Journal of Engineering, Project, and Production Management
2026, 16(6), 2025-251

Spatio-Temporal Correlation and Influence Paths between Digital Economy Development and Urban Carbon Emissions

Juan Ye
Associate Professor, Accounting College, Chongqing College of Finance and Economics, Chongqing, 402160, China,
E-mail: yelyjuan@outlook.com

Project Management
Received November 3, 2025; revised April 17, 2026; accepted June 17, 2026
Available online June 30, 2026

Abstract: As a powerful engine of modern growth, the digital economy is fundamentally transforming both economic structures and social systems. The coordinated development of the digital economy and carbon emission reduction will play an important role in achieving the goal of sustainable development. This paper takes Shenzhen as the research area and establishes a Spatial Durbin Model (SDM) and a Panel Vector Autoregression (PVAR) model. The results show that the proportion of the tertiary industry, high-tech enterprises, intelligent factories, and the coverage of digital inclusive finance are all significantly and negatively correlated with urban carbon emissions. The corresponding regression coefficients of -0.762, -0.838, -0.679, and -0.910, respectively, are all significant at the 1% level. The development of the digital economy in surrounding cities has spatial spillover effects on carbon emissions in Shenzhen, and the carbon emission intensity shows significant temporal differences from 2019 to 2023. The results show a strong spatio-temporal relationship between the digital economy and carbon emissions, and that the digital economy can reduce emissions through two channels: industrial upgrading and efficient resource use.

Keywords: Digital economy; carbon emissions; spatiotemporal linkage; spatial Durbin model; panel vector autoregression; impact pathways.

DOI 10.32738/JEPPM-2025-251

1. Introduction

In the context of intensified global climate warming and the rapid development of digital technology, promoting the coordinated development of the digital economy and carbon emission reduction has become an important issue for all countries (Niego et al., 2023; Orth, 2024). As one of the first low-carbon pilot cities in China, Shenzhen has a well-developed digital economy and has achieved significant results in controlling carbon emissions. Research on this city serves as a typical example (Wang et al., 2023; Pana et al., 2024). Therefore, analyzing the spatiotemporal correlations and influence pathways between Shenzhen's digital economy development and urban carbon emissions is highly significant. Accordingly, numerous scholars have conducted research on this topic. For example, Yan et al. (2023) used fixed effects, mediation, and moderation models to analyze panel data from 100 cities across six major Chinese urban agglomerations from 2011 to 2019. Their findings indicated that the advancement of the digital economy within these urban clusters substantially reduced carbon emissions intensity. Karaki et al. (2023) proposed a model based on an extended STIRPAT framework and analyzed panel data from developed countries from 2011 to 2021. Their findings revealed a long-term relationship between carbon emissions and factors such as the digital economy, population, gross domestic product, and technology level.

Despite some advances in research on the relationship between the digital economy and CO_2 emissions, three gaps remain, which include that most studies rely on provincial-level data, lack spatio-temporal analysis, and adopt macro-level approaches to digital empowerment pathways. Therefore, a Spatial Durbin Model (SDM) and a Panel Vector Autoregression (PVAR) model are adopted in this study. This study aims to analyze the core impact pathways between the digital economy and carbon emissions using small-scale, highly matched regional data, while avoiding interference from regional heterogeneity arising from overly large research areas. This study's innovations and contributions are reflected in three aspects. First, this study uses Shenzhen and its surrounding cities as a small-scale sample to accurately capture the intrinsic connection between the digital economy and carbon emissions, and to reduce analytical bias. Second, it reveals dynamic changes in the intensity of spatial spillover in the digital economy, quantifies the time-lag effects of digital economy emissions reduction, and fills the research gap regarding the dynamic correlation between time and space. Third, the study clarifies the core role of capital and technology as dual drivers, providing precise empirical evidence for coordinated emissions reduction in the regional digital economy.

2. Methods and Materials

2.1. Theoretical Framework and Hypotheses

2.1.1. Theoretical of digital economy development and city-level carbon emissions

The digital economy promotes the deep integration of data elements with the real economy through digital technologies, thereby enhancing production efficiency and optimizing resource allocation (Goldberg and Reed, 2023; Juhász and Lane, 2024). The impact of the digital economy on carbon emissions depends on the technology's application scenarios and its stage of development. For instance, urban carbon emissions mainly come from energy consumption, industrial production, and waste disposal (Wang and Zhang, 2024; Byrne et al., 2024). The structure of the digital economy and its relationship with city-level carbon emissions are shown in Fig. 1.

