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Study on how the digital economy affects urban carbon emissions

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A R T I C L E I N F O

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A B S T R A C T

The digital economy is crucial in advancing an economically sustainable and low-carbon future and plays a key role in achieving carbon neutrality and carbon peaking. We measured the digital economy development level of each prefecture-level city in China form 2011to 2019, then investigated the impact of on carbon emissions and its mechanism using the panel fixed effects model and the spatial Durbin model. Our results indicated that: Firstly, an inverted U-shaped relationship had been observed between the impact of digital economy on carbon emissions, which increased and then decreased, and this result was again verified by a threshold regression. Secondly, there was a nonlinear relationship between digital economy and green innovation and the digital economy had an indirect effect on carbon emissions through green innovation. Thirdly, the influence of digital economy on carbon emissions in the area followed an inverted U-shaped relationship that stimulated initially and then restrained, with spatial spillover effects. Fourth, the heterogeneity analysis found that digital economy had a greater emission reduction effect in areas east of the "Hu Huanyong line" and in in cities without resources. The conclusions provide new highlights on the relationship between digital economy and carbon emissions, along with policy recommendations for attaining the objectives of peak carbon and carbon-neutral strategies.

Nomenclature		WIPO	World Intellectual Property Organisation
Abbreviations			
CO2	Carbon dioxide	*Symbols*	
CE	Carbon emissions	A_0	Initial technology level
CAICT	China Academy of Information and Communications Technology	A	combined technology level
DE	The digital economy	*b*	Unit variable costs
EPL	Environmental Pollution Index	C_0	Fixed cost
FD	Financial development	C_i	Carbon emission factor for energy type *i*
FE	Fixed effect	C_{w0}	Initial cost of reducing carbon emissions
GI	Green innovation	D	Economic growth driven by digital economy
GDP	Gross domestic product	E	Energy input
GFS	Government Financial Support	E_i	Consumption of energy type *i*
ICL	Income level	F	Digital economy
IS	Industrial Structure	G	External production environment
ICT	Information and Communication Technologies	K	Capital input
IV	Instrumental variable	L	Labor input
OLS	Ordinary least squares	*L(0)*	Initial value of labour force L at initial time $t = 0$
POP	Population scale	*n*	Population growth rate
RE	Random effect	*p*	Product price
R&D	Research and Experimental Development	*q*	Output
SIPO	State Intellectual Property Office	*w*	Total carbon emissions
STS	Science and technology support intensity	Z_0	*Initial marginal level of carbon emissions*
SDM	Spatial Durbin model	Z	Carbon emissions from marginal output affected by the digital economy
SDE	Square of the digital economy		

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1. Introduction

Carbon emissions (CE) are one of the most serious social and environmental problems in the world today and have become one of the global challenges [1]. China is one of the countries with the highest carbon emissions, reaching9,894 million tonnes in 2020, accounting for 30.9 % of global CE [2]. For this reason, the Chinese government has made emission reduction commitments and plans to strive to achieve the goals of carbon peaking and carbon neutrality by 2030 and 2060, respectively. This is not only China's commitment as a global power, but also an intrinsic need to achieve high-quality development of China's economy. Notably, low carbon development is a key priority of China's policy, and trying to explore the methods and drivers of CE reduction. Meanwhile, the digital economy (DE)is now a key driver of China's economic recovery and future growth. With the development of the agricultural and industrial economies, DE is the latest form of economy to follow closely. As a new type of green economic form, DE, with the characteristics of high technology, wide penetration and deep integration, integrates data, information technology and other elements to promote the transformation of old and new kinetic energy [3], improves the level of intelligence and networking of socio-economic development, promotes the transformation of the real economy, and has become an important force driving the rapid development of the world economy, and has become an important force driving the rapid development of the world economy. By 2020, DE reached RMB 39.2 trillion, representing more than one-third of China's total gross domestic product (GDP), based on the report recently released by the China Academy of Information and Communications Technology (CAICT). In addition, from 2015 to 2020, China's DE grew from 27 % to 38.6 % of GDP, and is expected to continue to grow and be a major driver of its development. Especially in the context of the rapid development of digital technologies such as big data and the Internet of Things, DE has been regarded as one of the main paths to achieve low-carbon development by promoting the modernisation of production modes, integrating and penetrating into various industries, optimising the allocation and utilization efficiency of the energy structure, and promoting the upgrading of the industrial structure [4,5]. In the long term, DE offers new opportunities to reduce CE through its penetration, scale and network effects. However, there is no consensus on the impact of DE on CE. Therefore, it is of great practical importance to scientifically measure the level of development of DE in the region and to comprehensively assess and explore the impact of DE on CE in order to achieve the goals of carbon neutrality and carbon peaking.

Consequently, this study explored the relationship and transmission mechanism between DE and CE from the perspective of green innovation (GI) based on the panel data of 278 prefecture-level cities in China from 2011 to 2019. In addition, this study also conducted regional heterogeneity analysis based on the whole sample to identify the relationship between DE and CE among different regions and accordingly made targeted recommendations to achieve energy saving and emission reduction, and promoted green urban development. This work therefore helps to current research related to the relationship between DE and CE, and there are three marginal contributions as follows. First, at the study scale, cities are the "main battlefield" for promoting the synergistic development of economic development and green low-carbon development, and this work further refines the research object from the provincial level to the unit of cities, so as to further analyse the impact effect of DE and CE at a more specific spatial scale, and make the study results more scientific and valuable. Second, on the theoretical analysis, this study constructs a theoretical model on the relationship between DE and CE based on the Cobb-Douglas production function, and analyses the profit incentive effect and cost inhibition effect of DE on CE assuming a perfectly competitive market, which enriches the basic theory of DE and CE, and provides new theoretical support for green and low-carbon development. Third, for research methodology, this study explores the threshold effect of DE on CE based on city-level indicator data, and finds that GI is an important mechanism for DE to influence CE reduction, and develops heterogeneity analysis in terms of the city's resource endowment, city grade, economic development level and regional heterogeneity, which clarifies the important role of DE in achieving the goals of carbon neutrality and carbon peaking, and provides reliable empirical references to give full play to CE reduction effect of DE.

The remainder of the work is organized as follows. Section 2 presents the literature review. Section 3 presents the theoretical analysis and research hypotheses. Section 4 presents the research design, describing the econometric model and data. Section 5 reports the empirical results, including benchmark regression results, mediation effects, heterogeneity analyses and threshold effects, and extends the study of the spatial effects of the digital economy on carbon emissions. Section 6 summarises and discusses the results, and section 7 presents policy implications. The final section outlines limitations and suggests some directions for future research.

2. Literature review

2.1. Digital economy-carbon emissions nexus

With the global climate change, CE has gradually attracted attention, and the rapid development of DE has brought a new research perspective on carbon emission reduction. In recent years, research on the DE and CE has also gradually increased and penetrated into various aspects [6]. Searching the existing literature, it is found that relevant studies have examined the relationship between the development of DE and CE from various perspectives, but the views and conclusions are not consistent. Some studies believed that the development of DE will be conducive to the reduction of CE [7], which was more obvious in China and some developing countries [2,8]. Besides, the non-linear correlation between DE and CE had also been further explored, suggesting an inverted U-shape relationship and noting that as the DE developed to a higher level, the emission reduction effect will be more obvious [5]. Subsequently, many studies had analyzed the current status of CE and found that the DE had spatial spillover effects on CE reduction, and was characterized by regional heterogeneity, for example, the effect of CE reduction was more pronounced in eastern China than in other regions [9]. However, some studies took the opposite view on the effect of DE on CE, arguing that the development of DE exacerbated CE [10]. This was mainly owing to the fact that the Information and Communication Technologies (ICT)sector was not pollution-free and environmentally friendly, and the carbon impact generated increased tenfold as it developed. This was due to the fact that ICT operations required high carbon-emitting intermediate inputs from other sectors, resulting in significant emissions. Similarly, some studies hold a similar view, arguing that although the ICT industry had significant emission reduction effects, it will increase energy demand in disguise, which was not beneficial to the promotion of carbon reduction [11].

