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The spatial impact of digital economy on carbon emissions reduction: evidence from 215 cities in China

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Introduction: Within the global framework of carbon emissions constraints, the digital economy has become a new strategy for cities to achieve sustainable development. Scholarly literature exploring the spatial spillover and spatial mechanisms of the digital economy on carbon emissions is notably scarce.

Methods: To estimate the spatial impact of digital economy on carbon emissions, this paper conducted spatial analysis with the spatial Dubin model and panel data of 215 cities in China from 2011 to 2019.

Results: The results show that there is a growing regional agglomeration of the digital economy, whereas the spatial evolution of carbon emissions displays low liquidity and high stability. Second, the digital economy directly reduces urban carbon emissions, and this conclusion is supported through a series of robustness tests. However, there exist negative spatial spillover effects of digital economy on carbon emissions reduction in neighboring cities. Third, mechanism analysis reveals that the digital economy mainly affects urban carbon emissions through two paths: industrial structure upgrading and green technology innovation. Moreover, the influence of digital economy exhibits heterogeneity, with a more pronounced effect observed in the central cities and in large and medium-sized cities, as well as in cities with a high agglomeration of the new energy industry.

Discussion: Our paper not only presents new documentary evidence for understanding the relationship between digitalization and decarbonization, but also provides specific references for policy making to accelerate low-carbon urban development.

KEYWORDS

digital economy, urban carbon emissions, spatial spillover effect, mediating effect, heterogeneity

1 Introduction

With the exacerbation of global warming and intensification of economic competition, China, as the world's largest carbon emitter, confronts significant challenges in reducing carbon emissions. In 2022, China's total carbon dioxide emissions reached approximately 11.5 billion tons. 2023 United Nations Climate Change Conference (COP28) emphasized further curbing greenhouse gas emissions, and urged developing countries to progressively attain net-zero emissions of greenhouse gases. In response to the need for controlling carbon emissions and steering the economy toward green development, the Chinese government formally pledged at the 2020 United Nations General Assembly to achieve carbon peak by 2030 and carbon neutrality by 2060 (Dual-Carbon Target). Simultaneously, the breakthrough and innovation of information technology have propelled the ongoing expansion of the digital economy, facilitated the digital transformation of the industry, and led the society to the digital era (Goldfarb and Tucker, 2019). In 2022, China's digital economy has surged to 7.46 trillion dollars, contributing over 41% to GDP and ranking second in the global. Consequently, digital economy has indisputably emerged as a crucial metric for economic growth across all sectors, serving as a key driving force for bolstering the national competitiveness (Liu et al., 2022).

In recent research, the economic impact and spatial effect of the digital economy and low-carbon development have garnered significant attention. From the aspect of digital economy, a body of literature have underscored its capacity to reduce transaction costs (Müller, 2019; Xu et al., 2019), enhance resource allocation efficiency (Ma and Zhu, 2022), stimulate technology upgrading (Ning et al., 2022), optimize enterprise operation efficiency (Mikalef et al., 2019) and move the clean energy developing process forward (Chen, 2022), *etc.* Concurrently, the digital economy exhibits obvious spatial spillover effects (Varlamova and Kadochnikova, 2023), especially in the domains of urban green technology innovation (Dian et al., 2024), green total factor productivity (Lyu et al., 2023), and haze control (Tan and Chen, 2022). All these benefits mentioned associated with the digital economy could contribute to fostering high-quality economic development (Wang et al., 2022b). As for low-carbon development, its purpose is to achieve economic development while conserving energy and reducing carbon emissions. Carbon emission is a pivotal aspect of low-carbon development (Zhou et al., 2023). Scholars have analysed the temporal and spatial evolution of carbon emissions from the perspective of global (Smith et al., 2021), countries (Sporkmann et al., 2023) and regions (Shan et al., 2022). Moreover, existing literature still explores the relationship between low-carbon development and key dimensions including energy structure (Wang et al., 2016), transformation of economic development modes (Li and Wei, 2021), and industrial planning adjustment (Zheng et al., 2021).

With the implementing of China's Dual-Carbon Target, the intricate relationship between digital economy and carbon emissions has emerged as a research focus (Zhang J. et al., 2022). The impact of digital economy on urban carbon emissions is multi-dimensional and complex. Numerous studies have verified that the development of digital economy can foster a decline in regional carbon emissions (Zhang W. et al., 2022; Yi et al., 2022), thereby facilitating the achievement of Dual-Carbon Target. However, there are also studies showing the digital economy itself also needs a low-carbon transition (Thornbush and Golubchikov, 2019; Akberdina and Osmonova, 2021). Low-carbon is not an inherent nature of the digital economy. The extensive development of digital economy has also given rise to carbon emissions challenges. Additional studies highlight the non-linear relationship between digital economy and carbon emissions (Xu C. et al., 2023). Digital industrial technology, for instance, will increase carbon emissions intensity during the upgrading process, but the upstream and downstream enterprises empowered by digital technology will ultimately reduce the carbon emissions (Zeng and Yang, 2023). In the context of Dual-Carbon Target, there is a discernible and accelerating convergence between the digital economy and low-carbon development. This prompts scholarly reflection on the relationship between the digital economy and carbon emissions. Can the digital economy propel low-carbon development? What specific mechanisms underlie the potential impact of digital economy? Answering these questions holds substantial theoretical and practical significance for the low-carbon transformation of economic and social development.

The possible contributions of this paper include three main aspects. 1) Research perspectives. There is a scarcity of studies discussing the spatial mechanisms of digital economy despite many scholars have acknowledged the spatial effects of digital economy. This study delved into both direct and indirect effects, analyzing the spatial spillover mechanisms of digital economy and their impact on carbon emissions. This provides theoretical references for regional coordinated efforts aimed at carbon emissions reduction. 2) Research methodologies. We combined traditional econometric models with geographic information tools in our study. Using the Slope function, we visualized the spatial-temporal evolution of the digital economy and carbon emissions. Under the dual influence of geographic distance and economic distance, we empirically examined the spatial impact of the digital economy on carbon emissions using a spatial Durbin model. Furthermore, employing a two-stage transmission effect model with spatial effects, we explored the spatial mediation mechanism of the digital economy. 3) Research objects. We conducted heterogeneous analysis considering geographical location, city size, and the agglomeration of new energy industry. This provides specific recommendations for cites at different development levels in formulating policies related to digital economic development.

Using a panel dataset encompassing 215 cities from 2011 to 2019, we explored the spatial impact of the digital economy on carbon emissions. Initially, we conduct a thorough analysis of the spatio-temporal evolution between the digital economy and carbon emissions. Subsequently, we empirically investigate the direct and indirect effects of digital economy on carbon emissions by spatial econometric model. Furthermore, we check a series of robustness test and evaluate the heterogeneity. Finally, we discuss the mechanism affecting urban carbon emissions from the perspective of industrial structure upgrading and green technology innovation.

The remainder of this paper is structured as follows. Section 2 elucidates the theoretical analysis and provides research hypotheses. Section 3 details the methodologies and variable descriptions. Section 4 presents the results and discussion. Section 5 provides conclusion, policy implications and limitations.

2 Theoretical analysis and research hypotheses

2.1 Direct impact of digital economy on urban carbon emissions

As a new economic form, the digital economy has engendered new production and consumption patterns, spawning new business forms (Guo et al., 2023). The impact of digital economy on urban carbon emissions can be reflected in the following four aspects. First, the digital economy has accelerated the construction of urban digital infrastructure. Notably, the construction of digital infrastructure, represented by 5G base stations and cloud computing data centers, accelerates information dissemination, promotes telecommuting and remote work, thereby curtailing urban traffic activities (Huang et al., 2023). The shared economy model facilitated by digital technologies has enhanced the efficiency of urban resources utilization, consequently mitigating carbon emissions arising from resource profligacy. Second, the digital economy has propelled the widespread application of digital technologies in the industrial field, enhancing the production and organizational efficiency (Tan et al., 2023). Digital technology helps enterprises effectively monitor the energy consumption states, identify production process with high energy consumption, thereby reducing energy consumption during production stages (Zhang L. et al., 2022). Third, the digital economy facilitates the involvement of data as a crucial factor in production (Wang et al., 2023). It has reshaped the hierarchy of production factors, weakened the over-dependence of enterprises on labor and energy (Gan et al., 2023), and made data factor as the paramount production factor in the digital era (Farboodi et al., 2019). The digital economy optimizes the input structure of production factors and improves the allocation efficiency of resources, ultimately mitigating carbon emissions (Goldfarb and Tucker, 2019). Fourth, the digital economy has optimized the energy consumption structure of cities. On the one hand, digital technology helps to reduce the costs of renewable resources, facilitating increased penetration of renewable energy into the energy market (Lyu and Liu, 2021). On the other hand, digital technology is embedded in the production process of energy, assisting enterprises in achieving dynamic and efficient management of energy production, thereby contributing to the decarbonization of energy production (Wang and Shao, 2023).