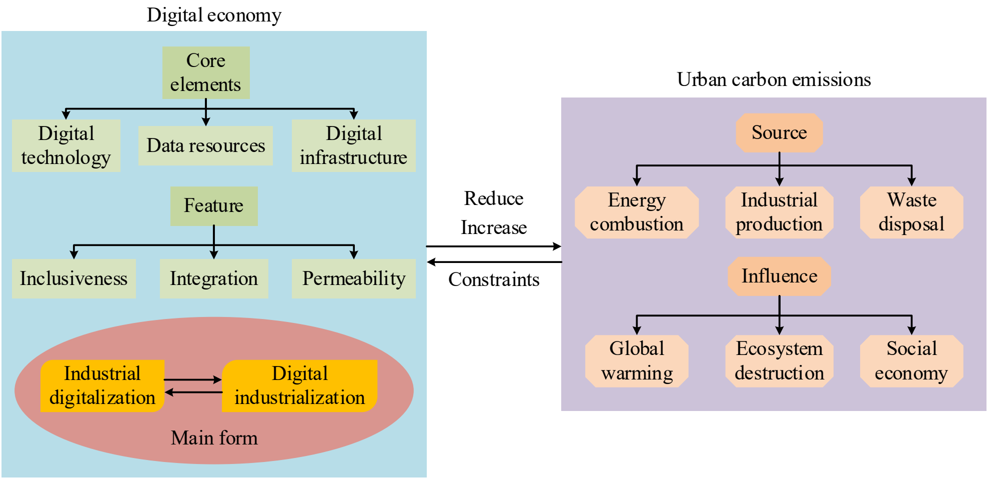


Fig. 1. Structural diagram of digital economy and city-level carbon emissions

As shown in Fig. 1, the main forms of the digital economy are digital industrialization and industrial digitalization. The former refers to industries based on digital technology, while the latter refers to the digital transformation of traditional industries (Wu et al., 2025; Bourdin and Torre, 2025). Urban carbon emissions mainly come from energy combustion, industrial production, and waste disposal (Treepongkaruna et al., 2024). The relationship between digital economy development and urban carbon emissions is bidirectional. The former affects total urban carbon emissions across different application scenarios and development levels, while the latter constrains digital economy development by tightening emission constraints.

2.1.2. Analysis of the impact pathways of digital economy on carbon emissions

Digital economy development impacts urban carbon emissions through two interactive dimensions: dynamic evolution over time and spatial transmission (Kuang et al., 2024; Raihan, 2024). Therefore, this study selects Shenzhen and its surrounding cities, such as Dongguan and Zhuhai, as the research area. Using open-source maps, the study explores the impact pathways from a spatiotemporal perspective. The geographic location of Shenzhen is shown in Fig. 2.

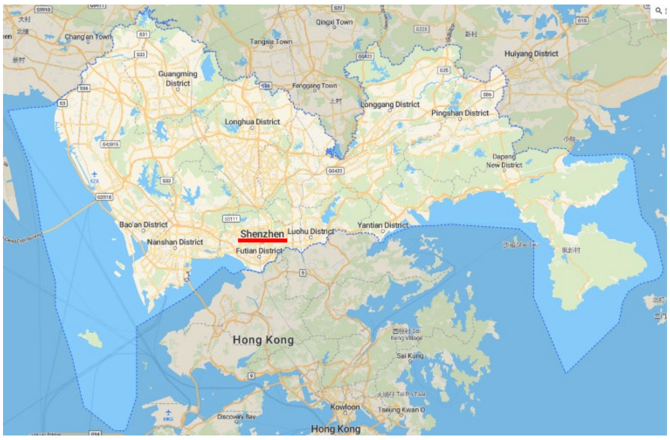


Fig. 2. Geographic location of Shenzhen

As shown in Fig. 2, Shenzhen is located on the eastern shore of the Pearl River Delta in southern Guangdong Province, China. It borders Hong Kong, Dongguan, Huizhou, and Zhuhai. Digital economy development in these cities affects both local and regional carbon emissions. In industrial digitalization, Shenzhen leverages digital technologies to drive the transformation of traditional manufacturing. In terms of energy consumption, the city has built a clean, low-carbon, efficient, and safe energy system through digital innovation.

2.1.3. Research hypotheses

Based on the theoretical framework above, this study proposes two hypotheses.

Hypothesis 1: Digital economy development in Shenzhen is negatively correlated with urban carbon emission intensity and exhibits significant spatiotemporal linkages.

Hypothesis 2: Digital economy development reduces city-level carbon emissions mainly through industrial structure upgrading and improved resource utilization.

2.2. Research Method Design

2.2.1. Data sources and processing

To accurately analyze the impact and pathways, the study uses panel data from 2019 to 2023 in Shenzhen as the research sample. The data are mainly collected from Shenzhen Statistical Yearbooks, government work reports, and geographic information from open-source maps.

2.2.2. Variable selection and explanation

To comprehensively analyze the relationship and influencing mechanisms between digital economy development and city-level carbon emissions, this study selects multiple key variables with clear definitions and consistent measurement methods. Two core variables, the digital economy output ratio and total carbon emissions, are defined as Core Variable 1 and Core Variable 2. Six additional indicators, including broadband users, digital industry value-added, employment in digital industries, total securities transactions, per capita carbon emissions, and forest coverage rate, are defined as Key Variables 1–6. Table 1 presents detailed information.

As shown in Table 1, the core variables are the digital economy output ratio and total carbon emissions. The former refers to the share of digital economy value added in gross domestic product, while the latter represents the total emissions of carbon dioxide and other greenhouse gases in a given area during a specific period. To avoid result bias, this study introduces several control variables, such as fiber broadband coverage and intelligent manufacturing adoption rates. Additionally, variables such as industrial structure and level of economic development are included as control variables.