2.2. Methodological analysis of DE and CE

Regarding research methodology, in addition to causality inference, some studies that used variable cointegration analysis to study the relationship between the two, which showed the existence of long-term cointegration relationships between CE, digitalisation, Research and Experimental Development(R&D)investment and other key macroeconomic variables [7]. Furthermore, some studies that used threshold effect and mediation effect models to conclude that the impact of DE on CE faced a huge resource endowment threshold and a city size threshold, pointing out that the green integration of DE and traditional industries was more important for CE reduction [5].

Regarding the impact mechanism, some studies showed that DE can indirectly reduce CE through energy structure optimization and unidirectional technological progress, i.e. from the perspective of digital technology, digital development was more conducive to technological progress and showed a trend of emission reduction, and it will be able to achieve the zero-carbon target by the middle of this century [12]. At the same time, the advanced industrial structure and the rationalization of industrial structure were also important mechanisms through which DE affected CE reduction, that was, DE can achieve green, efficient and low-carbon development by promoting the low-carbon transformation of industries. Related studies have used entrepreneurship and industrial upgrading as mediating variables to explore the role which played in digital finance to reduce pollution and carbon [13]. Other studies have shown that the digital economy can reduce carbon emissions by promoting industrial efficiency and integration through digital industrialisation and industrial digitalisation, optimising energy structure, promoting technological progress, improving resource allocation efficiency and total factor productivity, and expanding the scale of the economy [14,15].

2.3. Literature gaps

In summary, the current research about the DE on CE has been fruitful, but the existing research was mostly based on the correlation between DE and CE, as well as the impact and spatial effects caused by DE, without fully considering the regional heterogeneity of the impact of DE on CE reduction and the mediating effect mechanism of various influencing factors, besides the lack of theoretical analysis of the impact of DE on CE and the demonstration of the cause and effect relationship. In addition, few studies had thoroughly explored the non-linear relationship between the development of DE and CE reduction and the influence mechanism, and more often explored the correlation between the two. Therefore, the identification of the mechanism on DE and CE needed to be further expanded. This study re-examined the relationship between DE and CE, elaborated the mechanism of DE on CE from the perspective of GI, enriched the relevant research content, helped us better understand the relationship between DE and CE, and provided empirical evidence for the early realization of the goals of carbon neutrality and carbon peaking.

3. Theoretical analysis and research hypothesis

3.1. Digital economy and carbon emissions

DE improves the productive capacity and efficiency of society as a whole by facilitating mobility and integration between factors, thereby reducing CE. Relevant studies have shown that DE transforms and utilises data resources with digitisation and intelligent technology, improves overall efficiency through integration with traditional industries, promotes high-quality economic development, and has a significant contribution to reducing carbon emissions [16]. Specifically, DE reduced CE in two ways. First, it penetrated and integrated industries to reduce CE. DE had created more effective means of dissemination through mobile Internet technology, enabling the diffusion of knowledge and its rapid dissemination, and the sharing of information technology. Producers learned from the diffusion of knowledge and methods, and then used mobile communication, big data and the Internet of Things and other technologies to make DE penetrated into the economy, society, ecology and energy in all aspects of production, improved the efficiency of technology and information transfer, promoted innovation and clean production, and thus reduced CE. Second, it improved the efficiency of resource use and reduced carbon emissions. DE had the characteristics of mobility, diffusion and reproducibility, and in social life, DE made the traditional way of living and working change, the online mode could be promoted and optimised, and gradually penetrated into all aspects of clothing, food, housing and transportation. It is also able to break the shell of diminishing returns to scale of fixed factor inputs to outputs in production enterprises, achieve low-cost diffusion and increasing returns to scale [17], and improve utilization rates and output rates, thereby achieving CE reductions.

However, based on a review of the existing literature, there may be a 'green blind spot' of DE in reducing CE. It is true that the development of DE breaks downspatial and time barriers and increased the intensive use of resources, the digital infrastructure demand is increasing day by day in the development stage of DE, as well as Internet, telecommunications software and information technology services consumes a large amount of electricity resources, increasing the waste of resources and CE [5]. However, as the level of DE increases, it can guide cleaner energy use and the rational allocation of production resources, effectively reducing pollution control and thereby reducing CE. Accordingly, Hypothesis 1 is proposed.

H1. The effect of DE on CE has an inverted U-shaped relationship, first facilitating and then inhibiting.

3.2. The digital economy and green innovation

DE has brought about changes in information technology and is a key factor in technological innovation. Meanwhile, DE reduced the time and cost of people's access to external knowledge and science and technology, effectively reduced the information asymmetry among economic agents, facilitates communication and learning among innovation agents, and accelerated the transformation and application of knowledge, which provided a viable space for green innovation, thus promoting regional innovation output [19]. At the same time, the development of DE, through its network and mobility, reduced the threshold of information access and application, broke the production mode under the traditional model, promoted the deep integration of DE and industry, achieved resource integration, reduced the cost of production process, improved profitability, and then motivated economic subjects to increase R&D investment and promoted technological innovation [20].

Relevant studies have shown that DE is an important way to promote the development of GI, and its impact on GI runs through all production processes from inputs to outputs [21]. DE promotes the rapid input of GI through the use of innovation factors such as digital talent and capital, which in turn increases resource utilization, improves cumbersome processes and production costs in the product life cycle, and reduces the negative impact on the environment [22]. It can be seen that DE can significantly improve the level of GI and achieve high-quality development driven by GI [23]. However, some studies had also shown that with the development of DE, the promotion of GI, in contrast, will show a declining trend. This may be due to the fact that when the input reaches a certain level, the allocation efficiency of the industry and each resource factor reaches the optimum, and at this time there is still a large amount of input, which causes excessive resource agglomeration, which in turn causes a crowding effect. Consequently, DE on GI performance inhibiting effect. Based on this, hypothesis 2 is proposed.

H2. There is a non-linear relationship between DE and the degree of GI in cities.

3.3. Digital economy, green innovation and carbon emissions

DE is characterised by inter-temporal, economic sharing and openness, which reduces the digital and information divide, increases equity in information access and transfer, and improves the breadth and depth of learning and sharing of results between cities, which in turn promotes the level of urban innovation. And green innovation is an important way to achieve sustainable development of the economy, resources and the environment, promoting optimal changes in the production chain and reducing pollutants and carbon dioxide emissions [24]. Therefore, DE can have an indirect impact on CE by promoting the level of GI in cities.

Simultaneously, this study listed the relevant research results on the role of innovation in combating climate change and CE, and clarified the research framework, as shown in Table 1. Through the studies, it could be found that DE through digital application and management can save the city various costs such as manpower and capital, so that more funds can be used for research and development and promotion of green innovation technology in the city, to improve production efficiency and industrial structure upgrading, and then promote the level of GI in the city [25].Improving the level of GI can drive the city to recycle digital technology [26], promote the diffusion and application of green technology, make the city's industrial industry gradually transform into green-intensive industry, and eventually achieve carbon emission reduction [27]. At the same time, DE can also break down the barriers of human capital and information transfer between cities, achieve collaboration and sharing among innovation subjects, accelerate the digital transformation and GI of cities, and then lay the foundation for GI to promote CE reduction [28]. On this basis, Hypothesis 3 is proposed.

H3. DE can indirectly affect CE levels through the level of GI.