The digital economy has compressed the space-time distances, improved the efficiency of information transmission, and strengthened economic linkages between regions (Banalieva and Dhanaraj, 2019). The digital economy has spatial spillover effects on regional economic growth (Hao X. L. et al., 2023), technological innovation (Ren et al., 2022), and resource allocation (Ma and Zhu, 2022), subsequently influencing the carbon emissions of nearby areas. According to New Economic Geography Theory (Wilson, 2011), the phenomena of knowledge spillover and environmental spillover exhibit dual character in regional development, characterized by positive spillover and negative spillover. Consequently, the spillover effects of the digital economy on adjacent carbon emissions also manifest this duality. On one hand, there is a positive spillover. The digital economy expedites the cross-regional flow of funds, clean technologies, and environmental protection concepts (Zhang W. et al., 2022), thereby reducing transportation costs and resource waste and promoting regional carbon reduction. On the other hand, there may be a negative

spillover as well. The digital economic growth has driven the construction of digital infrastructure in surrounding regions, intensifying energy consumption. The rapid expansion and high value-added characteristics of the digital economy attract premium production factors, resulting in the loss of resources in surrounding areas, which is detrimental to regional carbon reduction.

Derived from the above analysis, our paper proposes the hypotheses 1a and 1b.

Hypothesis 1a: (H1a): The development of digital economy has a positive impact on the reduction of carbon emissions in cities.

Hypothesis 1b: (H1b): The impact of the digital economy on carbon emissions exhibits spatial spillover effects, but the direction of these spillover effects needs further empirical investigation.

2.2 Digital economy, industrial structure upgrading, and carbon emissions

The digital economy can promote the upgrading of industrial structure through digital industrialization and industrial digitalization (Yu et al., 2023). In terms of digital industrialization, the development of digital economy has fostered many emerging industries, including industrial Internet, software and information technology service industries. Compared with the traditional industry, the digital industry exhibits a fast growth rate in output value, featuring low dependence on fossil fuels, and gradually become the engine of urban economic growth. In terms of industrial digitization, the utilization of big data has advanced the construction of enterprise informatization, the transformation of operation models, and the innovation of production. The integration of data factor with the service industry has spawned new service industries like electronic payment, online shopping, and smart medical care, opening new markets for the tertiary industry.

The upgrading of industrial structure promotes carbon reduction through industrial structure rationalization and optimization. First, industrial structure rationalization can coordinate various production departments, fostering the rational allocation of production resources. This process facilitates the flow of capital and labor factors towards sectors characterized by higher added value and cleaner production (Zeng and Yang, 2023), guiding industries towards low-carbon development. Second, the upgrading of industrial structure promotes the transition of industries from lower to higher levels, thus fostering the adoption of cleaner production modes. Discernible variations exist in the energy consumption coefficients across diverse industries, with the secondary industry exhibiting a higher coefficient compared to the tertiary industry. The digital economy directly expands the proportion of tertiary industry in the overall economy (Wang et al., 2022a), accelerating the evolution of the secondary industry to the tertiary industry (Bai et al., 2023). This contributes to mitigate the energy consumption during industrial development, and realize the 'decoupling' between economic development and carbon emissions. According to above analysis, this paper proposes the second hypothesis.

Hypothesis 2: (H2): The upgrading of industrial structure plays an intermediary role between the digital economy and carbon emissions.

FIGURE 1
Influencing mechanism of digital economy on urban carbon emissions.
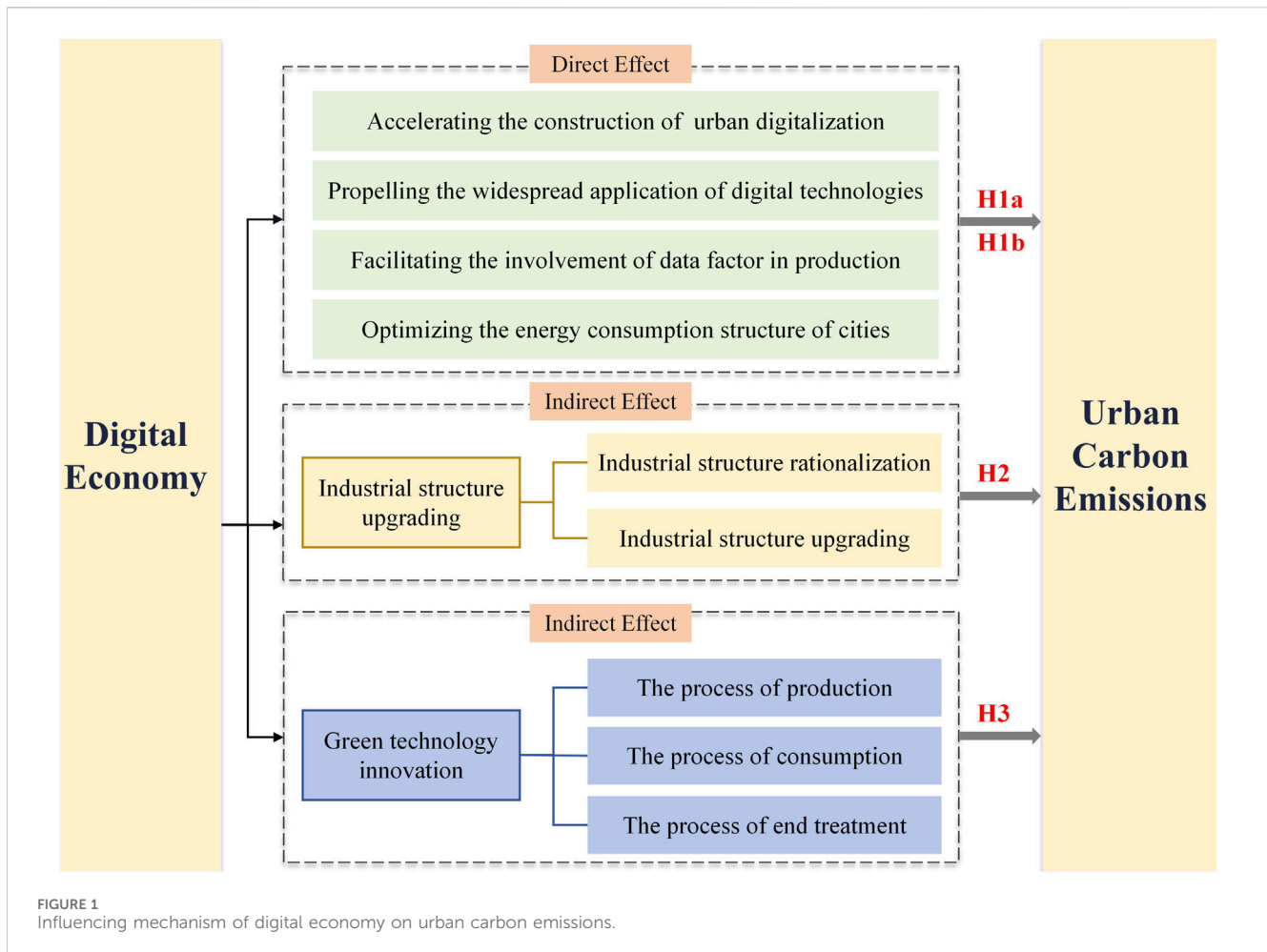
2.3 Digital economy, green technology innovation, and carbon emissions

The digital economy, characterized by high innovation and strong integration (Meng et al., 2023), significantly promotes the continuous progress of green technology innovation. First, it accelerates the integration and sharing of information resources, enriched the information acquisition channels for enterprises and academic setting. Si et al. (2023) believed that digital economy has speeded up knowledge dissemination and accumulation, thereby enhancing the efficiency of green technology innovation. Secondly, the digital economic agglomeration has promoted the agglomeration of innovative and scientific talents (Ren et al., 2022). The integration of digital technology with other industries expedites the formation of new industries (Yin et al., 2023), leading to the creation of new jobs that attract innovative talents. This job agglomeration generates a talent agglomeration effect, which could lay a foundation for urban green technology innovation. Additionally, the digital economy could mitigate the information asymmetry between lenders and borrowers in financial markets, broadening financing channels for green technology innovation activities (Ma, 2023).