2.2.3. Construction of evaluation models

The SDM introduces spatial lag terms for both the dependent and independent variables in the basic regression model, thereby improving its ability to capture spatial dependence. Therefore, this study constructs an SDM using a spatial weight matrix as the core component. The setting process is as follows. This study adopts a binary (0-1) adjacency spatial weight matrix as the base matrix. When two cities share an administrative boundary, they are defined as adjacent and assigned a matrix value of 1. When two cities do not share a boundary, they are defined as non-adjacent and assigned a value of 0. Based on this, the functional expression of the SDM constructed in this study is given in Eq. (1).

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{jt}\theta + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), Y_{it} and X_{it} represent the dependent and independent variables for region i during period t. $\sum_{j=1}^{N} W_{ij} Y_{jt}$ and $\sum_{j=1}^{N} W_{ij} X_{jt}$ are the spatial lag terms of the dependent and independent variables. W_{ij} is the spatial weight matrix. ρ and θ are the spatial lag coefficients. β is the direct effect coefficient of the independent variable, ε_{it} represents the random disturbance term, μ_i represents the individual fixed effect, and λ_t stands for the time fixed effect. To capture dynamic temporal relationships, this study constructs a PVAR model, whose mathematical formulation is given by Eq. (2).

$$y_{it} = \sum_{s=1}^{P} \Gamma_s y_{it-s} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In Eq. (2), y_{it} denotes the endogenous variable of individual i in period t. P is the lag order, and y_{it-s} is the s-th lag term of the variable, Γ_s is the coefficient matrix, ε_{it} is the random disturbance term with a mean of zero. For short datasets, the optimal lag order of the PVAR model is determined to be first order using the AIC and BIC criteria, combined with LR tests, to avoid excessive loss of degrees of freedom caused by high-order lags in short time series. The LSDV estimation method, which is suitable for short-term, small-sample panel data, is adopted to reduce estimation bias.

Table 1. Detailed information on variables

Variable class	Variable name	Variable definition and measurement methods	Measurement unit
Core	Variable 1	It reflects the extent to which the digital economy industry contributes to the regional economy (The proportion of the total annual added value of the digital industry in the regional GDP)	%
	Variable 2	The total emissions of carbon dioxide and other greenhouse gases produced by human activities within a certain period (Activity level multiplied by emission factor)	10,000 tons CO_2 eq
Control	Variable 1	Fixed broadband access users with a rate of ≥ 10 Mbps (Taken from the Shenzhen Communications Administration)	10,000 households
	Variable 2	New value created by the core industries of the digital economy (The total annual output of the core industries of the digital economy minus intermediate inputs)	100 million yuan
	Variable 3	The total number of employees in the digital industry at the end of the year (It is from the Shenzhen Statistical Yearbook)	10,000 people
	Variable 4	The total transaction amount of all securities varieties in the securities business departments within the jurisdiction of Shenzhen (Derived from the annual trading statistics report of the Shenzhen Stock Exchange)	Trillion yuan
	Variable 5	The ratio of total carbon dioxide emissions to the permanent resident population within a specific period (The total carbon emissions divided by the number of permanent residents in Shenzhen at the end of the year)	10,000 m^3/person
	Variable 6	It refers to the percentage of forest area in a certain region of the total land area (The ratio of forest area to land area)	%
Other variable	Industria structure	The composition and proportion of various industries within the region (The proportion of the added value of the tertiary industry in GDP)	%
	Economic development level	The comprehensive level of regional economic development (Annual GDP divided by the permanent resident population at the end of the year)	10,000 yuan/person

2.3. Data Analysis Methods

To thoroughly verify whether Shenzhen's digital economy development reduces carbon emissions and to explore the mechanisms underlying this effect, this study employs a range of data analysis methods. In addition, heterogeneity analysis and robustness checks are conducted to ensure the accuracy and reliability of the results.

3. Results

3.1. Descriptive Statistical Analysis

To better understand the selected data, the study first conducted a descriptive statistical analysis of the main variables. The results are shown in Table 2.

As shown in Table 2, Shenzhen's digital economy expanded steadily from 2019 to 2023. The added value of the digital industry increased from 36.96 billion yuan to 46.79 billion yuan, up 26.6%. The average number of internet broadband users reached 6.134 million, and the standard deviation (61.94) was relatively small compared with the mean, indicating limited dispersion and suggesting that Shenzhen's digital economy development showed a trend of steady expansion without extreme fluctuations. In addition, during the same period, per capita carbon emissions increased from 25,300 to 32,700 (units unchanged as reported in the dataset), indicating a gradual increase over the study period. This suggests the need to strengthen cooperation in emissions reduction associated with digital development.

3.2. Correlation Analysis

After gaining a basic understanding of the data, the study conducted a correlation analysis to briefly examine the relationships among variables. The results are presented in Fig. 3.