3.4. Spatial impacts of the digital economy and carbon emissions

With the development of DE and improvement of urban low-carbon transformation, various regions have continuously strengthened the policy design to achieve the goals of carbon peak and carbon neutrality. Research showed that some regions with a high level of DE development had gradually formed a green and low-carbon development model, and the experience of low-carbon development had provided a basis for other regions to learn from and refer to Ref. [32]. At the same time, owing to the no-threshold and mobility characteristics of DE itself, it made neighbouring regions learned advanced CE reduction methods through the learning effect of DE, and supported the low-carbon transformation of neighbouring regions with the digital technology of advanced regions, which in turn reduced CE [7]. In addition, as the industrial division of labour tended to become more sophisticated and specialised, the demand for regional low-carbon development inversely pushed the regions with a high level of DE development to make full use of digital technology and integrate it deeply with industrial industries to reduce CE, while the neighbouring regions will imitate and learn from the typical regions through the Internet, etc. by virtue of economic and social ties, thus reducing regional CE [33]. Simultaneously, studies had shown that the impact of DE on CE also had a spatial spillover effect [34].

Table 1
Research linking innovation and climate change.

Variable	Author	Scope of the study	Research progress
Innovation-climate change nexus	Aldieri et al. [29],	Three economic areas (Europe, Japan and the USA) from 2002 to 2017	Environmental innovation affects climate change by reducing economic activity.
	Su et al. [30],	70 countries	A country's innovation in climate change technologies is influenced by its level of carbon dioxide and other greenhouse gas emissions.
	Jin et al. [31],	The energy industry and the development of new energy vehicle industry	Low-carbon innovation contributes to the fight against climate change.
Innovation-carbon emissions nexus	Bonsu [24]	The EV industry in the UK.	GI helps to optimise production chains and reduce CE.
	Chang et al. [34],	Provincial panel data for China from 2010 to 2019.	DE affects CE intensity through structural effects.
	Hu et al. [27],	282 prefecture-level cities and above in China, from 2011 to 2019.	GI can drive industrial transformation and reduce CE.

Some studies have used the panel data for the 48 US states from 1970 to 1997, which argued that ICTs have spatial spillover effects [35]. Building on this, one study further confirmed have also proved that the use of ICT and broadband can increase regional cohesion, weaken the law of attenuation of technological spillovers due to geographical separation between market participants and generate spillovers [36]. On this basis, Hypothesis 4 is proposed.

H4. DE can influence CE in surrounding regions through spatial spillovers.

Based on these analyses, the following hypothesis and framework are proposed as follows (Fig. 1).

4. Methodology and data

4.1. Theoretical models

This study, constructs a theoretical model on the relationship between DE and CE to analyse it, drawing on literature such as Bai [37]and Li [5], and the specific model formulation is shown below.

$$q = A(D)L^{\alpha}GE^{\beta}K^{1-\alpha-\beta} \tag{1}$$

where q, A, D, L, G, E and K denote output, combined technology level, economic growth driven by DE, labor input, external production environment, energy and capital input, $A > 0$、$0 < \alpha < 1$、$0 < \beta < 1$.

Assuming a population growth rate of n, then

$$\dot{L} = nL(t), L(t) = L(0)e^{nt} \tag{2}$$

where *L(0)* represents the initial value of the workforce L at the initial time $t = 0$.

$$D = D\ (F) = \theta_D F \tag{3}$$

Where: $\theta_D > 0$, F stands for DE and θ_D denotes the marginal effect of DE.

In this study, the carbon emission function is derived based on the previous proposed pollution functions [5], as shown in Equations (4)–(6).

$$w = qz \tag{4}$$

$$z = z_0 + \theta_z D \tag{5}$$

$$z_0 = \sum E_i C_i \tag{6}$$

Where W is the total CE, Z represents the CE of the outputs affected by DE at the margin, Z_0 is the initial marginal level of CE, θ_Z is the change in marginal CE from digitalisation, Ei is the energy type i consumed, and Ci is the CE factor for energy type i, $\theta_z > 0, C_i > 0$.

Digitalisation optimizes the allocation of factors of production and increases total factor productivity(xiao,2019). Assuming that DE mainly affects technological progress, energy use and CE, *A(D)* can be expressed as:

$$A(D) = A_0 + \theta_A D \tag{7}$$

where A_0 stands for the level of technologies at the start, and θ_A denotes the progress of technologies driven by the development of DE, $\theta_A > 0$, equation (8) then reads as follows.

$$q = (A_0 + \theta_A D)L^{\alpha}GE^{\beta}K^{1-\alpha-\beta} \tag{8}$$

In this study, it is assumed to be a perfectly competitive market, at which time the vendors are price takers, and the product price is assumed to be p, and the unit variable cost is composed of b, the fixed cost C_0, and the

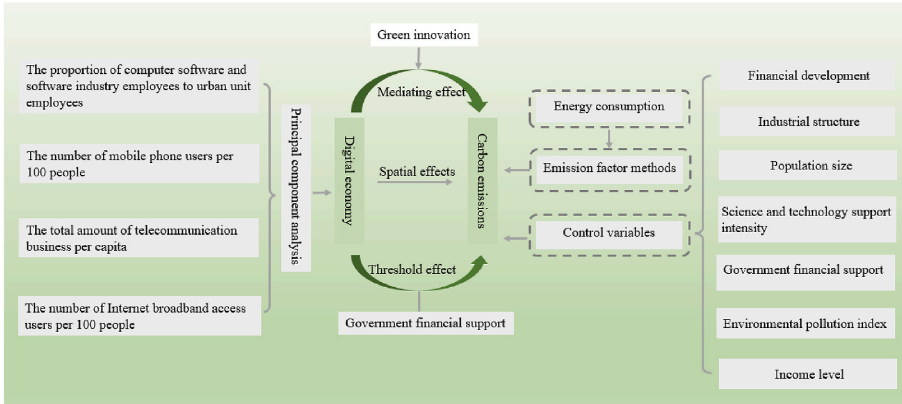

Fig. 1. Framework diagram.

consumed cost of reducing CE $C_{w0}+\theta_w W$, where C_{w0} denotes the starting cost of CE reduction, and θ_w denotes the change in the marginal cost of CE reduction caused by technological progress. Thus, the profit function is shown in equation (9):

$$\pi = (p-b)q - C_0 - C_{w0} - \theta_w w \tag{9}$$

Representative firms will bias D by choosing the optimal level of digitisation to maximise profits.

$$\partial\pi / \partial D = (p-b-\theta_z w)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} - \theta_z\theta_w q \tag{10}$$

If equation (10) equals 0, the output q of a representative firm choosing the optimal level of digitisation can be summarised as equation (11)

$$q = (p-b-\theta_z w)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} / \theta_z\theta_w \tag{11}$$

Subject to the profit maximisation objective, this leads to carbon emissions w as in equation (12):

$$w = z(p-b-\theta_z w)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} / \theta_z\theta_w \tag{12}$$

From equations (1)–(12), CE w is related to the economic growth of DE driven D and digital economy F. Therefore, in this study, in order to find the optimal solution of DE and CE, F is derived in the first order and second order respectively, as shown in Eqs. (13) and (14).

$$\mathrm{d}w / \mathrm{d}F = (p-b-2\theta_w z)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} / \theta_z\theta_w \tag{13}$$

$$(\hat{\mathrm{d}}2\ \mathrm{w}) / (\hat{\mathrm{d}}2\ \mathrm{F}) = -2\theta_A N^\alpha GE^\beta K^{1-\alpha-\beta}\theta_D \tag{14}$$

Letting equation (13) equal 0. The optimal DE level F_0 is obtained according to the objective constraints, as shown in equation (15) below:

$$F_0 = ((p-b)/2\theta_w - z_0)/\theta_D\theta_z \tag{15}$$

Since $\theta_D > 0$ and $\theta_A > 0$, so $\frac{d^2w}{d^2F} < 0$, F_0 is the maximum point of carbon emissions w. When $F < F_0$, CE gradually increase as the level of DE increases; when $F > F_0$, it shows the inhibiting effect of DE on CE. Meanwhile, to facilitate the analysis, this study deform equation (13) into differential form, as shown in equation (16).

$$dw = \left[(p-b)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} / \theta_z\theta_w\right]dF - \left[2\theta_w z\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta} / \theta_z\theta_w\right]dF \tag{16}$$

where $\theta_A dF$ represents the technological progress resulting from the increased level of DE, *p-b* represents the difference between price and variable costs, $(p-b)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}dF$ represents the increased profit resulting from technological progress, and the first term on the right-hand side of the equation, i.e.: $(p-b)\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}/(\theta_z\theta_w)dF$ denotes the increase in CE due to increased profits from technological progress. The first term on the left-hand side of equation (16) can therefore be thought of as the incentive effect of profit. $z\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}dF$ represents the incremental CE resulting from an increase in output, while $\theta_w z\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}dF$ represents the disposal cost of the incremental CE, so that $-2\theta_w z\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}dF$ represents the reduction in CE due to the incremental disposal cost. Therefore, $\left[2\theta_w z\theta_A L^\alpha GE^\beta K^{1-\alpha-\beta}/\theta_z\theta_w\right]dF$ in Eq. (16) can be considered as the cost suppression effect.