The green technology innovations affect carbon emissions throughout the production, consumption and end treatment phases (Du et al., 2019). In the process of production, green technology innovation helps to enhance energy efficiency (Xu X. et al., 2023), lowering carbon emissions per unit of output (Du and Li, 2019). In the process of consumption, the innovations of clean energy technology reduce the acquisition cost of clean energy, bringing more clean energy to the energy supply market, and fostering a low-carbon energy consumption structure (Lee et al., 2023). In the process of end treatment, the innovation of pollution control technology drives waste treatment, thereby reducing end carbon emissions (Xu et al., 2021). Therefore, the third hypothesis of this paper is proposed. The influencing mechanism of digital economy on urban carbon emissions is showed in Figure 1.

Hypothesis 3: (H3): The innovation of green technology plays an intermediary role between the digital economy and carbon emissions.

3 Methodology and data

3.1 Methods

3.1.1 Improved entropy method

Functioning as an objective weighting method, the entropy method can distinguish the impact intensity of various indicators,

thereby illustrating the effectiveness of the information they convey (Dong et al., 2022). The traditional entropy method is mostly utilized for cross-sectional data analysis, with limited applicability to panel data. Referring to Yi et al. (2022), we used an improved entropy method for weighting estimation in panel data.

First, normalize the indicators:

$$x'_{itj} = \frac{x_{itj} - \min(x_{itj})}{\max(x_{itj}) - \min(x_{itj})} \quad (1)$$

In Eq. 1, x'_{itj} and x_{itj} represent the standardized value and the original value of indicator j for the ith city in year t, respectively. $\max(x_{itj})$ and $\min(x_{itj})$ denote the maximum and minimum values of indicator j, respectively.

Second, calculate the information entropy value e_j for indicator j:

$$e_j = -\frac{\sum_{i=1}^{n}\sum_{t=2011}^{2019} y_{itj}\, ln\, y_{itj}}{\ln(C)} \quad (2)$$

In Equation 2, y_{itj} represents the proportion of indicator j for ith city in year t, which is calculated by $y_{itj} = \frac{x'_{itj}}{\sum_{i=1}^{n}\sum_{t=2011}^{2019} x'_{itj}}$. C is the number of cites. To avoid zero values in y_{itj}, we applied a suitable shift by $y_{itj} = y_{itj} + 0.000001$. The e_j satisfies $e_j > 0$.

Third, calculate the entropy redundancy g_j as Eq. 3.

$$g_j = 1 - e_j \quad (3)$$

The M is the total number of indicators. The weight w_j for indicator j is calculated as shown in Eq. 4:

$$w_j = \frac{g_i}{\sum_{j=1}^{M} g_i} \quad (4)$$

Finally, the $Dige_{it}$ representing the level of digital economic development is calculated through a multivariate linear weighted function in Eq. 5:

$$Dige_{it} = \sum_{i=1}^{n} w_j x'_{itj} \quad (5)$$

3.1.2 Trend analysis model

To detect the trend of carbon emissions and digital economy across various cities from 2011 to 2019, this paper utilized the slope function for trend analysis (Wang et al., 2020; Zhang H. et al., 2022). The trend serves as a direct indicator of the fluctuations in carbon emissions and the growth rate of digital economy within each city. The specific formula is as shown in Eq. 6:

$$Slope = \frac{n \times \sum_{i=1}^{n}(i \times V_i) - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} V_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \quad (6)$$

Where V_i denotes the carbon emissions or the level of digital economic development in the ith year, and n is the number of years. A positive or negative slope of V_i signifies a linear growth or decline trend in the time series, respectively.

3.1.3 Spatial correlation analysis

This paper employed the global Moran's I index to conduct a spatial autocorrelation test, examining the potential spatial

relationship between digital economic development and carbon emissions. The calculation formula is presented in Eq. 7:

$$W_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases} \quad (7)$$

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (8)$$

In Equation 7, W_{ij} represents the inverse-distance matrix, where d_{ij} denotes the geodesic distance between the centroids of cities i and j, calculated based on their respective latitudinal and longitudinal coordinates. In Equation 8, X_i and X_j represent the digital economic development level or carbon emissions of cities i and j respectively, where $\bar{X}$ and S^2 denote the corresponding mean and variance. n is the number of cities. Simultaneously, we used the local Moran's I index (LISA) to analyze the spatial clustering patterns as shown in Eq. 9:

$$LISA = \frac{X_i - \bar{X}}{S^2} \sum_{j=1}^{n} \left[w_{ij}(X_i - \bar{X}) \right] \quad (9)$$

According to the spatial distribution characteristics, spatial clustering can be classified into four types: High-High cluster (H-H), High-Low cluster (H-L), Low-High cluster (L-H), and Low-Low cluster (L-L).

3.1.4 Spatial econometrics model

Considering theoretical analysis and Hypothesis 1b, a potential spatial correlation emerges between the digital economy and urban carbon emissions. Conventional panel regressions neglect spatial interactions among variables, possibly leading to biased empirical results (Li and Wang, 2022). Therefore, a spatial econometric model needs to be established.

Commonly spatial econometric models include spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) (LeSage and Pace, 2009). The SDM, an extended form that combines the SLM and SEM, incorporates spatial effects of both independent and dependent variables into the model. Compared with the SLM and SEM, the SDM provides enhanced explanatory capabilities for relationships among spatial variables (Elhorst, 2010). For testing Hypothesis 1a and 1b, the following SDM is constructed:

$$lnCe_{it} = a_0 + \rho \sum w_{ij} lnCe_{it} + \alpha_1 Dige_{it} + \beta_1 \sum w_{ij} Dige_{it} + a_c lnX_{it} + \beta_c \sum w_{ij} lnX_{it} + \varphi_i + \sigma_t + \tau_{it} \quad (10)$$

In Eq. 10, Ce_{it} represents urban carbon emissions, X_{it} denotes control variables. ρ is the spatial autoregressive coefficient, α_1 and α_c are the estimated coefficients for Dige and control variables, while β_1 and β_c are the spatial lag coefficients. w_{ij} is the spatial weight matrix. a_0 is the constant term, φ_i represents city effects, σ_t represents time effects, and τ_{it} is the random perturbation term.

3.1.5 Two-stage transmission effect model

To test hypotheses 2 and 3, this study examined the influencing mechanism of Dige by setting industrial structure upgrading and

green technological innovation as mediating variables. Taking spatial effects into account, we built a two-stage transmission effect model for mechanism analysis (Li and Wang, 2022). The model helps circumvent the evident endogeneity issues in the third step of the traditional three-step method. The specific setting form is as follows:

$$Path_{it} = \beta_0 + \rho_1 \sum w_{ij} Path_{it} + \beta_1 Dige_{it} + \rho_2 \sum w_{ij} Dige_{it} + \beta_c lnX_{it} + \rho_c \sum w_{ij} lnX_{it} + \varphi_i + \sigma_t + \tau_{it}$$

$$(11)$$

$$lnCarbon_{it} = \gamma_0 + \theta_1 \sum w_{ij} lnCarbon_{it} + \gamma_1 Path_{it} + \theta_2 \sum w_{ij} Path_{it} + \gamma_c lnX_{it} + \theta_c \sum w_{ij} lnX_{it} + \varphi_i + \sigma_t + \tau_{it}$$

$$(12)$$

In Equation 11, $Path_{it}$ serves as the mediating variable. X_{it} functions as the control variables. Firstly, for Equation 11, β_1 needs to be significant, demonstrating that $Dige_{it}$ has a significant impact on the mediating variable $Path_{it}$. This is a prerequisite for conducting Equation 12. Secondly, when both β_1 in Equation 11 and γ_1 in Equation 12 are significant simultaneously, it indicates the presence of mediating effect.

3.2 Variables selection

3.2.1 Explained variable

The explained variable is the carbon emissions (Carbon) of cities. Carbon dioxide emissions intuitively reflect the carbon emissions status. The calculation of carbon emissions is based on the research findings of Shan et al. (2022). Fossil energy use and the production processes of industrial goods, such as cement, are identified as the primary sources of carbon emissions (Shan et al., 2022). The energy consumption of 47 socio-economic sectors is multiplied by the fuel emission coefficients to obtain energy-related carbon emissions. The cement production is multiplied by the emission coefficient per unit to obtain cement product-related carbon emissions. The summation of these two components yields the total carbon emissions for each city. To enhance data stability, logarithmic transformation (lnCarbon) was applied.