Table 2. Descriptive statistical analysis of key variables

Variable name	Maximum value	Minimum value	Mean value	Standard deviation	Measurement unit
Control variable 1	683	533	613.4	61.94	10000 households
Control variable 2	467.9	369.6	426.66	38.32	100 million yuan
Control variable 3	39.7	29.6	36.42	4.05	Ten thousand people
Control variable 4	14.4	7.3	11.82	2.53	Trillion
Control variable 5	3.27	2.53	2.83	0.36	10000 cubic meters/person
Control variable 6	39.8	39.1	39.34	0.27	Hectares

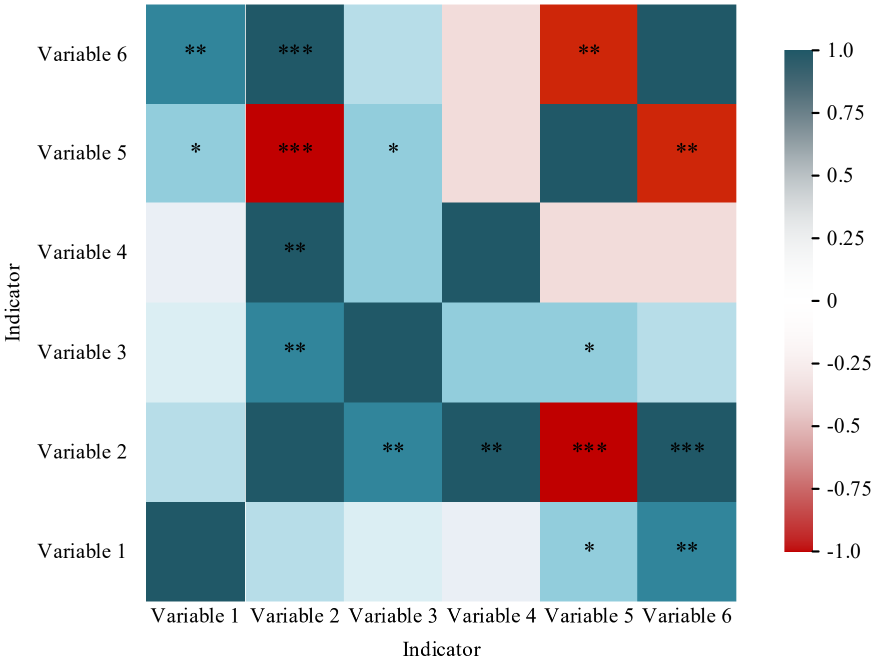


Fig. 3. Heatmap of correlations among key variables

As shown in Fig. 3, the correlation coefficient between digital industry value-added and per capita carbon emissions was -0.961, which supports the theoretical logic of the digital economy in suppressing carbon emissions and provides evidence for Hypothesis 1. The correlation coefficient between Internet broadband users and the forest coverage rate was 0.679, indicating a significant positive correlation. This suggests that improvements in digital infrastructure can promote cross-regional resource sharing, thereby reducing carbon emissions from resource waste and verifying Hypothesis 2.

3.3. Baseline Regression Analysis

The study conducted regression analysis with the digital economy as the independent variable and urban carbon emissions as the dependent variable. An intelligent factory is an industrial enterprise that achieves digital control of production processes through the Industrial Internet, automated equipment, and related technologies. Digital inclusive finance coverage was measured by the degree of integration between digital technology and inclusive finance. The results are shown in Table 3. In all tables, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

In Table 3, the regression coefficients for tertiary industry proportion, high-tech enterprises, smart factories, and digital inclusive finance coverage were -0.762, -0.838, -0.679, and -0.910, respectively. This indicated that digital financing empowerment and technological innovation were at the core of carbon reduction, once again verifying Hypothesis 1. The number of Internet broadband users (0.214*) and the scale of the electronic information manufacturing industry (0.175*) both showed a short-term positive correlation, reflecting phased carbon emissions associated with digital infrastructure and manufacturing production. To explore spatial differences in the impact of digital economy development on city-level carbon emissions, the study included regional control variables in additional regressions. The results are given in Table 4.

Table 3. Baseline regression results

Variable name	Coefficient	Standard error	t	p
The proportion of the tertiary industry	-0.762***	0.012	-7.43	0.007
Control variable 1	0.214*	0.076	2.31	0.073
High-tech enterprise	-0.838***	0.009	-9.57	0.005
The scale of the electronic information manufacturing industry	0.175*	0.044	2.09	0.061
Intelligent factory	-0.679***	0.017	-6.28	0.007
The coverage of digital inclusive finance	-0.910***	0.003	-10.34	0.002
R^2	0.89	/	/	/

Table 4. Results with regional control variables

Variable name	Coefficient	Standard error	t	p
The proportion of the tertiary industry economy	-0.734***	0.010	-7.88	0.006
Control variable 1	0.187*	0.058	2.46	0.061
High-tech enterprise	-0.812***	0.008	-10.09	0.004
The scale of the electronic information manufacturing industry	0.148*	0.030	2.23	0.057
Intelligent factory	-0.645***	0.014	-7.14	0.006
The coverage of digital inclusive finance	-0.889***	0.003	-10.76	0.002
Regional fixed effect	Controls	/	/	/
R2	0.90	/	/	/

As shown in Table 4, the regression coefficient for the tertiary industry proportion slightly decreased from −0.762 to −0.734, while both the correlation strength and significance level remained stable. The coefficients for broadband users and the scale of electronic information manufacturing declined to 0.187 and 0.148, respectively. These changes suggest that spatial differences among the studied cities influence the strength of the digital economy's impact on carbon emissions.

3.4. Heterogeneity Analysis

To further investigate the spatiotemporal linkage, the study conducted a heterogeneity analysis. It introduced three surrounding cities, which include Dongguan, Zhuhai, and Huizhou, and ran separate regressions to examine spatial relationships. The results are given in Table 5.