Thus, the level of DE has a combined profit incentive effect and cost disincentive effect on CE. The growth of DE will affect CE by influencing technological progress. Initially, the profit incentive effect dominates, increasing CE, whereas later, the cost disincentive effect dominates, with, for example, the introduction of cleaner technologies leading to lower CE.

4.2. *Variable selection and data*

4.2.1. *Explained variable*

The explanatory variables in this study are carbon emissions (CE). Currently, the sectoral accounting method and the emission factor method are the two main methods used in academia to measure carbon emissions. Drawing on Shan et al. [38], this study derives starting CE based on energy consumption multiplied by its corresponding carbon conversion factor, which is then subtracted from the portion of non-energy fuels consumed to ultimately obtain the total CO2 emissions of the region.

4.2.2. *Core explanatory variables*

This study used the development level of the digital economy (DE) as the core explanatory variable and also introduced its squared term of the digital economy (SDE) into the model. Currently, the measurement of DE tends to focus on the provincial level, while the measurement of DE development level at city is not yet a uniform practice. Taking into account the comprehensiveness, scientificity and accessibility of the index data, this work have referred to Zhao et al.'s [39] idea of measuring DE development levels from the perspective of Internet development, and adopted the four indexes of Internet broadband access subscribers per 100 people, the share of the employees in the computer software and software industry in the employees in urban units, per capita total telecommunication services and mobile phone subscribers per 100 people, and obtained the development level of DE by means of the principal through the method of principal component analysis, these four indicators are standardised to obtain the development level of DE, and the specific measurement indicators are shown in Table 2. Of these, Internet development indicators are mainly from the China Urban Statistical Yearbook.

4.2.3. *Mediating variable*

This study follow Dong and Wang [20], who use green patent

Table 2
Description of indicators to measure DE.

Indicator type	Indicator	Definition
Internet developments	Internet broadband penetration	Number of broadband internet connections (tens of thousands)
	Mobile phone penetration rate	The number of mobile phone users per 100 people (units/100 people)
	Number of employees	Number of persons employed in computer services and software (tens of thousands)
	Foundations of the digital industry	The total amount of telecommunication business per capita (units/per people)

application numbers to measure green innovation (GI). This study takes the green patent list and international classification code provided by the World Intellectual Property Organisation (WIPO) as reference, searches the database of the State Intellectual Property Office (SIPO) according to the green code therein and collates the green patent applications of each city, finally aggregating them to the city level and logarithmic processing.

4.2.4. Control variables

To avoid other factors influencing CE, this study have selected the following control variables with reference to previous studies: Income level (ICL): urban residents' disposable income is selected to indicate the region's economic development and prosperity, which could directly influence the region's consumption of energy and CE [40]. Environmental Pollution Index (EPL): considering the unavailability of data of solid waste volume at the prefecture level, this study learns from Dong and Wang [20] and uses industrial effluent emissions, industrial sulphur dioxide emissions, and environmental emissions of industrial fume (dust) calculated for each city. Population scale (POP): expressed as total population of each city at year-end [21]. Industrial Structure (IS): is represented by the ratio of tertiary sector output to secondary sector output. Government Financial Support (GFS): government support plays an important role in China's industrial restructuring, green technology innovation and emission reduction. And this study use total local government budget expenditure as a percentage of GDP to measure the level of government support for CE reduction [41]. Financial development (FD): represented by the credit balance of financial institutions in GDP. To eliminate heteroskedasticity, some of the control variables are logarithmically treated in this study. Science and technology support intensity (STS): this study follows the approach of Dong et al. [42] and uses the ratio of government fiscal expenditure on science and technology to GDP to express it. Table 3 shows the specific indicators and sources.Descriptive statistics of the variables are shown in Table 4.

Table 3
Description of variables.

Variable type	Variable name	Variable symbol	Source of variables
Explained variable	Carbon emissions	CE	Chinese Research Data Services Platform (CNRDS)
Core explanatory variables	Digital economy	DE	Chinese Research Data Services Platform (CNRDS) and China Urban Statistical Yearbook
	Squared term of the digital economy	SDE	China Urban Statistical Yearbook
Mediating variable	Green innovation	GI	Chinese Research Data Services Platform (CNRDS)
Control variables	Income level	ICL	China City Statistical Yearbook
	Population scale	POP	China City Statistical Yearbook
	Environmental pollution Index	EPL	Chinese Research Data Services Platform (CNRDS) China City Statistical Yearbook
	Industrial structure	IS	China City Statistical Yearbook
	Government financial support	GFS	China City Statistical Yearbook Regional statistical bulletin
	Financial development	FD	China City Statistical Yearbook
	Science and technology support intensity	STS	China City Statistical Yearbook Regional statistical bulletin

Table 4
Descriptive statistics of variables.

Variable type	Variable	Mean	Standard deviation	Min	Max
Dependent variable	CE	6.17	1.06	3.86	8.95
Core independent variable	DE	0.60	0.04	0.56	0.80
	SDE	0.36	0.05	0.31	0.65
Mediating variable	GI	5.21	1.64	1.79	9.30
Control variables	ICL	10.21	0.29	9.60	10.99
	POP	5.90	0.69	3.82	7.22
	EPL	0.07	0.07	0.00	0.40
	IS	0.97	0.50	0.31	3.37
	GFS	0.19	0.08	0.07	0.50
	FD	0.98	0.57	0.31	3.30
	STS	0.20	0.04	0.10	0.29

4.3. Econometric model

4.3.1. Basic regression model

Since CE are also affected by time-varying factors such as policy formulation and adjustment as well as climate change, in order to avoid omitted variable bias and endogeneity problems, this study finally used a fixed-effects model in the model setting and empirical analysis through the Hausmann test. In addition, the model is designed to not only identify the causal relationship between DE and CE, but also to solve the omitted variable and endogeneity problems due to reciprocal causation. Therefore, based on the fixed effects model, this study adopted the number of historical fixed telephone called as an instrumental variable of DE for the empirical test of the instrumental variables method, thus solving the possible endogeneity problem and making the research results more accurate. Considering that there may be a non-linear relationship between the impact of DE on CE, the quadratic term of DE is also introduced into the model to explore the relationship between DE and CE, and the model is constructed as shown in equation (17):

$$CE_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 SDE_{it} + \beta_j Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{17}$$

where CE_{it} represents the total CE of city i in year t. DE_{it} represents DE level of city i in year t, and SDE_{it} denotes the squared DE level term; $Control_{it}$ denotes control variables for city i affecting the total urban carbon emissions in year t; μ_i is the individual city fixed effect, φ_t is the year fixed effect; ε_{it} is the rational error term.