3.2.2 Explanatory variable

The core explanatory variable is the digital economy (Dige). Considering the extensive nature of Dige, a singular indicator falls short of providing a comprehensive reflection of the level of digital economic development. Consequently, this paper has constructed an evaluation index system to assess the urban Dige, encompassing four dimensions: digital infrastructure construction, digital industry, digital inclusive finance, and digital development vitality (Table 1). The construction of the index system draws upon existing research (Zhang J. et al., 2022; Yi et al., 2022; Wang and Shao, 2023) and incorporates indicators for Dige sourced from the International Telecommunication Union and the China Academy of Information and Communications Technology.

The digital infrastructure construction serves as a foundational element for the evolution of Dige. The digital industry constitutes the core of digital economic advancement. The digital inclusive finance expands the scope and forms of financial services, furnishing essential

financial support for Dige. The digital development vitality reflects the innovative prowess and inherent potential embedded within Dige.

3.2.3 Mediating variables

Industrial structure upgrading (Uis). The proportion of the three industries' output value to the GDP intuitively reflects the industrial structure. We utilized the ratio of the tertiary industry's output value to that of the secondary industry to characterize Uis (Zhang W. et al., 2022).

Green technological innovation (Gti). As the ultimate outcome of innovative activities, the quantity of patents serves as an indicator reflecting the level of technological innovation (Li and Wang, 2022). In our paper, the green technology innovation is delineated through two indicators: the number of green patent applications per 10,000 people (Gti1) and the number of green patents granted per 10,000 people (Gti2).

3.2.4 Control variables

Considering the impact of economic and social factors on carbon emissions, this study introduced the following control variables. 1) Economic development level (lnPGDP): The economic development level is recognized as a pivotal determinant impacting carbon emissions (Li and Wei, 2021), expressed by *per capita* GDP. 2) Financial development level (lnfinance): The advancement of financial markets is conducive to enhancing the efficiency of capital utilization. It enables businesses secure more capital for green technological innovation, assisting in reducing carbon emissions (Ran and Zhang, 2023), expressed by the proportion of year-end financial loan balances to GDP. 3) Transportation (lnProad): Urban expansion has heightened the demand for transportation, with transportation-related carbon emissions emerging as a main source of carbon emissions (Sun et al., 2017). It is characterized by the road mileage per 10,000 people. 4) Government intervention (lnPfe): Governments implement specific measures to intervene in urban activities, thus influencing carbon emissions (Zhang J. et al., 2022), expressed by *per capita* fiscal expenditure. 5) Urbanization level (lnUrban): As a key indicator of modernization, urbanization significantly impacts carbon emissions (Zhang et al., 2017), expressed by the proportion of urban population in the total population.

3.3 Data source

Based on the continuity and comprehensiveness of data, this study established a panel dataset with 215 cities in China from 2011 to 2019. Interpolation method was applied to address sporadic data gaps, culminating in a dataset comprising 1,935 observational samples. The carbon emissions data were sourced from the China Carbon Accounting Database (https://www.ceads.net.cn/). Other data mainly came from the "China Urban Statistical Yearbook", as well as the statistical yearbooks of individual cities. The data on green patents were obtained from the China National Intellectual Property Administration (https://www.cnipa.gov.cn/). The digital inclusive finance indices were derived from Peking University Digital Finance Research Center and Ant Group Research Institute (Guo et al., 2020). For non-ratio data, a logarithmic transformation was applied. For data points containing zero values, a logarithmic transformation with an addition of one was employed. Descriptive statistics for the variables are presented in Table 2.

TABLE 1 Evaluation index system for the development level of digital economy in Chinese cities.

	Primary indicators	Secondary indicators	Indicator description	Index attribute
Development level of digital economy	Digital infrastructure construction	Broadband internet foundation	Number of international internet users per 10,000 people	+
		Mobile internet foundation	Number of mobile phones users per 10,000 people	+
	Digital industry	Postal industry development	Total postal business	+
		Infrastructure of information industry	Number of employees in information transmission, computer services and software	+
		Telecommunications industry development	Total telecommunications business	+
	Digital inclusive finance	Extent of coverage	Index of extent of coverage	+
		Depth of usage	Index of depth of usage	+
		Degree of digitization	Index of degree of digitization	+
	Digital development vitality	Human capital	Number of university students per 10,000 people	+
		Government investment	Government expenditure on education as a share of GDP	+
		University support	Number of general higher education institutions	+

TABLE 2 Descriptive statistics.

Variables	Obs	Mean	Std.Dev	Min	Max
lnCarbon	1935	3.414	0.871	1.193	5.420
Dige	1935	0.138	0.112	0.030	0.660
lnPGDP	1935	10.802	0.541	9.664	12.061
lnfinance	1935	4.387	0.571	2.350	5.765
lnProad	1935	3.357	0.475	2.181	4.696
lnPfe	1935	8.998	0.537	7.870	10.463
lnUrban	1935	−0.588	0.254	−1.306	−0.052
Uis	1935	0.963	0.470	0.327	3.131
Gti1	1935	1.215	2.240	0.012	22.992
Gti2	1935	0.678	1.212	0.006	12.466

TABLE 3 Spatial autocorrelation test for urban carbon emissions and digital economy from 2011 to 2019.

Year	Carbon		Dige	
	Moran's I	Z value	Moran's I	Z value
2011	0.049 (0.000)	7.013	0.011 (0.033)	2.131
2012	0.054 (0.000)	7.608	0.013 (0.017)	2.397
2013	0.053 (0.000)	7.494	0.020 (0.001)	3.247
2014	0.056 (0.000)	8.000	0.017 (0.004)	2.878
2015	0.056 (0.000)	7.959	0.018 (0.003)	2.971
2016	0.064 (0.000)	8.984	0.020 (0.001)	3.187
2017	0.064 (0.000)	8.991	0.023 (0.000)	3.561
2018	0.060 (0.000)	8.392	0.021 (0.001)	3.330
2019	0.050 (0.000)	7.071	0.019 (0.002)	3.109

Note: p-value is in parentheses.

4 Empirical results and discussion

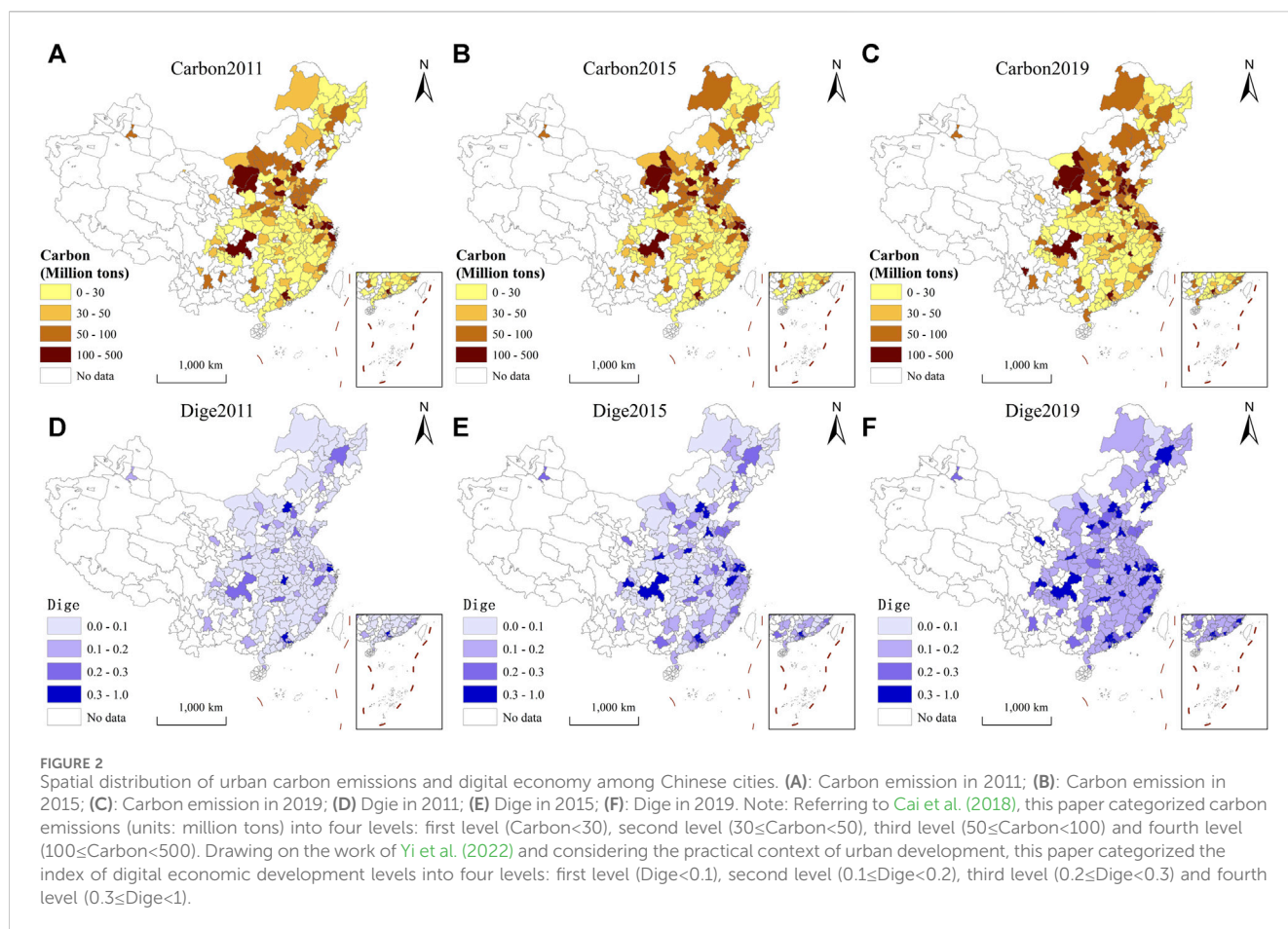## 4.1 The spatiotemporal evolution characteristics of the carbon emissions and digital economy

