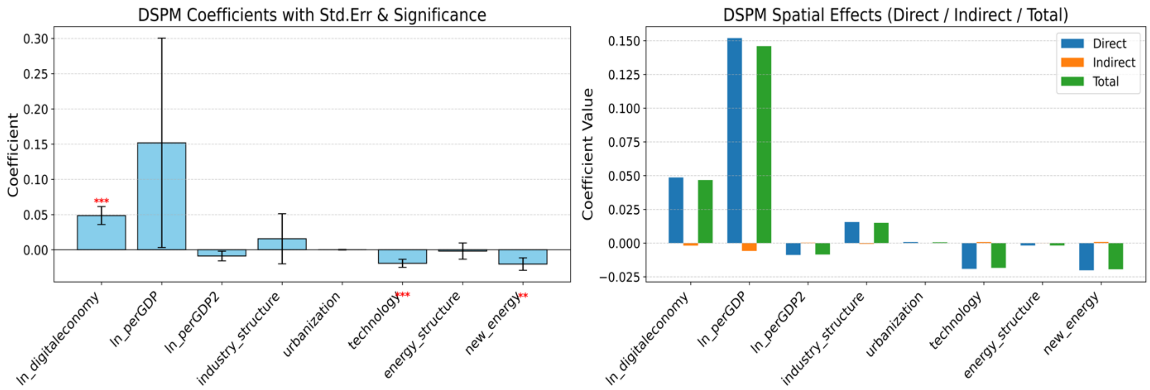


Figure 8. DSPM results

Compared to the baseline regression where the digital economy exerted a significantly negative effect on carbon intensity, this result reveals a divergence. Possible explanations include: first, the spatial econometric model incorporates temporal lags and spatial spillover pathways, allowing for a more realistic simulation of interregional carbon dynamics and externalities. This may cause the short-term positive emission effects of digital development to become more visible (Liu et al. 2022). Second, the current stage of digital economy development in China remains infrastructure-driven and energy-intensive, and its associated environmental burdens may temporarily overshadow its emission-reducing potential (Zhang et al. 2022).

The coefficient of the temporal lag term, L.ln_carbon, is 1.0168 and is highly significant at the 1% level, indicating strong persistence in carbon intensity. Meanwhile, the coefficient of the spatial lag term, W_ln_carbon, is −0.0402 and significant at the 5% level, supporting Hypothesis H3a. Two main reasons help explain this finding. First, the observed negative spatial spillover effect may stem from regional policy competition or coordinated governance, which contributes to a complementary regulatory mechanism within the spatial network. Second, the strong temporal inertia of carbon emissions reflects the high difficulty of restructuring carbon sources and the stability of existing energy use patterns, making it challenging to alter emission trajectories over the short term (Gao & Qu, 2025).

5.4.3 Analysis of Spatial Spillover Effects From the Perspective of GNN

5.4.3.1 Spatial Spillover Intensity and Digital Economy Sensitivity

Figure 9 presents two types of spatial feature learning results generated by the GNN model. The left panel of Figure 9 illustrates the average spatial spillover effect of carbon emissions across regions. Darker colors represent stronger spillover intensity. It can be observed that the central and western regions exhibit higher average neighbor influence, indicating that carbon emissions in these areas are not only driven by local factors but also exert significant external effects on surrounding regions—demonstrating a clear spatial diffusion pattern. In contrast, several eastern coastal provinces show relatively weaker spillover intensity, which may be attributed to their more independent industrial structures and energy systems, limiting regional interconnectivity.