In Table 5, the regression coefficient for the number of high-tech enterprises in Shenzhen was −0.811, an increase of 0.027 relative to earlier estimates. Meanwhile, the coefficient for smart factories declined from −0.679 to −0.692. Spatial heterogeneity characteristics were mainly reflected in two aspects: differences in the absolute values of core variable coefficients and differences in control variable coefficients. For example, the coefficient for the number of high-tech enterprises in Shenzhen was greater in absolute value than that in Huizhou, and the coefficient for the scale of the electronic information manufacturing industry in Shenzhen was higher than that in Zhuhai. The study then extended Shenzhen's panel data to cover 2014 to 2023 and repeated the heterogeneity analysis across cities. The results are given in Table 6.

As shown in Table 6, from 2014 to 2023, the regression coefficient for Shenzhen's tertiary industry value-added was −0.830, an increase of 0.096 relative to Table 4. Correspondingly, the coefficients for Dongguan, Zhuhai, and Huizhou were −0.741, −0.783, and −0.726, respectively, all indicating moderate variation relative to earlier results. The AR (1) *p*-values for all four cities were greater than 0.1, indicating no significant autocorrelation issues in the short-panel data, and the dynamic estimation results were reliable. To visually present the spatiotemporal linkage and impact strength, the study generated visualizations shown in Fig. 4.

Table 5. Comparison of regression results across four cities

Variable name	Shenzhen	Dongguan	Zhuhai	Huizhou
The proportion of the tertiary industry economy	-0.746*** (-7.61)	-0.652*** (-8.54)	-0.685*** (-8.72)	-0.607*** (-9.10)
Control variable 1	0.231* (2.20)	0.194* (1.87)	0.139* (1.28)	0.175* (1.66)
High-tech enterprise	-0.811*** (-9.82)	-0.746*** (-10.41)	-0.673*** (-11.35)	-0.714*** (-10.89)
The scale of the electronic information manufacturing industry	0.335* (1.50)	0.305* (1.21)	0.214* (0.76)	0.287* (1.30)
Intelligent factory	-0.692*** (-6.05)	-0.727*** (-5.69)	-0.651*** (-6.54)	-0.613*** (-6.80)
The coverage of digital inclusive finance	-0.895*** (-10.86)	-0.919*** (-10.03)	-0.862*** (-10.61)	-0.934*** (-9.87)
R2	0.88	0.85	0.86	0.83

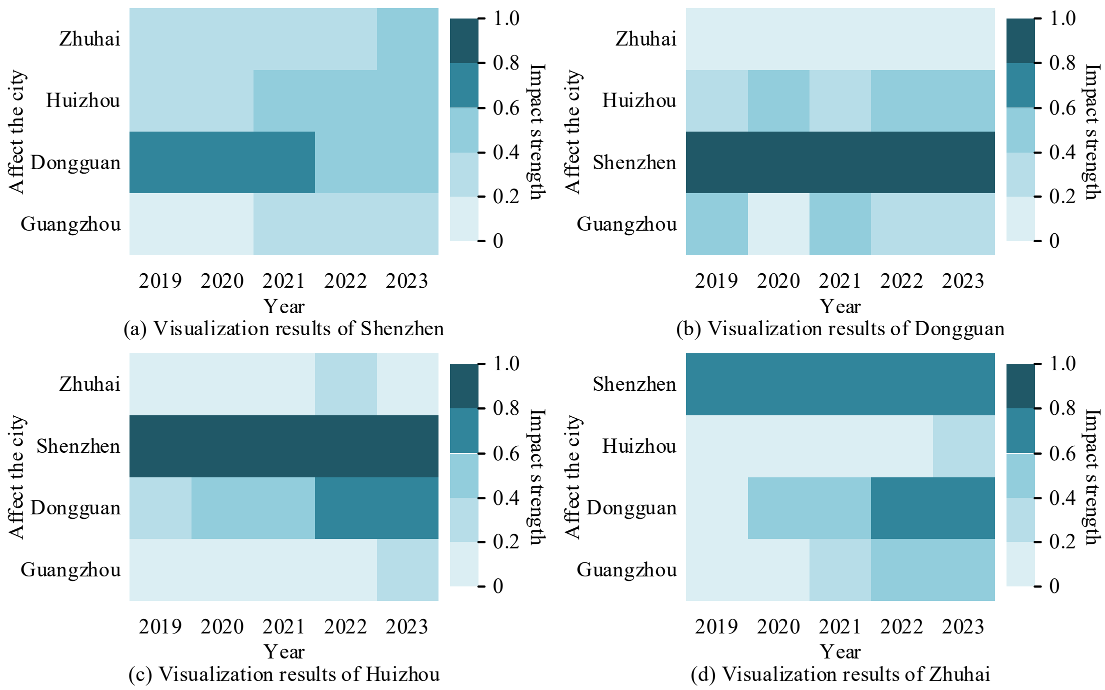
Table 6. Regression results considering the time dimension