4.3.2. Mediating effect model

According to the previous theoretical analysis, the development of DE will influence CE through GI, thus this study based on the mediation effect model of Wen and Ye [43], analyzed by stepwise regression, and constructed a mediation model to test the mediation effect of GI as shown in equations (18) and (19). Equations (18) and (19) reflected the indirect effect of DE on CE by influencingGI. In the mediation effect analysis, we should first check whether the coefficient β1 in the model of formula (17) is significant, if it is not significant, it means that DE has no effect on CE, if it is significant, it means that there is an effect, and then further analysis. Then, by analysing and observing the coefficient α_1 in formula (18) and the coefficient β_3 in formula (19), if both are significant, then observe the coefficient β_1 in formula (19), if β_1 is significant, then it is partially mediated, and if β_1 is not significant, then it is fully mediated. $GI_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 SDE_{it} + \alpha_j Control_{it} + \mu_i + \varphi_t + \varepsilon_{it}$ (18)

$$CE_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 SDE_{it} + \beta_3 GI_{it} + \beta_j Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{19}$$

where GI_{it} represents the mediating variable green innovation. The remaining variables are the same as in Ep. (17).

4.3.3. Spatial panel modelling

Previous studies showed that CE may be spatially dependent [9], and ignoring spatial effects may bias the results [44]. Meanwhile, according to the theoretical analysis, DE not only affects the local CE, but also relies on its own characteristics to break through the spatial boundaries, which in turn affects CE of the surrounding areas, and CE themselves have a certain spatial spillover effect. Therefore, this study adopted the spatial econometric model to analyse the DE-CE relationship. Among them, spatial econometric models include Spatial Error model, Spatial Lag model and Spatial Durbin model (SDM). This study finally selected the SDM based on the results of LM test, etc., which can explore the spillover effect from both time and space perspectives.

Therefore, to investigate the spatial spillover effect of DE on CE, this study introduced spatial variables into the model and extended it to a SDM, as shown in equation (20).

$$CE_{it} = \beta X_{it} + \delta W_{ij} CE_{it} + \theta \sum_{j=1}^{N} W_{ij} X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{20}$$

$$\varepsilon_{it} = \rho \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \xi_{it} \tag{21}$$

In equations (20) and (21), N represents number of cities. W_{ij} is the spatial weight matrix, the economic distance matrix is used in this study, δ and λ are the spatial autoregressivity and spatial correlativity coefficients, respectively; X_{it} denotes interpretative variables for the year t of city i, which includes DE term and its squared term, and a set of control variables. ε_{it} is the error spatial autocorrelation term and ξ_{it} is the random disturbance term. The remaining variables are the same as in Eq. (17).

4.4. Descriptive statistics and data sources

The study is based on 278 cities at district level from 2011 to 2019, Hong Kong, Macao and Taiwan are not involved. Statistics for the indicators are taken from the China Urban Statistical Yearbook and the yearbooks and bulletins of cities at various levels and above. Missing values were partially replaced by linear interpolation and moving average.

To deal with outliers, this study simultaneously shrink the tails for quartiles below 1 % and above 99 % for continuous variables.

5. Empirical results

5.1. Results of benchmark regressions

A baseline regression of DE on CE is shown in Table 5. The results are reported using both Ordinary least squares (OLS)and fixed effects (FE) estimates, and include SDE in the regression, controlling for other variables which might influence CE, as shown in Table 5, columns (1)–(4). Regardless of whether control variables were included in the OLS and FE models, DE and SDE were significant at least at the 5 % level. Among them, DE is significantly positive and SDE is significantly negative, i.e., the effect of DE on CE shows an inverted U-shaped non-linear relationship of promotion followed by suppression, and Hypothesis 1 is confirmed. This could be because the level of DE is still immature early in its development, and the promotion of digital industrialisation and industrial digitalisation involves a large amount of capital, labour and other cost elements, thus increasing CE. Meanwhile, DE contributes to CE in the early stages, as the deep integration of DE in real economy, such as industrial sector, facilitates scale expansion and energy

Table 5
Benchmark results.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	FE	FE	FE	FE
	CE	CE	CE	CE	GI	CE
DE	108.30***	29.85***	38.09***	11.58**	15.47**	10.02**
	(7.73)	(7.04)	(4.70)	(4.99)	(7.00)	(4.98)
SDE	−70.26***	−15.84***	−25.82***	−8.19**	−11.53**	−7.01*
	(5.89)	(5.22)	(3.62)	(3.77)	(5.27)	(3.76)
ICL		0.18***		0.43***	2.86***	0.23***
		(0.06)		(0.04)	(0.06)	(0.06)
POP		0.26***		0.29**	0.87***	0.22*
		(0.02)		(0.12)	(0.17)	(0.12)
EPL		3.79***		0.03	0.43**	−0.00
		(0.22)		(0.14)	(0.20)	(0.14)
IS		−0.03		−0.03	−0.03	−0.03
		(0.04)		(0.03)	(0.05)	(0.03)
GFS		−4.92***		−0.36	1.18***	−0.44*
		(0.20)		(0.24)	(0.35)	(0.24)
FD		0.36***		0.07**	0.06	0.06**
		(0.03)		(0.03)	(0.05)	(0.03)
STS		−2.88***		−0.72**	−0.56	−0.66**
		(0.36)		(0.31)	(0.44)	(0.31)
GI						0.07***
						(0.02)
cons	−33.42***	−8.54***	−7.36***	−3.73**	−32.41***	−1.17
	(2.52)	(2.30)	(1.52)	(1.77)	(2.67)	(1.84)
N	2502	2502	2502	2502	2502	2502
R^2	0.38	0.65	0.09	0.17	0.75	0.18

Note: *, ** and *** denote significance at the 10 %, 5 % and 1 % confidence levels respectively. The following tables are identical.

consumption in real industries. When the DE achieves a mature stage of development, DE can improve the green technology research and development efficiency of enterprises and optimise the industry structure, so that CE reduction from the "technology effect" of DE exceeds the CE increase at the initial stage, thus significantly decreasing the CE.

Regarding the control variables, *ICL* is positively significant at 1 % level, suggesting that as residents' income increases, so do their carbon emissions. This is because as income increases, residents' consumption demand is further stimulated, and the increase in demand for goods results in an increase goods supply, which promotes CE. *POP* is significantly positive at 5 % level, human production and living activities are inextricably linked to energy and the environment, and the larger the population, the more energy will be consumed to meet the basic needs of people's daily lives, such as electricity, heating and transport, ultimately resulting in an increase in CE, in agreement with the findings of Wang et al. [1] and Yu et al. [45]. *FD* is significantly positive at 5 % level, representing that as FD increases, so does CE. This could be because at higher levels of financial development, regions place relatively more emphasis on developing the economy in order to return capital, which leads to an increase in CE as controls and restrictions on CE are relaxed. The *STS* is significantly negative at 5 % level, and a higher intensity of government financial support for science and technology, the better it shows that the area values investment in science and education, which promotes technological progress and thus reduces CE through human capital and innovation capacity [46].

Furthermore, (1)–(2) in Table 5 are the results of least squares regressions and it can be seen that the results are not significantly different, suggesting that the estimates in this study are robust.

5.2. Mechanism analysis

As mentioned above, DE can influence CE through GI. Therefore, the impact mechanisms of DE and CE are tested. Results in column (5) of Table 5 show that DE is positive and SDE is negative, i.e., the relationship between DE and GI is non-linear. Probably due to the fact that the development and investment in DE in early stage the use and transformation of technology innovations, which in turn will improve the level of GI. When DE has developed to a certain extent, the continuous input will lead to an excessive concentration of capital and human capital in region, resulting in an imbalance between the structure of innovation input and output, and causing a phenomenon of unreasonable and wasteful allocation of resource factors, at which time the amount of input and output will not match, thus showing the inhibiting effects of DE on GI. Notably, DE's effect on GI shows a non-linear relationship, first increasing and then decreasing, and Hypothesis 2 is tested. Therefore, GI is included in the DE on CE model, see column (6) of Table 5 for regression results. The effect of DE on CE is still in an inverted "U" shape, and the coefficients of DE on CE show a different magnitude of decline after adding the mediating variable of GI, which indicates that GI played a partial intermediary role, that is, by testing Hypothesis 3, DE affects GI.