Table 3 shows the results of spatial autocorrelation tests. The Moran's I indices for carbon emissions and Dige from 2011 to 2019 have passed significance tests at the 1% and 5% levels, respectively. Both Dige and carbon emissions exhibit significant spatial correlation during the study period.

Figure 2 illustrates the spatiotemporal distribution of urban carbon emissions and Dige in 2011, 2015, and 2019. It reveals significant regional variations, indicating distinctive disparities across the country. From 2011 to 2019, the evolution of carbon emissions exhibited characteristics of low mobility and high stability. In comparison to 2011, the carbon emissions levels of 157 cities remained unaltered in

2019, accounting for 73.02%. Cities with elevated carbon emissions are mainly concentrated in the north of the Qinling Mountains and the Huaihe River. This distribution aligns with the higher coal proportion in the energy structure in the northern region. Meanwhile, cities in the southern regions such as the Yangtze River Delta and the Pearl River Delta also demonstrate high carbon emissions, associated with factors such as industrial agglomeration and high population density.

From 2011 to 2019, the average level of urban Dige has significantly increased. The index values of Dige in 189 cities have experienced a growth exceeding 100%, constituting 87.91% of all cities. The numerical range has shifted from 0.02 to 0.63 in 2011 to 0.09–0.86 in 2019. However, a widening gap in development level among cities has emerged. Spatially, cities in the southern region exhibit higher levels compared to those in the northern

FIGURE 2
Spatial distribution of urban carbon emissions and digital economy among Chinese cities. **(A)**: Carbon emission in 2011; **(B)**: Carbon emission in 2015; **(C)**: Carbon emission in 2019; **(D)** Dgie in 2011; **(E)** Dige in 2015; **(F)** Dige in 2019. Note: Referring to Cai et al. (2018), this paper categorized carbon emissions (units: million tons) into four levels: first level (Carbon<30), second level (30≤Carbon<50), third level (50≤Carbon<100) and fourth level (100≤Carbon<500). Drawing on the work of Yi et al. (2022) and considering the practical context of urban development, this paper categorized the index of digital economic development levels into four levels: first level (Dige<0.1), second level (0.1≤Dige<0.2), third level (0.2≤Dige<0.3) and fourth level (0.3≤Dige<1).

region. Meanwhile, cities in the eastern region surpass those in the central region, while the central region outperforms the western region.

Figure 3 illustrates the dynamic trends in carbon emissions and Dige for each city from 2011 to 2019. For carbon emissions (Figure 3A), 37.67% of cites showed a decreasing trend in carbon emission, while 62.33% of cities demonstrated an increasing trend. The most obvious increasing trends appeared in the central and eastern regions of Inner Mongolia, the northern part of Shaanxi Province, and the border region encompassing Hebei, Shanxi, Henan, and Shandong provinces. For digital economy (Figure 3B), over 43.26% of cities have a growth slope below 0.01, indicating slower growth. Cities with elevated levels of Dige are predominantly concentrated in key regions, including the Beijing-Tianjin-Hebei Region, Yangtze River Delta, Sichuan-Chongqing, and Pearl River Delta areas. Regions with a stronger economic foundation tend to attract digital technology talents, fostering innovation and the development of Dige.

Figure 4 depicts the spatial agglomeration of carbon emissions and digital economy in 2011, 2015, and 2019. For carbon emissions, the spatial agglomeration effect is more pronounced in the northern regions. High-high (H-H) agglomeration areas are primarily located in the Beijing-Tianjin-Hebei region, central Inner Mongolia, northern Shaanxi Province, the Shandong Peninsula and the Yangtze River Delta region, displaying a tendency toward contraction. Low-low (L-L) agglomeration regions are contiguous in western Hunan Province,
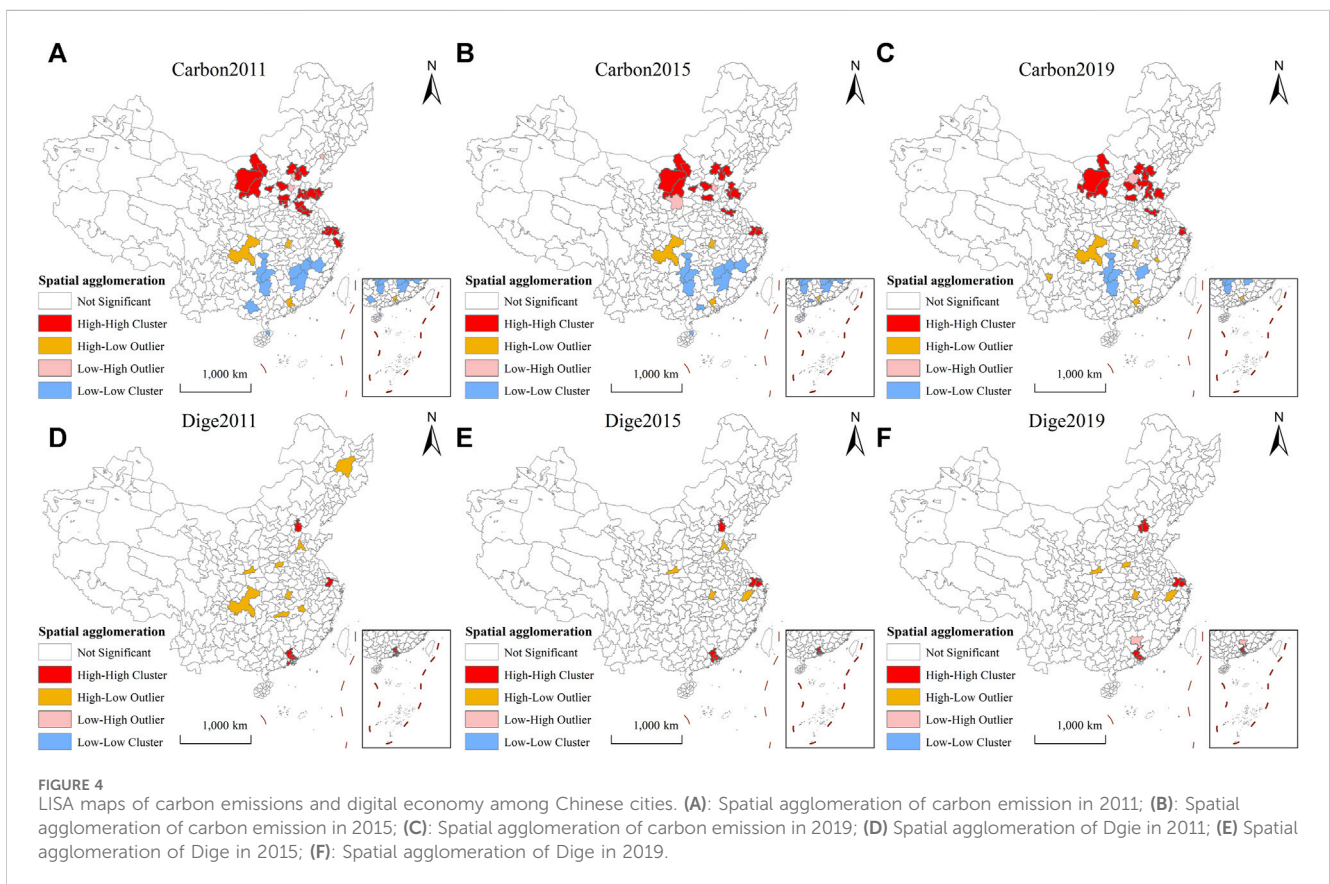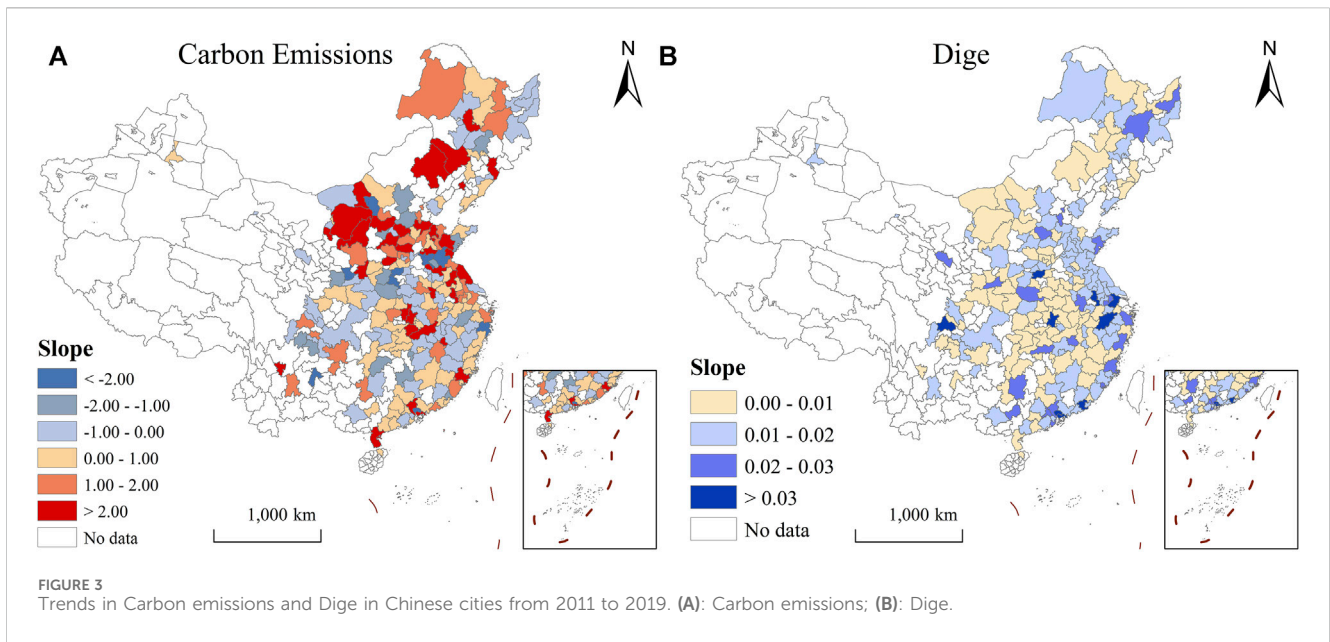
central-southern Jiangxi Province, and northwestern Fujian Province. High-Low (H-L) agglomeration regions encompass Chongqing, Wuhan, and Guangzhou, while Low-high (L-H) agglomeration regions include cities like Langfang, Hengshui, and Cangzhou. For digital economy, the spatial agglomeration effect is exhibiting an expanding trend. H-H agglomeration regions include Tianjin, Shanghai, and Guangzhou, while H-L agglomeration regions encompass provincial capitals like Chongqing, Wuhan, Changsha, Nanchang, and Zhengzhou. The radiating effect of regional digital economic centers is intensifying.

