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Digital economy, spatial spillover and carbon intensity: concurrently on the threshold effect of human capital

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ABSTRACT

Under the new development pattern, green low-carbon and digital economy become two mainstream development directions in China. Against the background 'dual carbon' strategies, based on the data of China between 2010 and 2018 at the city level, The paper adopts dynamic spatial Durbin models to investigate the causal links causal between digital economy and carbon intensity by constructing different spatial weight matrices, and explore the influence of human capital with threshold model. Results show that: (1) Urban digital economy and carbon intensity show significant positive spatial correlation characteristics. The carbon reduction of digital economy has obvious spatial spillover effect under different spatial weight matrices. (2) Industrial structure upgrading, technological innovation and resource allocation optimization are effective channels through which digital economy contributes to carbon emission reduction. (3) A double-threshold effect of human capital is evident in the carbon reduction of digital economy. The findings offer new perspectives and empirical evidence for understanding the causality relation between the digital economy and carbon emission, and those conclusions have important policy implications for how to promote the digital economy development and thus achieve the 'double carbon goal'.

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1. Introduction

Environmental risk is the most pressing issue in the following decades, and the greenhouse effect caused by carbon dioxide is one of the biggest threats to humankind today, Global Risk Report of the World Economic Forum in 2021 stated. China committed to peak carbon emissions before 2030 and achieves carbon neutrality before 2060. In light of current national conditions, establishing a long-term emission

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reduction mechanism therefore is crucial for economic development under the ‘double carbon ’target.

It is stated in the Energy outlook 2020 that improving energy efficiency is the most effective practice for saving energy and reducing emissions. The spread of digital technology applications can significantly decrease energy consumption and lower CO_2 emissions (Schulte et al., 2016). However, digital economy development is inevitably accompanied by the expansion of information infrastructure, the updating and iteration of digital products, and the subsequent upgrading of related hardware facilities, all of which will raise the need for energy-intensive products (Zhou et al., 2019).

Digital economy has become an important source of high-quality economic development. *China Digital Economy Development White Paper 2021* reported that digital economy is worth 39.2 trillion-yuan, accounting for 38.6% of the GDP By 2020. There is a lot of evidence that the digital economy conduces to economic development, government management, social development, industrial technology, company governance, etc. (Litvinenko, 2020).

Digitalization, while empowering the economy significantly, has also changed the demand for human capital in related industries, including workforce skills, educational attainment, etc. On the one hand, digital technology-driven economies require high levels of human capital (Y. Li et al., 2014). On the other hand, high levels of human capital reduce CO_2 emissions by accelerating the conversion of production factor allocation, improving product quality, increasing economic efficiency, and promoting cleaner production. However, there is a shortage of digital talent in China at present.

Against this background, our research is centred on the following questions: Can the digital economy become a new path to lower city carbon emissions? As the Internet and information technology advances by leaps and bounds, the spatial mobility of production factors has become more frequent and convenient. Is there some spatial spillover effect of digital economy on carbon intensity? Moreover, what is its internal influence mechanism? Over the years, China has been striving to work on promoting the reform of talent introduction and cultivation mechanisms to effectively strengthen the intellectual support for constructing the digital economic system. Does human capital affect the carbon emission reduction of the digital economy?

The current study makes several contributions to the existing research. In theory, this paper constructs spatial matrices based on urban geographic location and economic development characteristics, and uses dynamic spatial Durbin model (DSDM) to reveal the local and spatial spillover effects of digital economy on carbon intensity, expanding the scope of digital economy welfare evaluation, and extending the existing environmental economics research on the margin. In application, we have explored the mechanisms through which digital economy decreases carbon intensity, and verified the influence of human capital on carbon reduction effect with the threshold effect model, providing a feasible path for China to promote low-carbon transformation and regional coordinated development. In literature, most existing studies are from the national, industrial or provincial perspective. As China’s provincial administrative regions are vast, there are significant differences between provincial cities, and the Chinese economy shows a prominent path of urbanization, so this paper adopts the data of city-level as the research object, effectively overcoming the limitations of sample size.

2. Literature review

As a new production factor, Digital economy will fundamentally change the growth mode and drive systemic changes in the economic and social systems. therefore, digital economy has become a hot topic of academic research, including economic growth (Latif et al., 2018), total factor productivity improvement (Meng & Zhao, 2022), trade efficiency (Abeliansky & Hilbert, 2017), and so on.