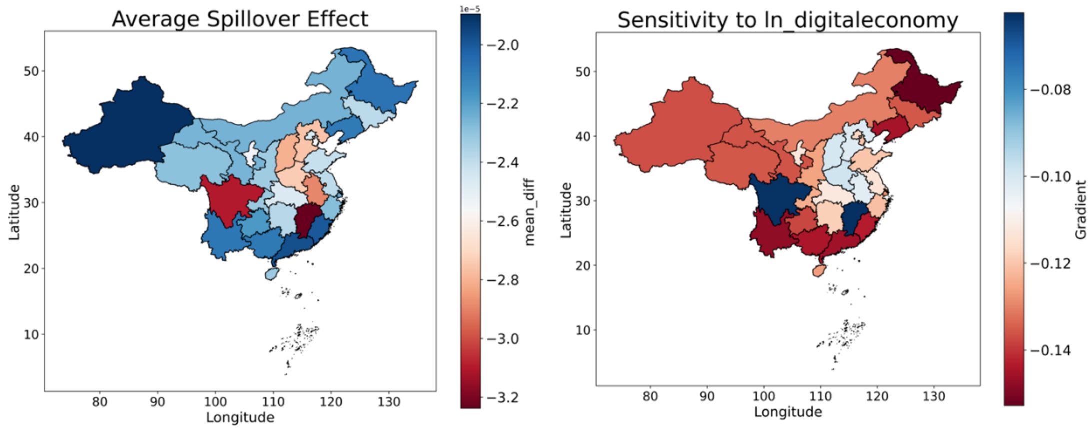


Figure 9. GNN Visualization analysis

The right panel of Figure 9 depicts the sensitivity distribution of the digital economy in predicting carbon emissions. Here, deeper colors represent stronger marginal impacts of the digital economy variable on the model's prediction results. The figure shows that central China is more sensitive to changes in digital economic development, suggesting a higher responsiveness of carbon emissions in this region to digital infrastructure and related factors. This may reflect a "digital dividend release phase," where digitalization begins to play a more prominent role in shaping carbon outcomes. In contrast, northeastern and some northwestern provinces show lower sensitivity, possibly due to lower digital penetration rates or structural constraints in their industrial bases.

5.4.3.2 Regional Heterogeneity of Spatial Spillover Effects

Figure 10 illustrates the spatial spillover intensity of carbon emissions across different regions, as estimated by the GNN model. The results show that intra-regional spillover effects are consistently stronger than inter-regional ones, highlighting the presence of robust internal feedback mechanisms. Among all regions, Northeast China exhibits the strongest self-spillover effect, with a coefficient of 0.074—significantly higher than that of other regions. The central and western regions also show notable internal linkages, with spillover coefficients of 0.044 and 0.049, respectively. In terms of cross-regional spillovers, the influence from the eastern region to the central region is 0.044, while the reverse effect from the central region to the east is 0.030, indicating a relatively strong bidirectional carbon emission association between these two regions. In contrast, the spillover intensities involving the northeast and western regions remain relatively weak, reflecting spatial asymmetries and non-uniform distribution patterns.

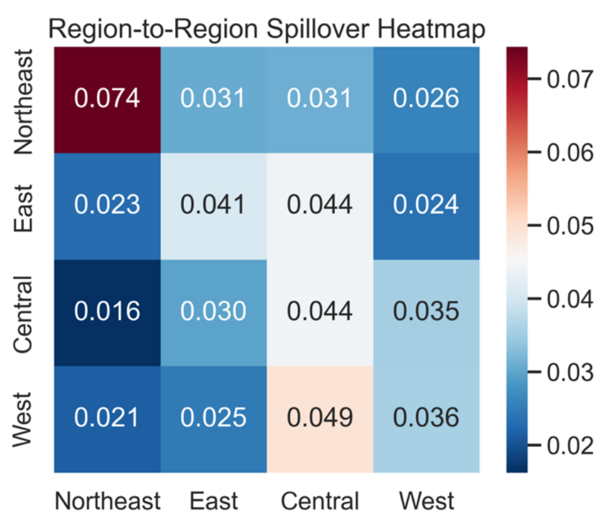


Figure 10. GNN Heatmap

Figure 11 further reveals the heterogeneity in average spatial spillover effects across regions. The central region shows the most pronounced effect, with an average value of −0.020, followed by the western and eastern regions (−0.018 and −0.016, respectively), while the northeast region displays the weakest spillover effect at −0.014.