5.3. Endogeneity and robustness testing

For accuracy of findings, this section performs series of endogeneity treatments and robustness tests, mainly using the instrumental variables approach and the exclusion of cities, among others.

5.3.1. Instrumental variables

To further mitigate potential endogeneity issues, avoid possible bidirectional causality biasing the results of the study, and ensure the accuracy of the findings, drawing on the work of Huang et al. [47] and Zhu et al. [48], among others, and selects the number of historical landline phone calls as an instrumental variable for DE. For one thing, traditional communication equipment is the prototype for modern DE development, with the development and progress of the times, enabling the development of modern communication technology, which DE is rapidly developing. Thus, regions where traditional communication infrastructure is developed at a superior degree, DE starts earlier and develops to higher levels, fulfilling the correlation requirement of instrumental variables. For another, as communication technology advances, the frequency of use of fixed telephones is gradually decreasing and tending to disappear, and for the time being its difficult for the historical numbers of landlines to affect present CE and meet the exclusion requirements. Therefore, this study construct instrumental variables for DE using fixed telephones per 10,000 inhabitants in 1984 for each area, and national internet users from 2010 to 2018 as cross-multiplication terms. At the same time, two-stage least squares were used to conduct empirical tests, and column (1) of Table 6 shows the results. As we can see, both DE and SDE were significantly positive, consistent with inverted U-shaped nonlinearity, proving the previous results were robust.

5.3.2. Deleting regions lagging behind in the digital economy

Due to the fact that DE starts at different times and development levels across different areas, to avoid the influence of late-starting areas within the findings, refer to Wang's [49] research, exclude the cities corresponding to the late-starting cities in Qinghai Province from the sample, and re-run the regression, and the regression results are shown in Table 6, Column (2). It shows that DE still has an inverted U-shaped non-linear relationship to CE, once again confirming the results.

5.4. Heterogeneity analysis

5.4.1. Through the "Hu Huanyong Line"

To explore the heterogeneous effects of DE on CE further, this study conduct a regression analysis of cities on the east and west sides of the "Hu Huanyong Line" from a geographical demographic divide perspective. Columns (1)–(2) of Table 7 show that the effects of the digital economy on carbon emissions have an inverted-U non-linear relationship in both the eastern and western regions. The eastern side is significant at the 5 % level, while the western side is not. This is because the "Hu Huanyong Line" is an important demographic boundary in China, as well as a boundary between uneven and inadequate socio-economic development within China [50]. On the western side, where the population is sparse, and the economy is slow, the effects of DE on CE are not yet significant.

5.4.2. Heterogeneity of resource endowments

The abundance of natural resources in each region is a fundamental requirement for the establishment and development of cities. Therefore, according to the plan for resource city sustainable development issued by the State Council, this study divided the research s samples into raw material cities and non-resource cities, and investigated the heterogeneous effects of DE on CE in areas with different resource endowments. The results are detailed in Table 7, columns (3)–(4). It showed that DE still showed an upside-down U-shaped curve. The effects on CE in non-resource cities was more significant, while in resource cities it was not,

Table 6
Robustness tests.

	(1)	(2)
	CE	CE
DE	89.22***	11.63**
	(39.61)	(5.01)
SDE	−53.84*	−8.24**
	(29.99)	(3.79)
Control Variable	YES	YES
_cons	−25.28**	−3.76**
	(12.70)	(1.78)
N	1992	2429
R2	0.61	0.17

Table 7
Heterogeneity analysis results.

Variable	(1)	(2)	(3)	(4)
	Eastern	Western	Resource	Non-resource
DE	CE	CE	CE	CE
	11.88**	16.09	9.88	13.32**
	(5.66)	(31.00)	(28.02)	(5.74)
SDE	−8.36**	−12.41	−6.80	−9.73**
	(4.02)	(23.67)	(23.01)	(4.25)
Control Variable	YES	YES	YES	YES
_cons	−3.83	−9.30	−1.10	−5.94***
	(2.35)	(10.10)	(8.41)	(2.18)
R2	0.17	0.19	0.12	0.23

which is similar to Xiang et al.'s [51] findings. This may be because resource cities are overly dependent on their abundant natural resources, creating a "resource curse". Meanwhile, the difficulty of industrial restructuring and the small number of new industries in these areas limit application of DE to some extent, making it difficult to reap the digital dividend of CE.

5.4.3. *Economic development*

As economic conditions vary across China, this study classify municipalities into low, medium and high economic development levels based on per capita income [52], and analyses the heterogeneous effect of DE on CE. Table 8 shows that the inverted U-shaped relationship between DE and CE is still present, but is only significant for highly economically developed regions. This could be because more developed regions have a more complete infrastructure for the DE and are more advanced in terms of levels of innovation and green technologies, which can achieve full carbon emission reductions and thereby have a greater effect on reducing emissions in regions where economic development is higher.

5.4.4. *Quantile regression*

To further analyse the effects of DE on CE under diverse conditions, a panel quantile regression model is adopted to examine the carbon reduction effect of DE at different levels of CE, and results are presented in Table 9. DE has an inverted U-shaped relationship with CE, with different coefficients for different quartiles. SDE is insignificant at the 0.25 quartile, but significant at the 0.5 and 0.75 quartiles, suggesting that CE effect of DE only comes into play when CE reach a certain level, meanwhile, the coefficient of DE becomes progressively smaller as quantiles increase, implying that the emission reduction effects of DE are less pronounced in areas with higher CE than in areas with lower CE. The reason might be that DE is relatively weak in cities with high emissions because of slower economic growth and the presence of energy-intensive industrial industries, which makes it difficult to integrate DE with industry without delay, in agreement with Xiang et al.'s [51] findings.

Table 8
Regressing for heterogeneity in economic development levels.

Variable	(1)	(2)	(3)
	Low income	Moderate income	High income
DE	CE	CE	CE
	−18.50	54.38	9.17**
	(33.44)	(33.97)	(4.09)
SDE	16.37	−41.76	−6.57**
	(27.64)	(27.74)	(2.97)
Control Variable	YES	YES	YES
_cons	3.33	−15.12	−3.40**
	(10.17)	(10.78)	(1.53)
R^2	0.18	0.04	0.30

Table 9
Quantile regression.

Variable	(1)	(2)	(3)
	25	50	75
DE	CE	CE	CE
	8.31**	100.80***	47.81***
	(2.17)	(4.67)	(5.61)
SDE	−2.71	−78.46***	−32.27***
	(-1.01)	(-4.38)	(-5.89)
Control Variable	YES	YES	YES

5.5. *Spatial effects of DE on CE*

5.5.1. *Spatial correlation test*

This study used Moran's I to examine the spatial correlation between DE and CE for each annual variable under the economic distance matrix. Moran's I is not 0 for either DE or CE for 2011 and 2019, as shown in Table 10. This implies that DE and CE are significantly spatially correlated. Meanwhile, to observe more intuitively the characteristics of spatial evolution in DE and CE on municipality level, this study visualised the data for 2011 and 2019, respectively, using ArcGIS 10.2 software, as shown in Figs. 2–3.

5.5.2. *Analysis of spatial effects*

The results of SDM showed in Table 11 that the influence of DE on CE is an inverted U-curve relationship, and there is a spatial spillover effect, which confirms Hypothesis 4. Among them, the main and direct effects of SDE did not pass tests of significance, indicating that the spatial suppression of CE by DE was not yet significant. Column (4) reflects the spillover effect of DE, which can significantly reduce CE in surrounding areas, i.e. the local and surrounding areas are able to achieve the CE reduction target through exchange and learning and resource sharing. And SDE's indirect influence is significantly positively, probably because once the local DE reaches a certain degree, the local digital industrialisation becomes higher, while some industries that are difficult to digitalise their industries will move to the peripheral regions, causing the level of CE in the peripheral areas to increase significantly.