4.2 Benchmark regression results

Table 4 presents the results of the fitness tests for spatial models. Firstly, all LM test statistics are significant at the 1% level, indicating the superiority of choosing the spatial econometric model. Secondly, the LR test results are all significant at the 1% level, leading to the rejection of SLM and SEM, thus favoring the selection of SDM. Lastly, the Hausman test is passed at the 1% significance level, suggesting that the fixed-effects SDM is the optimal choice.

Table 5 shows the benchmark regression results. A double fixed effects OLS was used for comparison in (1) column. (2)–(5) columns display the estimated coefficients and effect decomposition of the SDM. The spatial autoregressive coefficient (ρ) of carbon emissions is significantly positive at the 5% level, indicating a pronounced

FIGURE 3
Trends in Carbon emissions and Dige in Chinese cities from 2011 to 2019. **(A)**: Carbon emissions; **(B)**: Dige.

FIGURE 4
LISA maps of carbon emissions and digital economy among Chinese cities. **(A)**: Spatial agglomeration of carbon emission in 2011; **(B)**: Spatial agglomeration of carbon emission in 2015; **(C)**: Spatial agglomeration of carbon emission in 2019; **(D)** Spatial agglomeration of Dgie in 2011; **(E)** Spatial agglomeration of Dige in 2015; **(F)**: Spatial agglomeration of Dige in 2019.

spatial dependence in the distribution of carbon emissions. The coefficients of Dige are consistently significantly positive in columns (1)–(5), indicating that digital economic development has effectively reduced urban carbon emissions. Hypothesis 1a is validated. Simultaneously, the coefficient of the spatial interaction term for Dige (W×Dige) is significant at the 5% level, implying the potential

presence of spatial spillover effects of digital economy on carbon emissions.

We further decomposed the impact of various variables on carbon emissions into direct effects, indirect effects, and overall effects. In columns (3)–(5), the direct effect of Dige is significantly negative at the 1% level, while the indirect effect demonstrated a positive correlation at

TABLE 4 Fitness tests for spatial econometric models.

Test	Statistical value	p-Value
LM-error	474.771***	0.000
Robust-LM-error	370.638***	0.000
LM-lag	131.567***	0.000
Robust-LM-lag	27.434***	0.000
LR_spatial_lag	24.93***	0.000
LR_spatial_error	29.97***	0.000
Hausman test	25.40***	0.000

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively.

the 5% significance level. Increases in the level of Dige in neighboring regions amplify the pressure for carbon reduction in the local regions. It could be that the development of the local digital economy has driven the construction of digital infrastructure in surrounding areas, thereby exacerbating energy consumption and carbon emissions in those neighboring regions. Moreover, the high value-added nature of the digital economy squeezes the survival space of high carbon-emitting, low-profit industries, which compels these industries to relocate to surrounding areas, resulting in a geographical shift of carbon emissions.

Hypothesis 1b is validated, and the spatial spillover of digital economy to carbon emission is negative.

Regarding the control variables, the economic level has exerted a catalytic effect on the carbon emissions, suggesting that the economic growth has not fostered a low-carbon development model. The financial development does not show a significant impact on carbon emissions in the local region, but it markedly stimulates carbon emissions in neighboring regions. It could be that the financial capital tends to flow more towards high-carbon industries than green enterprises. The transportation infrastructure significantly promotes carbon emissions. The transportation infrastructure enhances inter-city transport capacity, thereby amplifying carbon emissions from motor vehicles. As a powerful approach for controlling carbon emissions, government intervention demonstrates a notable reduction in carbon emissions. Through fiscal measures and administrative interventions, local governments guide enterprises towards low-carbon development. The urbanization rate does not distinctly affect regional carbon emissions.

4.3 Robustness test

4.3.1 Instrumental variable test

A potential reverse causality exists between the digital economy and urban carbon emissions. To relieve the endogeneity, we used the

TABLE 5 Benchmark regression results.

Variables	OLS (1)	SDM (2)	Decomposition of effect		
			Direct effect (3)	Indirect effect (4)	Total effect (5)
Dige	−0.531*** (−2.920)	−0.475*** (−2.800)	−0.462*** (−2.650)	2.826** (2.060)	2.364* (1.700)
lnPGDP	0.035 (0.690)	0.092* (1.730)	0.089* (1.760)	−0.238 (−0.870)	−0.149 (−0.580)
lnfinance	−0.012 (−0.270)	−0.031 (−0.730)	−0.025 (−0.640)	0.641** (2.200)	0.616** (2.170)
lnProad	0.107* (1.950)	0.118** (2.010)	0.116** (2.090)	−0.264 (−0.500)	−0.147 (−0.290)
lnPfe	−0.132*** (−2.730)	−0.132*** (−2.800)	−0.131*** (−2.950)	−0.237 (−0.830)	−0.368 (−1.310)
lnUrban	−0.077 (−1.120)	−0.068 (−1.010)	−0.065 (−0.970)	−0.082 (−0.140)	−0.147 (−0.260)
W×Dige		2.168** (2.270)			
W×lnPGDP		−0.188 (−0.970)			
W×lnfinance		0.451** (2.240)			
W×lnProad		−0.207 (−0.590)			
W×lnPfe		−0.132 (−0.650)			
W×lnUrban		−0.041 (−0.100)			
City fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
P (rho)		0.297** (2.150)	0.297** (2.150)	0.297** (2.150)	0.297** (2.150)
Sigma²		0.035*** (31.090)	0.035*** (31.090)	0.035*** (31.090)	0.035*** (31.090)
N	1935	1935	1935	1935	1935
R^2	0.552	0.621	0.621	0.621	0.621
Log_L		507.612	507.612	507.612	507.612