Variable name	Shenzhen	Dongguan	Zhuhai	Huizhou
The proportion of the tertiary industry economy	-0.830*** (-6.92)	-0.741*** (-7.50)	-0.783*** (-7.71)	-0.726*** (-7.84)
Control variable 1	0.256*** (2.12)	0.205*** (1.69)	0.183*** (1.17)	0.167*** (1.80)
High-tech enterprise	-0.795*** (-10.04)	-0.733*** (-10.67)	-0.660*** (-11.52)	-0.702*** (-11.10)
The scale of the electronic information manufacturing industry	0.304*** (1.85)	0.238*** (1.53)	0.230*** (1.39)	0.216*** (1.22)
Intelligent factory	-0.713*** (-5.87)	-0.695*** (-5.76)	-0.662*** (-6.35)	-0.601*** (-6.93)
The coverage of digital inclusive finance	-0.928*** (-10.37)	-0.902*** (-10.26)	-0.881*** (-10.79)	-0.895*** (-10.22)
R2	0.86	0.82	0.82	0.80
AR (1)	0.181	0.207	0.199	0.215

As shown in Fig. 4(a), the impact intensity of Dongguan's digital economy development on Shenzhen's carbon emissions exceeded 0.6 between 2019 and 2021. Huizhou and Zhuhai followed, with impact intensity ranging from 0.2 to 0.6. Guangzhou's impact strength was below 0.4. Figs. 4(b) to 4(d) showed that Dongguan and Huizhou had carbon emission intensities greater than 0.8 between 2019 and 2023, while Zhuhai's impact strength remained below 0.8 during the same period. Overall, the development of the digital economy in Shenzhen had a significant effect not only on its own carbon emissions but also on those of surrounding cities, demonstrating spatial linkages. Moreover, the intensity of the impact of digital economy development on urban carbon emissions varied annually, reflecting their spatiotemporal correlation.

3.5. Robustness Check

To ensure the reliability and accuracy of the results, the study conducted robustness checks using three estimation methods: ordinary least squares, ridge regression, and Bayesian estimation. Coefficient stability analysis and causal identification strategies were employed to assess differences in coefficient signs, numerical fluctuations, and causal relationships across models. The results are given in Table 7.



(a) Visualization results of Shenzhen
(b) Visualization results of Dongguan
(c) Visualization results of Huizhou
(d) Visualization results of Zhuhai

Fig. 4. Visualization of spatiotemporal linkage and impact strength

Table 7. Regression results from different estimation methods

Variable name	Ordinary least square	Ridge regression	Moment estimation	Coefficient stability	Causality
The proportion of the tertiary industry economy	-0.702*** (-8.16)	-0.753*** (-7.65)	-0.720*** (-7.97)	0.031	-0.730*
Control variable 1	0.169* (2.58)	0.207* (2.26)	0.176* (2.53)	0.097	0.181*
High-tech enterprise	-0.795*** (-10.41)	-0.828*** (-9.73)	-0.804*** (-10.30)	0.024	-0.812*
The scale of the electronic information manufacturing industry	0.132* (2.40)	0.169* (2.07)	0.137* (2.33)	0.118	0.144*
Intelligent factory	-0.628*** (-7.35)	-0.677*** (-6.89)	-0.636*** (-7.24)	0.040	-0.646*
The coverage of digital inclusive finance	-0.863*** (-11.08)	-0.902*** (-10.25)	-0.879*** (-10.88)	0.025	-0.889*
Regional fixed effect	Controls	Controls	Controls	/	Controls
Time-fixed effect	Controls	Controls	Controls	/	Controls
R2	0.88	0.91	0.89	/	0.89

As shown in Table 7, after coefficient stability testing, although the regression coefficients for each major variable differed across estimation methods, the amplitudes of their fluctuations remained within statistically reasonable ranges. Meanwhile, after causal identification, the coefficients for each digital economy variable remained significant at the 1% level, suggesting a stable causal transmission path underlying the negative correlation between the digital economy and urban carbon emissions, thereby indirectly verifying Hypothesis 2. Finally, the study replaced electronic information manufacturing scale and smart factory variables with population density and per capita GDP and conducted additional regressions. The results are shown in Table 8.

Table 8. Regression results with substituted variables

Variable name	Coefficient	Standard error	t	p
The proportion of the tertiary industry economy	-0.753***	0.018	-7.56	0.008
Control variable 1	0.201*	0.085	2.19	0.080
High-tech enterprise	-0.822***	0.014	-9.66	0.007
Population density	0.159	0.053	1.97	0.069
Per capita GDP	-0.076	0.024	1.63	0.046
The coverage of digital inclusive finance	-0.896***	0.006	-10.67	0.004
R2	0.86	/	/	/

As shown in Table 8, regression coefficients for population density and per capita GDP were 0.159 and −0.076, respectively, with neither significantly related to carbon emissions. However, the significance levels for the tertiary industry proportion, high-tech enterprises, and digital inclusive finance coverage remained unchanged, supporting the robustness of the original results. Overall, the main impact pathways through which digital economy development affected city-level carbon emissions were industrial structure upgrading and improved resource utilization, rather than factors such as population size or income level.