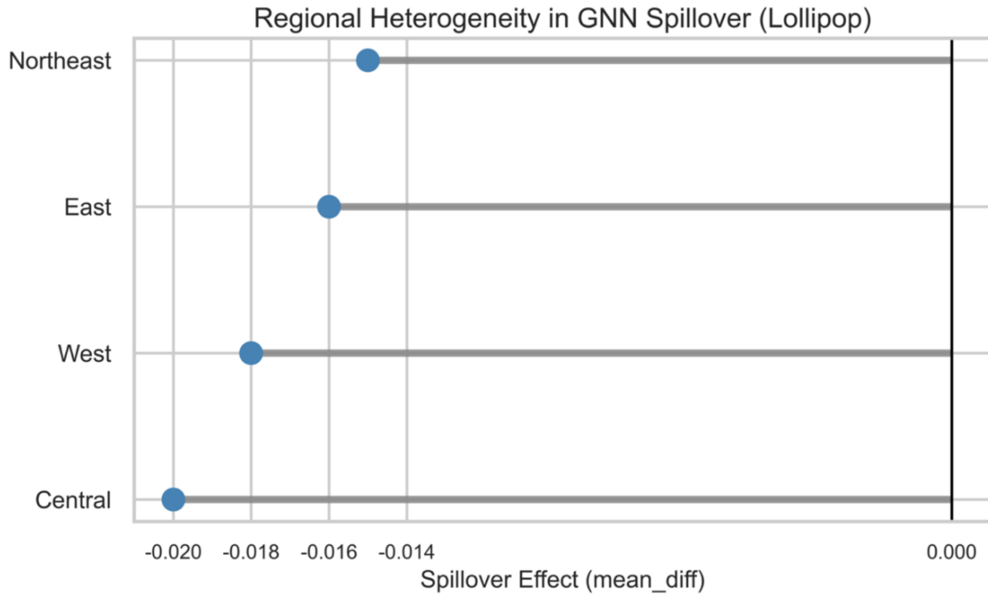


Figure 11. GNN Lollipop

Taken together, these findings confirm Hypothesis H3b and lead to the following conclusion: carbon emission spillover effects in China exhibit a spatial structure of "stronger internal than external, tight linkages in the east-central axis, and relative detachment in the west and northeast." On the one hand, all regions demonstrate strong intra-regional coupling of carbon emissions; on the other hand, the central and western regions exert greater influence on adjacent areas, suggesting a stronger spatial radiation effect.

Several factors contribute to this pattern. First, differences in development stages: central and western provinces are still in the phase of integrating digital economy development with industrial upgrading. Guided by supportive policies and technology diffusion, these regions exert stronger spillover effects on their neighbors (Wang, 2023). Second, disparities in energy structure: traditional energy sources dominate in the central and western regions, and their broader energy supply radius tends to foster cross-regional carbon emission linkages (Liu, Li & Ji, 2021). Third, differences in policy coordination and infrastructure: eastern and central regions benefit from stronger interregional policy communication and transportation connectivity, facilitating the diffusion of carbon reduction pathways. In contrast, the northeast region—facing challenges such as industrial decline and population outflow—exhibits weaker transmission capacity and responsiveness in carbon emissions, resulting in relatively modest spillover effects (Gao et al. 2022).

6. Robustness Checks

To ensure the reliability of the mixed-effects model estimation results, this study conducts a series of robustness checks. First, correlation analysis and multicollinearity diagnostics are carried out. As shown in Tables 9 and 10, apart from the constructed variables of per capita GDP and its squared term—which exhibit expected correlation due to design—correlations among other variables remain within acceptable ranges, with all VIF values below the conventional threshold of 10, indicating no serious multicollinearity issues that might compromise the baseline model.

Table 9. Pearson correlation

Variable	ln_carbon	ln_carbon	ln_perGDP	industry_structure	urbanization	technology	energy_structure	new_energy
ln_carbon	1							
ln_digital	0.694**	1						
ln_perGDP	-0.404**	0.388**	1					
industry_structure	-0.163	0.346**	0.100	1				
urbanization	-0.500**	0.678**	0.868**	-0.379**	1			
technology	-0.698**	0.922**	0.797**	-0.250	0.625**	1		
energy_structure	-0.155	0.640**	0.701**	-0.076	0.811**	0.654**	1	
new_energy	-0.505**	0.478**	0.868**	-0.679**	0.680**	0.534**	0.145	1

Table 10. VIF results

Variable	VIF	1/VIF
ln_digital	8.75	0.114
ln_perGDP	5.11	0.196
industry_structure	6.23	0.161
urbanization	5.76	0.173
technology	2.83	0.353
energy_structure	1.31	0.766
new_energy	1.17	0.856

Second, the Hausman test yields a p-value of 0.12, suggesting that the difference between the random effects and fixed effects estimators is not statistically significant. Nevertheless, given that the dataset used in this study is a short panel and the fixed effects model offers stronger control over unobserved heterogeneity and time-specific shocks across provinces, we adopt the fixed effects specification to ensure more robust estimation.