Environmental effects of the digital economy have also drawn academic interests, there is few literature empirically testing the relationship between digital economy development and carbon emissions, but research in related fields is increasing. Relevant studies mainly draw three viewpoints: First, digital economy development can decrease carbon emissions. For instance, Lee and Brahmasrene (2014) conducted a study on nine ASEAN member countries and found that information industry development reduced greenhouse gas emissions. Asongu et al. (2017) found that ICTs contributed to a reduction in greenhouse gas emissions in African countries. Kalmaz and Kirikkaleli (2019) concluded that information technology has accelerated financial development and significantly reduced carbon emissions in emerging countries. Haseeb et al. (2019) Analyzed national data of BRICS, and found that use and popularization of the Internet positively contributed towards environmental quality on long terms. Godil et al. (2020) found in Pakistan, ICT reduced CO_2 emissions, supporting the EKC hypothesis.

Research on China, the development of information technology resulted in a significant carbon reduction in Central and East China, according to C. Zhang and Liu (2015). Lin and Zhou (2021) reported a significant improvement in energy and carbon emissions by Internet development performance. S. Cao et al. (2021) found that China's improved energy and environmental performance is due to the development of digital finance. Similarly, W. Zhang et al. (2021) pointed out that the Internet reduced the carbon intensity China's industrial system in varying degrees. Digital economy plays an growing significant role in achieving low carbon development (J. Zhang et al., 2022).

Much literature has drawn the opposite conclusion, the growth of electricity consumption in the information technology and related services industry (Salahuddin & Alam, 2015) aggravates regional carbon emissions. Raheem et al. (2020) concluded that ICT remarkably increased the carbon emissions by analyzing G7 countries. Using data from emerging economies, Sadorsky (2012) found that ICT growth increased electricity demand. Salahuddin and Alam (2015) found in Australia, the Internet stimulated electricity consumption, increased carbon reduction, and the country has yet to realize the energy efficiency gains that ICT has brought. Salahuddin et al. (2016) conducted an empirical study on the panels of OECD countries and found that Internet usage has increased CO_2 emissions significantly. Likewise, Magazzino et al. (2021) concluded that ICT boosted electricity consumption, thus increased CO_2 emissions in OECD countries. Lange et al. (2020) suggested digitalization has brought additional energy consumption instead of saving energy by theoretic analysis. Chen et al. (2020) concluded that the informatization process led to a relatively stable growth of carbon emissions, due to the development of e-commerce and takeout industries in China.

In addition, it has also been found that the impact of the digital economy on carbon emissions shows non-linear characteristics. For instance, Añón Higón et al. (2017) found that ICT production processes, machinery and equipment, and electronic waste drastically increased carbon dioxide emissions, while information technology would also achieve energy savings and emissions reductions through the transformation of transportation, power grids, and industrial processes. In combination, these two factors cause a nonlinear relationship between ICTs and carbon emissions. According to their study, most developed world have been beyond the 'inflection point' and gained the environmental dividend offered by ICTs, and the developing countries have yet to reach it. X. Li et al. (2021) concluded that the effect of digital economy on urban carbon intensity has the nonlinear characteristics of inverted U-shaped after examining data from 190 countries from 2005–2016. Analysing the data of China provinces, J. Li and Wang (2022) found that digital economy's influence on the logistics industry's carbon emissions shows a U-shape feature.

In general, this literature has done some work on the environmental effects of Internet and Information industry. However, as the connotation of digital economy expands, defined as a new economic development model generated by digital technology, it has a broader implication than the information industry and digital finance. Through combing the works of literature, we found the following deficiencies in related studies:

1. Digital economy transcends time and space limitations, enabling the rapid dissemination of knowledge and information and smoother communication of economic activities (Mi & Coffman, 2019). Therefore, there may be a spatial correlation between both digital economy development and pollution emissions of cities. However, there is currently little literature on the carbon reduction effects of digital economy from the spatial perspective, particularly on developing countries like China.
2. Most existing literature on carbon emissions of China are at the national, industrial or provincial level, lacking discussions from the city perspective and theoretical elaboration of its mechanism.
3. Whether the digital economy's development or carbon reduction cannot do without the support of technological innovation, while cultivating and enhancing the Core technology advantages largely relies on the quality of human capital, which is one of the critical elements of technological progress. However, human capital has not been given sufficient attention in the existing research.