4. Discussion

This study adopts the SDM and PVAR models to explore the spatiotemporal relationships between digital economy development and carbon emissions in Shenzhen. Moreover, heterogeneity analysis and robustness checks validated the results obtained. Results indicated that variables strongly associated with the digital economy had negative effects on urban carbon emissions. Their coefficient values were -0.762, -0.838, -0.679 and -0.910, respectively and were significant at the 1% level. This finding was supported by Shen et al. (2024), who analyzed the relationship between digital economy development and carbon emissions intensity across 30 Chinese provinces. This can be explained by the fact that digital economy empowerment facilitates structural optimization through both industrial digitalization and digital industrialization, hence reducing carbon emissions. For instance, in industrial digitalization, Shenzhen restructured traditional manufacturing production processes by leveraging smart factories, which had a regression coefficient of -0.679, directly reducing carbon emissions in industrial production. After introducing regional control variables, the regression coefficient for high-tech enterprises decreased in absolute value from −0.838 to −0.812, while the coefficient for smart factories increased in absolute value from −0.679 to −0.645, an increase of 0.034. However, the significance levels of both variables remained stable. This was similar to the approach adopted by Liu et al. (2024), who used fixed-effects panel data models to analyze panel data from multiple provinces in China between 2011 and 2022, identifying key factors in the digital economy that influenced carbon emissions. In addition, digital empowerment could also enhance resource utilization efficiency and reduce carbon emissions through dynamic resource allocation. For instance, Shenzhen established a cross-regional resource-sharing platform via its Internet broadband infrastructure (regression coefficient: 0.214), thereby reducing carbon emissions from waste treatment processes.

In the heterogeneity analysis, the regression coefficient for high-tech enterprises in Shenzhen increased in absolute value to -0.811, up by 0.027 compared to the previous value. In contrast, the coefficient of smart factories increased in absolute value from -0.679 to -0.692. This result is consistent with the findings of Yu et al. (2024), who used the SDM to examine the impact of the digital economy on carbon-emission efficiency. In the temporal dimension, the coefficients for tertiary industry value-added in Dongguan, Zhuhai, and Huizhou were −0.741, −0.783, and −0.726, all lower in absolute value than the corresponding coefficients in the spatial dimension. Yu et al. (2024) also found that digital economy development primarily reduced carbon dioxide emissions through industrial upgrading, and that this impact pathway exhibited both spatial and temporal heterogeneity. Their conclusions are consistent with the results of this study. Finally, the study conducted robustness checks using two approaches: applying different estimation methods and replacing selected variables. The results showed that although the regression coefficients for the major variables differed between the two approaches, their correlations with carbon emissions and significance levels remained unchanged, supporting the reliability of the regression results. This approach was similar to that used by Xu et al. (2024), who applied principal component analysis to validate their results. In conclusion, the research results demonstrate spatiotemporal correlations between Shenzhen's digital economy development and urban carbon emissions, and that the main influence pathways involve industrial structure upgrading and improved resource utilization.

5. Conclusion

The SDM and PVAR models were used to examine the relationships and causal channels between digital economy growth and carbon emissions at the city level in Shenzhen. The findings revealed that all key variables representing the digital economy exhibited negative correlations with cities' carbon emissions at the 1% significance level, suggesting that the digital economy contributes to reducing carbon emissions in two ways: industrial restructuring and increased resource-use efficiency. Based on these findings, this study offers two policy recommendations. First, given that the proportion of the tertiary industry is significantly and negatively correlated with carbon emissions, cities in the Guangdong-Hong Kong-Macao Greater Bay Area are encouraged to prioritize the green digital economy transformation in conjunction with tertiary industry development. Second, given that the emission-reduction effects of high-tech enterprises are strongest in Shenzhen and weakest in Huizhou, local governments should implement differentiated policies based on regional levels of digital economy development. Meanwhile, this study provides clear guidance for managers seeking to make better decisions: Corporations are encouraged to consider digital, low-carbon transformation during the investment decision-making process, and it is essential that they focus on developing advanced technologies in production. At the urban level, managers should consider both digital empowerment and carbon reduction when allocating resources. And regional managers should establish a collaborative decision-making mechanism based on spatial spillover effects to achieve integrated management of the digital economy and low-carbon development.

Although this study focuses only on Shenzhen and cities in the Pearl River Delta, the research conclusions are feasible and have reference value for promotion in different countries and regions worldwide. For economically developed and digitally infrastructure-advanced countries and regions, the Shenzhen model can be adopted, focusing on relying on high-tech enterprises, intelligent factories and digital inclusive finance to promote the digitalization and low-carbon transformation of industries. Developing countries and areas lacking robust digital infrastructure should first focus on developing digital infrastructure and encouraging the use of digital technologies within existing dominant industries, thereby achieving a synergistic effect between the digital economy and carbon reduction. Furthermore, although this empirical analysis achieved certain results, two limitations remain. First, this study examined only Shenzhen and its surrounding cities, limiting its ability to capture regional heterogeneity nationwide. Second, the research time span was relatively short, limiting verification of long-term causal relationship stability. Future research is recommended to collect panel data from 30 Chinese provinces covering 2014 to 2023, verify the adaptability of impact pathways across different regions through multiple heterogeneity analyses, and quantify the long-term dynamic effects of the digital economy on carbon emissions.

Funding

The research is supported by the Science and Technology Project of Chongqing Education Commission: Construction and Exploration of the “Four Party Joint Talent Education” Industry Education Integration and Collaboration Mechanism in Vocational Education from the Perspective of High-quality Development (Project number: KJQN202304202). Chongqing Education Science Planning and Reform Project: Research on the Construction and Application of Bilingual Curriculum “Inheritance and Changes of Chinese Accounting Culture” from the CLIL Perspective (Project number: K24ZG3210333). Chongqing Vocational Education Teaching Reform Research Project: Research on the Mixed Teaching Mode of Accounting Bilingual Curriculum from the CLIL Perspective-Taking the Course of “Inheritance and Changes of Chinese Accounting Culture” as an Example (Project number: Z233147).

Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The author confirmed that they did not use AI tools for extensive content creation. The core content, such as the research idea design, model construction, empirical analysis, result interpretation, conclusion and policy recommendations, was all independently completed by the author, without using AI tools to generate the main body, analysis or conclusion. The article used AI only as an auxiliary tool, such as local sentence polishing, English expression checking and table format arrangement, which are non-core content.

References

Bourdin, S. and Torre, A. (2025). Economic geography's contribution to understanding the circular economy. *Journal of Economic Geography*, 25(2), 293-308.

Byrne, B., Liu, J., Bowman, K. W., Pascolini-Campbell, M., Chatterjee, A., Pandey, S., and Sinha, S. (2024). Carbon emissions from the 2023 Canadian wildfires. *Nature*, 633(8031), 835-839.

Goldberg, P. K. and Reed, T. (2023). Is the global economy deglobalizing? If so, why? And what is next?. *Brookings Papers on Economic Activity*, 2023(1), 347-423.

Wu, L., Duan, X., Yang, F., Guo, L., and Zhou, H. (2025). Does digital economy help reduce carbon emissions from tourism? *Evidence from China. Current Issues in Tourism,* 28(18), 2998-3015.

Kuang, Y., Fan, Y., Bin, J., and Fan, M. (2024). Impact of the digital economy on carbon dioxide emissions in resource-based cities. *Scientific Reports*, 14(1), 16514-16529.

Juhász, R., and Lane, N. (2024). The political economy of industrial policy. *Journal of Economic Perspectives*, 38(4), 27-54.

Karaki, B. A., Al-Kasasbeh, O., Alassuli, A., and Alzghoul, A. (2023). The impact of the digital economy on carbon emissions using the STIRPAT model. *International Journal of Energy Economics and Policy*, 13(5), 139-143.

Liu, Y., Dong, F., Yu, J., and Liu, A. (2024). Examining the impact of digital economy on environmental sustainability in China: Insights into carbon emissions and green growth. *Journal of the Knowledge Economy*, 15(4), 18044-18080.

Wang, Q., Cheng, X., and Li, R. (2024) Does the digital economy reduce carbon emissions? The role of technological innovation and trade openness. *Energy & Environment*, 36(4), 1670-1695.

Zhu, Y. and Lu, S. (2024). Digital economy and carbon neutrality: Exploring the pathways and implications for China's sustainable development. *Journal of the Knowledge Economy*, 15(4), 20390-20407.

Pana, K., Mitan, W., and Lamawitak, P. L. (2024). The influence of digital economy development on the income of micro, small, and medium enterprises in East Alok District. *Neo Journal of Economy and Social Humanities*, 3(2), 145-159.

Raihan, A. (2024). The interrelationship amid carbon emissions, tourism, economy, and energy use in Brazil. *Carbon Research*, 3(1), 11-34.

Shen, Y., Wang, G., Wu, X., and Shen, C. (2024). Digital economy, technological progress, and carbon emissions in Chinese provinces. *Scientific Reports*, 14(1), 23001-23013.

Treepongkaruna, S., Au Yong, H. H., Thomsen, S., and Kyaw, K. (2024). Greenwashing, carbon emission, and ESG. *Business Strategy and the Environment*, 33(8), 8526-8539.

Liu, Y., Dong, F., Yu, J., and Liu, A. (2024) Examining the impact of digital economy on environmental sustainability in China: Insights into carbon emissions and green growth. *Journal of the Knowledge Economy*, 15(4), 18044-18080.

Wang, Z. and Zhang, Z. (2024). The carbon emission reduction effect and mechanism analysis of digital economy: Evidence of prefecture-level cities in China. *Applied Economics*, 56(53), 6803-6820.

Xu, C., Zhao, W., Li, X., Cheng, B., and Zhang, M. (2024). Quality of life and carbon emissions reduction: does digital economy play an influential role? *Climate Policy*, 24(3), 346-361.

Yan, X., Deng, Y., Peng, L., and Jiang, Z. (2023). Study on the impact of digital economy development on carbon emission intensity of urban agglomerations and its mechanism. *Environmental Science and Pollution Research*, 30(12), 33142-33159.

Yu, Y., Liu, D., and Dai, Y. (2024). Carbon emission effect of digital economy development: Impact of digital economy development on China's carbon dioxide emissions. *Clean Technologies and Environmental Policy*, 26(8), 2707-2720.

Yu, Z., Liu, Y., Yan, T., and Zhang, M. (2024). Carbon emission efficiency in the age of digital economy: New insights on green technology progress and industrial structure distortion. *Business Strategy and the Environment*, 33(5), 4039-4057.

Juan Ye is an associate professor from Yubei, Chongqing. She earned her dual bachelor’s degrees in Management and Literature from Southwest University in 2011, followed by a master’s in Business Administration from Chongqing Technology and Business University in 2017. She has led three provincial and ministerial-level projects and participated in over fifteen provincial, ministerial, and university-level projects. She is the holder of two patents, has co-edited twelve textbooks, authored one monograph, and published more than twenty papers, including three Peking University core papers, one IE (JA) paper, and one theoretical edition in a provincial party newspaper.