Third, a sensitivity test is performed by replacing the core explanatory variable—"digital economy development level"—with an alternative indicator, "number of internet ports," which serves as another proxy for digital infrastructure. As shown in column (1) of Table 11, the coefficient remains significantly negative, demonstrating that the core conclusion is not sensitive to indicator selection.

Fourth, stepwise regression is conducted to assess the stability of the digital economy coefficient under varying model specifications. Columns (2) and (3) in Table 11 show that the coefficient of the digital economy remains significantly negative across all models, with minimal fluctuation in magnitude, reinforcing the robustness and interpretability of the main findings.

Table 11. Robustness tests

	(1)	(2)	(3)	(4)	(5)
Internet	-0.003***				
	(0.001)				
$\mathrm{Digitaleco}_{it}$		-0.509***	-0.227*	-0.050***	-0.056***
		(0.085)	(0.057)	(0.013)	(0.013)
perGDP_{it}	0.425		-0.862***	0.123	0.197
	(0.361)		(0.106)	(0.150)	(0.151)
$\mathrm{perGDP}^{2}{}_{it}$	-0.052***			-0.008	-0.010
	(0.015)			(0.007)	(0.007)
Industry structure	0.640*	-0.608	0.351	0.030	0.003
	(0.315)	(0.279)	(0.206)	(0.037)	(0.036)
Urbanization	0.030***	0.009*	0.028	0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)
Technology	-0.096***	0.033	0.099	-0.019***	-0.021***
	(0.032)	(0.031)	(0.035)	(0.006)	(0.006)
Energy structure	-0.223***	-0.385***	-0.248***	-0.004	-0.008
	(0.073)	(0.060)	(0.054)	(0.011)	(0.011)
New energy	-0.038*	-0.005	-0.025	-0.0182**	-0.015*
	(0.019)	(0.014)	(0.019)	(0.009)	(0.009)
L.ln_carbon				1.017***	1.016***
				(0.006)	(0.006)
W_ln_carbon				-0.039***	0.000
				(0.014)	(0.000)
Region FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	510	510	510	510	510
R-squared	0.682	0.596	0.577	0.812	0.844

Fifth, the Driscoll–Kraay standard errors are employed in the estimation. This approach is particularly suitable for the long-panel fixed effects model used in this paper, as it simultaneously addresses cross-sectional dependence, serial correlation, and heteroskedasticity.

Sixth, columns (4) and (5) of Table 11 present results from alternative spatial weight matrix specifications, replacing the geo-economic nested matrix with pure geographic and pure economic matrices. The estimation results remain consistent, further confirming the robustness of the conclusions.

7. Conclusion

Based on panel data from 30 Chinese provinces spanning 2007 to 2023, this study constructs an extended EKC framework and integrates traditional machine learning techniques with GNN models to systematically assess the impact pathways and spatial spillover effects of the digital economy on carbon intensity. The empirical findings reveal the following: first, the digital economy significantly reduces carbon intensity, and a clear inverted U-shaped relationship is observed between carbon emissions and economic growth, thereby confirming the validity of the EKC hypothesis in the Chinese context. Second, the mitigation effect of the digital economy exhibits notable heterogeneity across both economic development levels and regional contexts, with stronger impacts observed in more developed areas. Third, carbon emissions display pronounced temporal inertia and spatial negative spillovers, and GNN-based models outperform traditional machine learning approaches in both predictive accuracy and the representation of spatial structures.

Theoretically, this research advances the understanding of the mechanisms linking the digital economy and carbon emissions, extends the EKC analytical framework to incorporate digitalization, and introduces an innovative methodological synthesis of spatial econometric models with graph-based deep learning, offering a new approach for modeling the spatial dynamics of carbon emissions.