5.5.3. *Analysis of threshold effects*

Based on the benchmark regression analysis, a non-linear relationship existd between the impact of DE on CE, but the SDE was not significant in the spatial Durbin model analysis, somewhat differing from the previous benchmark regression findings. Therefore, this study adopted the model of panel threshold to explore the existence of a threshold for DE's impact on CE, and the model of regression as follows. Formula (22) is a single-threshold model, and formula (23) is a double-threshold model.

$$CE_{it} = u_i + \beta_1 DE_{it} * I(DE_{it} \le \gamma) + \beta_2 DE_{it} * I(DE_{it} > \gamma) + \varepsilon_{it} \tag{22}$$

Table 10
Spatial correlation test.

Year	(1)		(2)	
	CE		DE	
	Moran's I	P value	Moran's I	P value
2011	0.16	0.00	0.04	0.06
2012	0.17	0.00	−0.00	0.47
2013	0.17	0.00	0.02	0.25
2014	0.18	0.00	0.06	0.01
2015	0.18	0.00	0.06	0.02
2016	0.18	0.00	0.06	0.01
2017	0.17	0.00	0.07	0.00
2018	0.17	0.00	0.05	0.03
2019	0.16	0.00	0.07	0.01

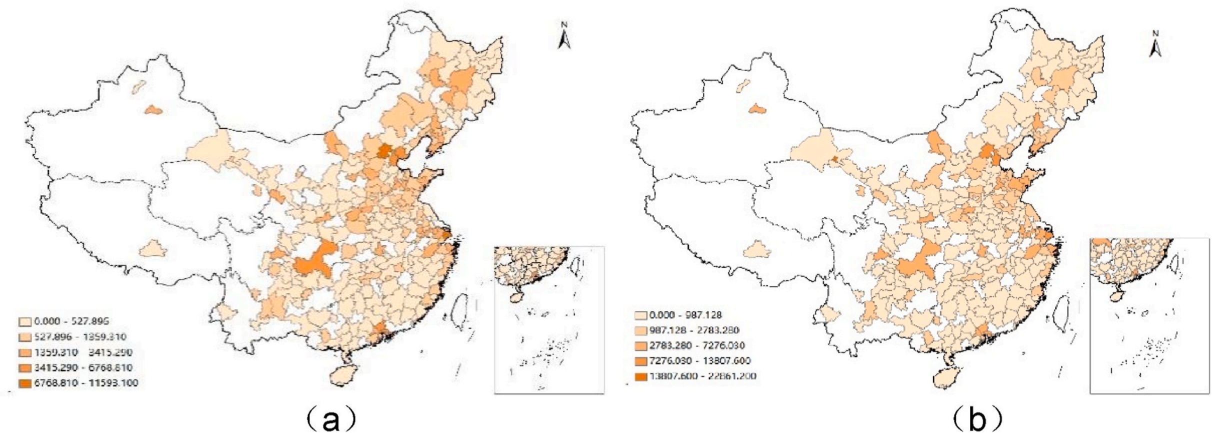

Fig. 2. Evolution of carbon emissions in space and time of 278 cities in China for 2011 (a) and 2019 (b).

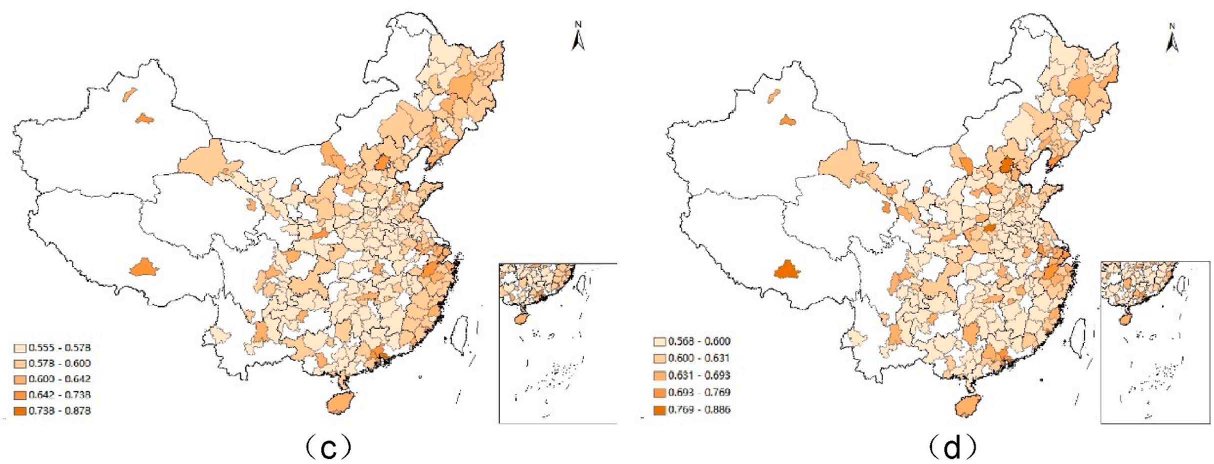

Fig. 3. Evolution of digital economy in space and time of 278 cities in China for 2011(c) and 2019(d).

Table 11
Results of the spatial Durbin model.

Variable	(1)				
	Main	WX	Direct effects	Indirect effects	Total effects
DE	22.44**	−54.68**	24.24**	−50.41**	−26.17
	(10.23)	(25.69)	(10.70)	(22.86)	(22.48)
SDE	−11.73	36.22*	−12.96	32.81*	19.85
	(7.60)	(18.78)	(7.96)	(16.78)	(16.46)
Control Variable	YES	YES	YES	YES	YES
Spatial rho	−0.18***	sigma2_e	0.81***	N	2502
	(0.04)		(0.02)	R^2	0.52

$$CE_{it} = u_i + \beta_1 DE_{it} * I(DE_{it} \leq \gamma) + \beta_2 DE_{it} * I(\gamma_1 < DE_{it} \leq \gamma_2) + \beta_3 DE_{it} * I(DE_{it} > \gamma_2) + \varepsilon_{it} \tag{23}$$

where *CE* denotes the explanatory variable, u_{it} denotes the individual fixed effect, β denotes the coefficient to be estimated on the threshold variable, q_{it} denotes the threshold variable, γ denotes the threshold value, $I(\cdot)$ denotes the indicator function and ε_{it} denotes the disturbance term.

This study took GFS as threshold variable to be tested, as detailed in Table 12. From the results, DE was only significant at 1 % level in the single threshold effect test, which indicated that DE has a non-linearity characteristic of a single threshold effect on CE, again confirming

Table 12
Threshold effect test results.

Test Parameter	Threshold	*F* Value	*P* Value	The Critical Value 10 % 5 % 1 %		
DE	Threshold1	26.21	0.08	23.78	31.37	40.07
	Threshold2	11.82	0.52	22.24	27.93	34.94
	Threshold3	7.39	0.81	20.04	23.48	26.30

Hypothesis 1.

To better examine the effect of DE on CE, this study used the single threshold model for estimation, as shown in Table 13. If the DE was less than 0.340, its coefficient of impact on CE was 0.790 and significant positive at 10 % level. When the level of DE was higher than 0.340, the coefficient of its impact on CE was 1.139 and was significantly positive at 5 % level. In the benchmark regression, from the inverted U-shaped relationship between DE and CE, the inflection point for a restraining

Table 13
Threshold regression results.

Variable	Coefficient	Variable	Coefficient
DE < 0.34	0.79*	DE ≥ 0.34	1.14**
	(0.44)		(0.45)
Control Variable	YES		
_cons	−0.44		
	(0.75)		
N	2502	R^2	0.16

effect was 0.707, i.e. when the level of DE was greater than 0.707, it will have a restraining effect on CE. In contrast, the threshold value in the threshold regression was significantly lower than the inflection point value in the benchmark regression. As a result, SDE in Spatial Durbin model was different from the coefficient significance in benchmark regression. Overall, DE effects on CE were all significant in increasing CE in the early stage, possibly because DE belongs to the construction and promotion application stage, coupled with the unbalanced resource endowment and economic development between regions, etc., which limited the effect of DE on CE.