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively. Z value is in parentheses.

instrumental variable (IV) estimation. The first IV is the geographical distance from each city to Hangzhou (lndigiv1) (Li and Wang, 2022). Hangzhou, birthplace of digital financial giants like Alibaba and home to Electronic World Trade Platform (eWTP), is driving the development of digital economy in China. Proximity to Hangzhou is expected to enhance the spillover effects, correlating with a higher level of digital economy. Thus, the first IV satisfies the correlation. Meanwhile, it is noteworthy that Hangzhou is merely one of the provincial capitals, and proximity to Hangzhou does not dictate carbon emissions levels, satisfying the exogeneity. The second IV is the *per capita* postal and telecommunication services (lndigiv2) across cities in 1984 (Bai et al., 2023). The application of digital technology originated with the popularization of postal and telecommunications services. Consequently, regions with advanced postal and telecommunications infrastructure are expected to demonstrate a high level of digital economy, thus meeting the correlation. Additionally, the historical data in 1984 have a negligible impact on contemporary carbon emissions, satisfying the exogeneity. We interacted the IVs with time trend terms to obtain panel data.

We employed a Two-Stage Least Squares (2SLS) regression analysis, and the results are presented in Table 6. The Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F serve as the outcomes of the Underidentification test and Weak Identification test, respectively, both significantly rejecting the null hypothesis of weak instrument variables. This underscores the effectiveness of IVs. Even with two IVs, the digital economy still significantly promoted carbon emissions reduction. The instrumental variable test further confirms Hypothesis 1.

4.3.2 Other robustness test

Table 7 shows the results of other robustness tests. Firstly, column (1) indicates that, in the absence of control variables, the restraining effect of the digital economy on carbon emissions has also passed the significance test at the 1% level.

Secondly, we introduced the *per capita* carbon emissions as a new explained variable for robustness testing. In column (2), after replacing the explained variable, the regression coefficient of the digital economy remains significantly negative at the 1% level. Compared with the coefficient in benchmark regression, the digital economy demonstrates a more pronounced effect on reducing *per capita* carbon emissions.

Thirdly, this paper introduced lagged periods of one and two for the digital economy. Column (3) shows that coefficient for lag one is significantly negative, which not only affirms the robustness of the benchmark regression results but also indicates a temporal lag in the impact of the digital economy on urban carbon emissions. However, the estimated coefficient for lag two Dige is not significant in column (4), indicating a diminishing effect of the digital economy over time.

Fourthly, this study conducted a robustness test by substituting the inverse-distance matrix with the economic distance matrices (Xu et al., 2021). Two economic distance weighting matrices are denoted as $W_{2,ij}$ and $W_{3,ij}$, where $W_{2,ij} = \begin{cases} \dfrac{1}{|gdp_i - gdp_j|} & i \neq j \\ 0 & i = j \end{cases}$ and

$W_{3,ij} = \begin{cases} \dfrac{1}{|pgdp_i - pgdp_j|} & i \neq j \\ 0 & i = j \end{cases}$. Here, $|gdp_i - gdp_j|$ and $|pgdp_i - pgdp_j|$ respectively represent the differences in the annual average values of actual GDP and *per capita* GDP between cities i and j. The columns (5) and (6) correspond to the regression outcomes under $W_{2,ij}$ and $W_{3,ij}$, respectively. The estimated coefficients for Dige are significantly negative at the 5% level, thereby reinforcing the core findings of this study.

4.4 Mechanism analysis

Table 8 reports the results of the mechanism tests. Both industrial structure upgrading and green technological innovation play a significant mediating role in the process of carbon reduction facilitated by the digital economy. Column (1) and (2) show that the digital economy does enhance urban carbon reduction by propelling industrial structure upgrading, thus confirming Hypothesis 2. The indirect effects of the digital economy on industrial structure upgrading are found to be negative. The "Internet plus" broadens the value-added scope of the service industry. In pursuit of higher returns, service industries in regions with lower digital economy levels tends to migrate towards regions with higher digital economy levels. Consequently, neighboring regions with advanced digital economies act as a siphon, attracting high value-added industries away from the local region and diminishing the capacity for industrial upgrading.

According to the columns (3) to (6), the digital economy could reduce carbon emissions through green technological innovation. The Hypothesis 3 is confirmed. Combining the regression results of (3) and (5), it can be observed that the promotion effect of the digital economy on green patent applications surpasses that on green patent grants. This discrepancy may arise from the long review period for patent grants, introducing its statistical time lags. The impact of the digital economy on current green technological innovation activities is more immediately evident in the number of green patent applications. The digital economy exhibits positive indirect effects on green patent applications and green patent grants in neighboring regions. The acceleration of information dissemination within the digital economy enhances the spatial spillover of knowledge and technology (Luo et al., 2023). This contributes to reduce the acquisition costs for enterprises pursuing green technologies, which facilitates the establishment of environmentally friendly production patterns within regions.

4.5 Heterogeneity analysis

4.5.1 Analysis of geographical location

Due to regional disparities, there exists obvious heterogeneity in both the levels of digital economic development and carbon emissions. In accordance with Chinese regional classification, cities are divided into three regions: eastern, central, and western. Columns (1) to (3) of Table 9 are the regression results. For eastern

TABLE 6 The test results of IV.

Variables	The first IV		The second IV	
	Dige (1)	lnCarbon (2)	Dige (3)	lnCarbon (4)
lndigiv1	−0.051** (−2.340)			
lndigiv2			0.012*** (3.840)	
Dige		−1.662*** (−3.790)		−3.076* (−1.750)
Kleibergen-Paap rk LM	4.557	4.557	16.115	16.115
Kleibergen-Paap rk Wald F	40.242	40.242	19.762	19.762
Control variables	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
N	1935	1935	1935	1935
R^2	0.952	0.953	0.952	0.949

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively. Z value is in parentheses.

TABLE 7 Robustness test results.

Variables	Without control variables	Replace the explained variable	One period lag	Two periods lag	Change the spatial weight matrix	
	(1)	(2)	(3)	(4)	$W_{2,ij}$ (5)	$W_{3,ij}$ (6)
Dige	−0.520*** (−3.110)	−0.682*** (−3.940)			−0.360** (−2.190)	−0.342** (−2.080)
W×Dige	1.219*** (4.830)	2.335** (2.440)			−0.147 (−0.590)	0.390 (1.090)
F.Dige			−0.412** (−2.120)			
W×F.Dige			1.072 (1.060)			
F2.Dige				−0.142 (−0.640)		
W×F2.Dige				1.060 (0.700)		
Control variables	NO	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
N	1935	1935	1720	1,505	1935	1935
R^2	0.549	0.730	0.577	0.093	0.411	0.301

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively. Z value is in parentheses.

cities, the digital economy significantly reduces carbon emissions in local regions, but its impact on neighboring cities is not significant. For central cities, the digital economy have the stronger emission reduction effect compared to other regions. However, it also exacerbates carbon emissions in neighboring cities. For western region, the coefficient of the digital economy is insignificant. The coal utilization rate and carbon emissions intensity in the central cities are relatively high. Concurrently, the digital economy is rapid ascending in the central region, thereby rendering the marginal emission reduction effects more pronounced.

4.5.2 Analysis of city scale

Population size is an important heterogeneity factor affecting both carbon emissions and digital economy. According to the Chinese criteria for urban scale classification, cities are categorized as large and medium-sized cities (population below 5 million) or mega-cities (population equal to or exceeding 5 million). Considering the dispersed geographical distribution and low spatial correlation arising from this classification, we utilized a double fixed-effect OLS for analysis. According to columns (4) and (5) of Table 9, for

TABLE 8 Mechanism verification.