Based on these findings, policy recommendations are proposed as followings: First, efforts to expand digital infrastructure should be intensified, particularly in central and western regions, by accelerating the deployment of foundational technologies. This would enable digital tools to drive the green transformation of traditional industries, promoting carbon reduction alongside economic growth and translating the EKC framework into practice. Second, differentiated digital governance strategies should be adopted to unlock the decarbonization potential of the digital economy across development stages. While more developed regions should focus on platform regulation and digital equity, less developed areas require enhanced foundational support to strengthen their digital responsiveness to green development. Third, interregional coordination mechanisms should be reinforced to facilitate shared carbon governance. The construction of cross-regional carbon information platforms and joint action frameworks should be prioritized, along with the application of GNN intelligent systems to improve the spatial precision and adaptability of emission reduction policies, thus fully leveraging the collaborative potential embedded in spatial spillover effects.

8. Limitations

This study has several theoretical and methodological limitations. While the provincial-level panel data analysis reveals the spillover effects of the digital economy on carbon emission reduction, the restricted data coverage limits the generalizability of findings, particularly due to the lack of urban-rural differentiation and micro-level entity analysis. Although graph neural networks effectively capture spatial correlations, their "black-box" nature impedes the mechanistic interpretation of how specific digital technologies differentially contribute to emission reduction.

Future research can advance along three dimensions: First, constructing a multi-scale analytical framework incorporating city-level and microdata while conducting cross-national comparative studies. Second, integrating explainable AI techniques with spatial econometric methods to enhance model interpretability. Third, dynamically tracking the emission-reduction effects of emerging digital technologies and utilizing agent-based modeling to evaluate policy effectiveness.

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Authors' contributions

The author solely conceived, designed, conducted, and analyzed the study, as well as drafted and revised the manuscript. The author has read and approved the final version of the manuscript.

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The author declares no conflict of interest.

Informed consent

Not applicable.

Ethics approval

The Publication Ethics Committee of the Sciedu Press.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

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The data presented in this study are available on request from the corresponding author.

Data sharing statement

No additional data are available.

References

Alper, A., & Onur, G. (2016). Environmental Kuznets curve hypothesis for sub-elements of the carbon emissions in China. *Natural Hazards*, *82*(2), 1327-1340. https://doi.org/10.1007/s11069-016-2246-8

Bao, L., Zhang, C., Zhang, J., & Guo, R. (2024). A two-stage spatial prediction modeling approach based on graph neural networks and neural processes. *Expert Syst. Appl., 258,* 125173. https://doi.org/10.1016/j.eswa.2024.125173

Chen, H., Hou, N., Zhao, W., Hou, N., & Liu, W. (2023). The digital economy, industrial structure upgrading, and carbon emission intensity —— empirical evidence from China’s provinces. *Energy Strategy Reviews*, *50*, 101218-101218. https://doi.org/10.1016/j.esr.2023.101218

Chen, L., Xu, L., & Yang, Z. (2017). Accounting carbon emission changes under regional industrial transfer in an urban agglomeration in China’s Pearl River Delta. *Journal of Cleaner Production, 167,* 110-119. https://doi.org/10.1016/j.jclepro.2017.08.041

Chen, M., Zhao, S., & Wang, J. (2023). The Impact of the Digital Economy on Regional Carbon Emissions: Evidence from China. *Sustainability, 15*(20), 14863-14863. https://doi.org/10.3390/su152014863

Chen, P. (2022). Relationship between the digital economy, resource allocation and corporate carbon emission intensity: new evidence from listed Chinese companies. *Environmental Research Communications, 4*(7), 075005. https://doi.org/10.1088/2515-7620/ac7ea3

Cheng, Y., & Yao, X. (2021). Carbon intensity reduction assessment of renewable energy technology innovation in China: A panel data model with cross-section dependence and slope heterogeneity. *Renewable and Sustainable Energy Reviews, 135*, 110157. https://doi.org/10.1016/j.rser.2020.110157

Feng, D., Shen, Y., Xie, X., & Huang, Y. (2023). Digital economy and carbon emission reduction: evidence from China. *China Economic Journal, 16*(3), 272-301. https://doi.org/10.1080/17538963.2023.2244276

Gao, P., & Qu, C. (2025). Assessing the impact of green transformation on carbon emissions: a dynamic spatial Durbin model. *Frontiers in Environmental Economics,* 4. https://doi.org/10.3389/frevc.2025.1478861