6. Conclusions and discussion

This study used principal component analysis to measure DE in each region, based on panel data from 278 cities in China from 2011 to 2019, and then used panel fixed effects and mediation effects models to explore DE and SDEeffects on CE and the mechanism. Furthermore, Spatial Durbin Modelling was applied to examine spillovers from DE and CE in space. The results are as follows: first, there is a significant inverted U-shaped relationship between DE and CE, which is first promoted and then suppressed, and still holds after the test. The nonlinear association of DE and CE was again verified using a threshold regression model, with the threshold located to the left of the inflection point of the baseline regression. Second, DE can significantly increase the level of GI in cities, with an inverted U-shaped non-linear relationship. Third, DE has an indirect influence on CE through GI. Fourth, analysing heterogeneity showed that DE affects CE more in regions with faster economic development, such as central cities and regions along the eastern "Hu Huanyong line". In contrast, the impact of DE on CE is not significant in resource-based cities, which face the resource curse, compared with non-resource-based cities. Fifth, when the spatial factor is added, DE's impact on CE has a spatial spillover effect.

Unlike most of the previous studies [53,54], first, this study examined the effect of DE also including its squared term on CE. To measure the overall impact of DE, the previous research used Internet development levels; the amount of energy consumed was selected to measure the carbon emissions [5]. However, this study also examined the mediating effects of GI in a number of ways, providing additional new perspectives on carbon reduction [55]. It is generally found that DE and CE have a spatial effect and that there is a significant effect between the two. That's consistently with previous findings and confirms those that DE contributes to CE reduction [56]. However, the results of this study are different from others [57], which do not consider the non-linear relationship and the mediating effect. The studies report that DE has an inverted U-shaped relationship. Considering the different levels of development and geographical location of different regions, our results were also verified for robustness.

Second, previous research and analysis has considered the impact of GI on CE under certain socio-economic conditions [58], and currently, GI is an important strategy for influencing CE. So, the moderating effects of GI have been a prominent factor in the carbon reductions. The results also show that DE affects CE through GI. However, previous studies have failed to adequately consider the non-linear impact of DE on GI [19], so we have fully explored the non-linear relationship between DE and GI when analyses mechanisms to reduce CE, which provides new perspectives for future reductions.

Third, these findings offer additional information on how factors such as DE and GI affect CE, complementing previous findings on how DE affects CE [41]. This study also incorporate the data at the municipal level in China to enrich and complement the framework of previous studies, exploiting the ameliorative effects of DE on urban CE.

Fourth, this study focus on a sample of cities in China, and it is possible that our findings may not be identical to those of other regions of the world. Data from five EU countries (Germany, France, Spain, Italy and the UK) show that economic growth and CE show an N-shaped relationship, and renewable energy can improve environmental quality, that is, when the economic growth reaches a certain level, the economic growth can have an inhibiting effect on CE [59]. DE can also inhibit CE by bringing economic growth. This is consistent with the results of the latter half of the inverted "U"-shaped curve of the impact of DE on CE obtained in this study. The first half of the inverted "U" -shaped curve shows that DE stimulates carbon emissions when DE is at an early stage of development, while EU countries are generally developed countries, and their economies are more advanced compared to China's, because only the second half of the inverted "U"-shaped curve is reflected. The second half of the inverted "U"-shaped curve. Unlike the EU, studies in the Middle East and North Africa (MENA) region have shown that urbanization and carbon emissions are positively correlated in both directions in the long term [60]. The results showed that DE accelerates rural urbanization, the development of DE in this region stimulates CE, reflects only the first half of the inverted "U"-shaped curve. This result may be due to the fact that the MENA region is relatively underdeveloped compared to China. To summarize, different countries and regions have different resource endowments and economic levels, and other studies should use our findings to extrapolate according to local conditions.

This study examines the impact of DE on CE from a digital economy perspective and provides preliminary empirical evidence for achieving carbon emission reductions, but there are still some limitations.

One is the measurement of DE. At present, DE data are still scarce and the method of measuring it has not yet been universally agreed, and only exploratory decisions can be made in conjunction with relevant previous studies, making the level of DE subject to a degree of variability. Nevertheless, as DE is a data indicator that integrates several dimensions. To better explore the impact of DE on CE, the key numerical elements of CE and the splitting of DE into different dimensions will be further explored in the future study to explore the impact of DE of different dimensions on CE. The second is related to the study sample. The data sample of this study is Chinese cities, and there are differences in the level of economic development and resource endowment of each country, which may make it difficult to generalise the results of the study. In the future, this study will conduct in-depth research on the impact of DE on CE in several countries. Last but not least, when measuring CE, this study calculates the total CE of each region, but it is not known whether the population size of different regions is also one of the factors affecting CE. Meanwhile, GDP-related carbon emissions intensity is also an important indicator of CE, which is not considered in this study. Therefore, in the subsequent research, the team will replace the measurement of CE and construct a more complete CE measurement system.

7. Policy implication

Based on the above findings, the following policy recommendations are made in this study.

First, the government should accelerate the construction of DE infrastructure and strongly support the development of DE. The above analysis shows that DE can reduce CE after reaching the inflection point of reducing consumption expenditure, and has spatial spillover effects on CE in neighbouring cities. Therefore, the government should promote the development of urban DE, especially for the relatively underdeveloped western region, through strengthening the cooperation of neighbouring cities to improve the level of DE development. Specifically, efforts can be made in the following areas. First of all, we need to improve China's DE and strengthen digital infrastructure coverage, so that regions can reach the inflection point of DE in terms of CE reduction as soon as possible. Then, to ensure the sustained and healthy development of DE, the government should improve the relevant policy protection, especially the protection of property rights, to provide a good environment for the development and innovation of the DE. Last but not least, to strengthen the integration of DE with the primary, secondary and tertiary industries, and to promote the high-quality development of DE.

Second, we should focus on innovative technologies development and raise green tech. Sustainable development can have an indirect impact on consumption levels through green technological innovation, and in order to reach the inflection point of reduced consumption expenditure as soon as possible, the government should increase its investment in technological innovation, strongly support enterprises to carry out green technological innovation, encourage the development of the use of green energy and reduce the use of fossil fuels such as coal and oil. This initiative can promote energy transformation and realize the upgrading of the energy structure in order to achieve the purpose of reducing carbon emissions. While promoting the DE, more attention should be paid to cultivating talents and supporting GI technologies, and a mechanism for transforming the results of GI should be established to enable traditional industries to upgrade, and guide them towards green and low-carbon industries.

Thirdly, we should harmonise the co-ordinated development of DE across regions and implement a differentiated policy programme of 'one place, one policy'. The government should adopt different levels of CE control policies for cities in different regions based on their level of development and geographic characteristics, and strictly test CE. For cities with different industrial structures, especially those with well-developed secondary industries, the government can optimise the industrial structure and improve the energy utilization rate by promoting clean energy. For areas with different geographical characteristics, for regions with slow economic development and weak DE infrastructure, the construction of information technology facilities should be strengthened; for regions with abundant natural resources, the iterative upgrading of DE and industries should be implemented, and the role of DE in CE reduction should be effectively played, so as to promote the large-scale development of DE and low-carbon transformation in an integrated manner.

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CRediT authorship contribution statement

Zhuoya Ma: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Software, Validation. **Hui Xiao:** Methodology, Investigation, Writing – original draft, Writing – review & editing, Software. **Jing Li:** Investigation, Methodology. **Hanting Chen:** Methodology. **Wenhui Chen:** Writing – review & editing, Funding acquisition, Resources, Supervision, Validation, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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