Variables	Path = Uis		Path = Gti1		Path = Gti2	
	Uis (1)	lnCarbon (2)	Gti1 (3)	lnCarbon (4)	Gti2 (5)	lnCarbon (6)
Dige	1.005*** (8.770)		16.325*** (27.960)		7.578*** (25.540)	
W×Dige	−2.201*** (−3.580)		14.885*** (4.670)		8.620*** (5.190)	
Uis		−0.097*** (−2.940)				
W×Uis		0.066 (0.560)				
Gti1				−0.015*** (−2.640)		
W×Gti1				0.088*** (3.560)		
Gti2						−0.030*** (−2.630)
W×Gti2						0.156*** (3.320)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Direct effect	0.971*** (7.980)	−0.096*** (−2.840)	17.964*** (20.800)	−0.015** (−2.500)	8.232*** (22.010)	−0.029** (−2.490)
Indirect effect	−7.773* (−1.670)	0.036 (0.180)	29.891** (2.370)	0.116*** (3.270)	30.398*** (2.560)	0.206*** (3.080)
Total effect	−6.802 (−1.450)	−0.060 (−0.300)	47.855** (2.490)	0.102*** (2.970)	38.630*** (2.710)	0.177*** (2.750)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.703	0.512	0.567	0.526	0.554	0.476
N	1935	1935	1935	1935	1935	1935

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively. Z value is in parentheses.

TABLE 9 Heterogeneity analysis.

Variables	Geographical location			City scale		The agglomeration of new energy industries	
	Eastern cities (1)	Central cities (2)	Western cities (3)	Large and medium-sized cities (4)	Mega-cities (5)	Listed cities (6)	Unlisted cities (7)
Dige	−0.653*** (−3.120)	−1.592*** (−3.500)	0.087 (0.220)	−1.039** (−2.430)	−0.221 (−1.240)	−0.616*** (−3.780)	−0.245 (−0.620)
W×Dige	−0.364 (−0.360)	9.033*** (3.960)	−2.815 (−1.570)				
Direct effect	−0.644*** (−3.000)	−1.563*** (−3.360)	0.108 (0.270)				
Indirect effect	−0.198 (−0.220)	9.467*** (3.670)	−2.745 (−1.380)				
Total effect	−0.843 (−0.910)	7.903*** (2.990)	−2.637 (−1.260)				
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.470	0.411	0.163	0.536	0.439	0.591	0.162
N	783	756	396	1,098	837	450	1,485

Note: *, **, *** represent the 10%, 5% and 1% significance levels, respectively. Z value is in parentheses.

large and medium-sized cities, the digital economy exhibits a significantly positive effect on carbon reduction. However, for mega-cities, the estimated coefficient of Dige did not pass the significance test. This could be that population agglomeration increases regional resource consumption and enhances transportation intensity, leading to higher carbon emissions.

Furthermore, the development of digital economy could enhance residents' consumption capacity, partially offsetting the carbon reduction effect inherent to the digital economy itself.

4.5.3 Analysis of the agglomeration of new energy industry

The development of new energy industry has become a key of addressing the contradiction between global climate warming and escalating energy consumption (Xu and Lin, 2018). The impact of the digital economy on carbon emissions exhibits heterogeneity based on the agglomeration of new energy industry. The Hurun Institute assessed the agglomeration of new energy industry in various cities from three dimensions: the agglomeration of high-quality enterprises, the agglomeration of small and medium-sized enterprises, and the agglomeration of investment enthusiasm. "2023 Hurun Chinese New Energy Industry Agglomeration City Ranking" has been issued, featuring a total of 50 cities. Leveraging the Hurun Report, this paper categorized cities into listed cities and unlisted cities, employing a double fixed-effect OLS regression for analysis.

The results in columns (6) and (7) demonstrate that the digital economy significantly reduces carbon emissions in listed cities, whereas its impact on carbon emissions in unlisted cities is not significant. This phenomenon is mainly ascribed to the robust integration between the digital economy and the new energy industry. The digital economy plays a crucial role in offering technological support for the new energy industry (Kittner et al., 2017). Concurrently, the advancement of new energy industry further catalyzes the growth of digital economy. Cities with a high agglomeration of the new energy industry exhibit an elevated level of digital economic development, leading to a more pronounced effect in reducing carbon emissions.

5 Conclusion and policy implications

5.1 Conclusion

With the panel data of 215 cities from 2011 to 2019, this study calculated the development level of digital economy and explored the spatial-temporal evolution trend of digital economy and carbon emissions. Then, employing spatial empirical methods, this study quantitatively analysed the spatial impact of digital economy on urban carbon emissions, examining its mechanism and heterogeneity. The main conclusions are as follows.

(1) Digital economy development and urban carbon emissions both show strong spatial correlation. The levels of digital economy development have significantly improved in most cities, but the gap between cities shows a widening trend. The spatio-temporal evolution of digital economy is conspicuous, with a gradual rise in spatial agglomeration. Meanwhile, carbon emissions exhibit a relatively stable spatio-temporal evolution.

(2) The development of digital economy has a positive effect on urban carbon emissions reduction. After a series of robustness tests, this conclusion remains valid. The impact of digital economy on carbon emissions exists negative spatial spillover.

While digital economy helps reduce carbon emission in the region, it concurrently heightens the burden of carbon reduction in neighboring regions. The spatial mechanism test shows that industrial structure upgrading and green technology innovation play mediating roles between digital economy and carbon emissions.

(3) The impact of digital economy on carbon emissions is heterogeneous with geographical location, city scale and new energy industry agglomeration. The reduction in emissions is more obvious in central cities, large and medium-sized cities as well as cities with a high agglomeration of new energy industry.

5.2 Policy implications

Based on the conclusions, the following policy implications for urban carbon reduction are proposed.

(1) It is supposed to expand the scale of digital economy to empower cities for digital transformation. Given the low development status of digital economy in many cities, there is huge space for digital economic growth in Chinese cities. The construction of the information infrastructure should be promoted to achieve higher quality connectivity, facilitating the development of digital industries such as big data, the Internet, and 5G.

(2) The focus should be on fostering the development of key metropolitan areas such as Shanghai, Beijing, Guangzhou, etc., and extend the regional radiation effect of digital economy center cities. It is suggested to establish regional digital technology research platforms to break digital barriers, so as to propel the diffusion of digital technologies among cities. Western region cities could be encouraged to cooperate with the central and eastern region cities in the digital economy sphere, aiming to narrow the "digital gap" through technology transfer and industrial cooperation.

(3) Greater attention should be paid to upgrading the industrial structure and strengthening green technology innovation. It is recommended to drive urban industrial upgrading by advancing digital industries and leverage the role of the digital economy in promoting the tertiary industry. Increase the supply of premium digital products and services on the supply side, while expand the digital consumer market on the demand side. The government should intensify its support for green technology innovation and augment financial support for related innovation activities. Direct efforts should be made towards researching key low-carbon technologies, such as carbon storage and carbon capture, aiming to provide technical support.

(4) Differentiated policies based on the specific urban development are proposed to be implemented. According to local conditions such as the geographical position, the city scale and the agglomeration of new energy industry, the specific plans for digital economy should be made. Policy formulation could be appropriately tilted toward western cities to expand their digital economy scale. Additionally, in cities with a pre-existing foundation in the new energy industry, it is imperative to intensify substantial support for these industries.

5.3 Limitations and future research

This study also exists some limitations, necessitating some improvements in future research. First, our study covers the period 2011–2019. Since 2020, the global COVID-19 outbreak has catalyzed the rapid expansion of digital economy, particularly online activities. In the era of the pandemic and its aftermath, it is imperative to delve deeper into the relationship between the digital economy and carbon emissions. Secondly, our study focuses on the city level, lacking the micro-level exploration. The deep integration of digital economy into enterprise-societal progress has hastened shifts in production and lifestyle. Consequently, there is a necessity to integrate micro and macro research perspectives and systematically examine the impact of digital economy on carbon emissions. Micro-level research centered around enterprises could be further expanded. Thirdly, limited by data availability, this study does not define specific indicators related to data factor within the evaluation system. Considering the growing importance of data factor in productive activities (Hao X. et al., 2023), future research need incorporate relevant evaluation indicators. Fourthly, the measurement of green technological innovation requires further refinement. While the number of patents can reflect the outcomes of technological innovation activities, its capacity for elucidating the process of technological innovation is limited. Future efforts may study the process from perspectives such as financial investment, technical personnel, and related factors.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: China Carbon Accounting Database (https://www.ceads.net.cn/); China Urban Statistical Yearbook; China National Intellectual Property Administration (https://www.cnipa.gov.cn/); Peking University Digital Finance Research Center and Ant Group Research Institute.

Author contributions

HZ: Conceptualization, Data curation, Methodology, Writing–original draft. RQ: Conceptualization, Methodology, Writing–review and editing. YL: Writing–review and editing. TW: Data curation, Methodology, Writing–review and editing. FZ: Data curation, Writing–review and editing. QZ: Data curation, Writing–review and editing. KW: Conceptualization, Writing–review and editing.

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Conflict of interest

Authors FZ and QZ were employed by Safecleen Technology Co., Ltd.

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

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2024.1370938/full#supplementary-material

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