Gao, Z., Li, S., Cao, X., & Li, Y. (2022). Carbon Emission Intensity Characteristics and Spatial Spillover Effects in Counties in Northeast China: Based on a Spatial Econometric Model. *Land, 11*(5), 753. https://doi.org/10.3390/land11050753

Gong, M., Zhang, Y., Li, J., & Chen, L. (2024). Dynamic spatial–temporal model for carbon emission forecasting. *Journal of Cleaner Production, 463*, 142581-142581. https://doi.org/10.1016/j.jclepro.2024.142581

Grossman, G. M., & Krueger, A. B. (1991). Environmental Impacts of a North American Free Trade Agreement. *NBER Working Paper No. 3914.*

Guo, J., Xu, Z., Wu, S., Huang, Y., & Guo, Y. (2024). The dynamic process mechanism of carbon reduction under the digital economy perspective. *Highlights in Business, Economics and Management, 26,* 58-66. https://doi.org/10.54097/2gf1j391

Hu, L., Yao, S., Zhu, T., & Wang, D. (2024). Examining the Impact of China's Digital Economy on Carbon Emissions Intensity: Mechanisms, Regional Variations, and Policy Implications. *South Asian Journal of Social Studies and Economics*, *21*(1), 43-61. https://doi.org/10.9734/sajsse/2024/v21i1761

Jing, S., Wu, F., Shi, E., Wu, X., & Du, M. (2023). Does the Digital Economy Promote the Reduction of Urban Carbon Emission Intensity?. *International Journal of Environmental Research and Public Health, 20*(4), 3680. https://doi.org/10.3390/ijerph20043680

Li, X., Liu, J., & Ni, P. (2021). The Impact of the Digital Economy on CO2 Emissions: A Theoretical and Empirical Analysis. *Sustainability, 13*(13), 7267. https://doi.org/10.3390/su13137267

Li, X.-N. (2021). Environmental regulations, government subsidies, and regional green technology innovation. *Economic Survey*, *38*(3), 14-23. https://doi.org/10.15931/j.cnki.1006-1096.2021.03.002

Liao, Z., Bai, Y., Jian, K., & Chalermkiat, W. (2024). The Spatial Spillover Effect and Mechanism of Carbon Emission Trading Policy on Pollution Reduction and Carbon Reduction: Evidence from the Pearl River–West River Economic Belt in China. *Sustainability, 16*(23), 10279. https://doi.org/10.3390/su162310279

Liu, F., & Liu, C. (2019). Regional disparity, spatial spillover effects of urbanisation and carbon emissions in China. *Journal of Cleaner Production*, *241*, 118226. https://doi.org/10.1016/j.jclepro.2019.118226

Liu, J., Li, S., & Ji, Q. (2021). Regional differences and driving factors analysis of carbon emission intensity from transport sector in China. *Energy, 224*, 120178. https://doi.org/10.1016/j.energy.2021.120178

Liu, L., Zhang, Y., Gong, X., Li, M., Li, X., Ren, D., & Jiang, P. (2022). Impact of Digital Economy Development on Carbon Emission Efficiency: A Spatial Econometric Analysis Based on Chinese Provinces and Cities. *International Journal of Environmental Research and Public Health, 19*(22), 14838. https://doi.org/10.3390/ijerph192214838

Liu, S. (2023). Impact of the Digital Economy on Carbon Intensity. *Transactions on Economics, Business and Management Research, 3,* 80-92. https://doi.org/10.62051/c6gvg060

Liu, X., Niu, Q., Dong, S., & Zhong, S. (2023). How does renewable energy consumption affect carbon emission intensity? Temporal-spatial impact analysis in China. *Energy*, *284*, 128690. https://doi.org/10.1016/j.energy.2023.128690

Liu, Y.-Q., Sun, W., & Zhu, Z.-S. (2022). The impact and pathway of carbon market on low-carbon transformation of energy structure. *China Environmental Science*, *42*(9), 4369-4379. https://doi.org/10.19674/j.cnki.issn1000-6923.20220602.001

Luo, H., Zhang, Y., Gao, X., Liu, Z., Song, X., Meng, X., & Yang, X. (2024). Unveiling land use-carbon Nexus: Spatial matrix-enhanced neural network for predicting commercial and residential carbon emissions. *Energy*, *305*, 131722. https://doi.org/10.1016/j.energy.2024.131722

Lyu, Y., Zhang, L., & Wang, D. (2023). Does digital economy development reduce carbon emission intensity?. *Frontiers in Ecology and Evolution,* 11. https://doi.org/10.3389/fevo.2023.1176388

Sheraz, M., Qin, Q., Mumtaz, M. Z., & Khan, M. H. (2024). Moving toward sustainable goals 7 and 13: An inclusive mechanism to achieve environmental sustainability through digitalization and energy transition in OECD countries. *Journal of Environmental Management, 369*, 122288. https://doi.org/10.1016/j.jenvman.2024.122288

Song, M., Wu, J., Song, M., Zhang, L., & Zhu, Y. (2020). Spatiotemporal regularity and spillover effects of carbon emission intensity in China's Bohai Economic Rim. *Science of the Total Environment, 740*, 140184. https://doi.org/10.1016/j.scitotenv.2020.140184

Sun, J., & Chen, J. (2023). Digital Economy, Energy Structure Transformation, and Regional Carbon Dioxide Emissions. *Sustainability, 15*(11), 8557-8557. https://doi.org/10.3390/su15118557

Sun, Q., Chen, H., Wang, Y., Huang, H., Deng, S., & Bao, C. (2023). Analysis of spatial and temporal carbon emission efficiency in Yangtze River Delta city cluster — Based on nighttime lighting data and machine learning. *Environmental Impact Assessment Review, 103*, 107232-107232. https://doi.org/10.1016/j.eiar.2023.107232

Sun, X., Lian, W., Gao, T., Chen, Z., & Duan, H. (2023). Spatial-temporal characteristics of carbon emission intensity in electricity generation and spatial spillover effects of driving factors across China's provinces. *Journal of Cleaner Production, 405*, 136908-136908. https://doi.org/10.1016/j.jclepro.2023.136908

Tang, K., Liu, Y., Zhou, D., & Qiu, Y. (2020). Urban carbon emission intensity under emission trading system in a developing economy: evidence from 273 Chinese cities. *Environmental Science and Pollution Research, 28*(5), 5168-5179. https://doi.org/10.1007/s11356-020-10785-1

Wang, J., Zhu, J., & Luo, X. (2021). Measurement of the Development Level and Evolution of China's Digital Economy. *The Journal of Quantitative & Technical Economics*, *38*(7), 26-42. https://doi.org/10.13653/j.cnki.jqte.2021.07.002

Wang. (2023). A Study on the Impact of Network Infrastructure Development on Carbon Emissions in China's Border Regions. *International Journal of New Developments in Engineering and Society, 7*(7). https://doi.org/10.25236/ijndes.2023.070704

Wu, R., Hua, X., Peng, L., Liao, Y., & Yuan, Y. (2022). Nonlinear Effect of Digital Economy on Carbon Emission Intensity—Based on Dynamic Panel Threshold Model. *Frontiers in Environmental Science*, 10. https://doi.org/10.3389/fenvs.2022.943177

Yan, X., & Zhang, Y. (2023). Empirical study on the impact of digital economy on carbon emission intensity--based on the mediating role of technological innovation. *Frontiers in Energy Research,* 11. https://doi.org/10.3389/fenrg.2023.1300158

Yin, J., Ding, Q., & Fan, X. (2021). Direct and indirect contributions of energy consumption structure to carbon emission intensity. *International Journal of Energy Sector Management, 15*(3), 665-677. https://doi.org/10.1108/ijesm-08-2020-0009

Zhang, K., Li, S., Qin, P., & Wang, B. (2022). Spatial and Temporal Effects of Digital Technology Development on Carbon Emissions: Evidence from China. *Sustainability, 15*(1), 485. https://doi.org/10.3390/su15010485

Zhang, Y., Guo, B., Liu, C., Li, H., & Xu, W. (2023). Graph Convolution Network for Carbon Emission Factor Forecast of Power Grid. *2022 4th International Conference on Power and Energy Technology (ICPET)*, 893-898. https://doi.org/10.1109/icpet59380.2023.10367568

Zhu, Z., Liu, B., Yu, Z., & Cao, J. (2022). Effects of the Digital Economy on Carbon Emissions: Evidence from China. *International Journal of Environmental Research and Public Health, 19*(15), 9450. https://doi.org/10.3390/ijerph19159450