Given this, we employ dynamic spatial metrology to measure the effect of digital economy on carbon intensity and mechanisms at the city level. Moreover, the threshold effect of human capital is discussed. In recent years, China has been under the high pressures from energy-saving and emission reduction; the conclusions offer new perspectives and empirical evidence for understanding the causal link between digital economy development and carbon emissions. Meanwhile, it provides directions and paths for green and low-carbon development of societies worldwide.

3. Research hypotheses

3.1. Spatial spillover effect of digital economy on carbon intensity and its influence mechanism

Digital economy uses data and information technology as factor inputs, that is characterized by replicability, rapid dissemination and sharing, low marginal costs, etc., thus breaking the restrictions of limited factor inputs to make it spread at low cost and increasing return to scale.

Firstly, digital economy upgrades the industrial structure effectively; the nature of which is the transfer of resource elements from inefficient industry sectors to efficient industry sectors, thus improving labour productivity, ultimately reducing carbon emissions intensity. Based on 'Internet+', digital economy overturns the profit mode, changes the market structure and expand the resource allocation boundary. Thus, it contributes to the shift from an industrial structure mainly heavy industries, high energy consumption to an industrial structure primarily technology-intensive and environment-friendly (Laudien & Pesch, 2019). With the rapid integration of digital technology into the financial and other tertiary industries in recent years, digital economy facilitates the dematerialization of production, consumption and the entire economic process (Ishida, 2015). Online offices, education, healthcare, shopping, and other industries have reduced energy use and lowered emissions in daily production and life.

Secondly, digital technology reduces information barriers, facilitates technology spillover, accelerates research and innovation, and reduces carbon intensity. Digital technology promotes the agglomeration of enterprises, talents, capital and other elements, this helps reduce R&D costs and accelerate technology diffusion. Meanwhile, companies enhance their R&D investments and foster technological innovation due to the competition effect among enterprises. For the energy industry, digital technology embedded in production and development promotes the industry's transformation (Lu, 2018), empowering the energy industry to optimize and upgrade (Murtishaw & Schipper, 2001). For other industries, digital economy can facilitate the tight integration between information technology and the real economy, transform traditional industries using digital technologies or digital industries (Yang et al., 2021), help enterprises to upgrade intelligently (May et al., 2017), and thus reduce urban carbon intensity.

Thirdly, digital economy promotes the mobility of productive factors such as data and information, actualize efficient allocation of resources, reducing waste of materials and carbon emissions. Digital and other technologies enable the original infrastructure, such as roads and networks, to the Internet of Everything, forming a low-carbon and efficient integrated network system, enabling the rapid flow of various elements, realizing the effective docking and precise matching of resources (Y. Cao & Shen, 2019), improving production and consumption efficiency and resource utilization, and avoiding non-essential consumption of factors and energy (Ramirez Lopez et al., 2019). Moreover, the coordination and information sharing under the digital economy facilitates the unified integration of domestic markets by breaking down barriers to local protection and industry, forming a mechanism for the free flow of resource factors, which will be continuously transferred to high-innovating, low-energy and low-polluting enterprises and industries, achieving reasonable and effective allocation among industries, thus reducing resource consumption and lowering CO_2 emissions.

At the regional level, the digital economy is easier to break through the limitations of geographic space, thus, more conducive to promoting inter-regional exchanges and cooperation. For one thing, the advancement of digital economy realizes cross-regional resource integration and synergistic effects and promotes advanced technological innovation and rational production layout. Data flow provides the basis for decision-making and sharing solutions, and information flow can drive the flow of capital and production materials. Therefore, local carbon reduction effects of the digital economy will bring good 'demonstration effect' and positive external effect to the low-carbon development of other regions. For another, there are still obvious spatial differences in the development of China's regional digital facilities and talent. The 'digital divide' further widens the development gap between regions, intensifying the 'competition effect' between cities, resulting in the loss of talents and resources in underdeveloped areas, thus showing a negative external effect in space. Therefore, the effect of the digital economy on proximity areas depends on the strength of these two effects. Accordingly, we propose the hypothesis:

Hypothesis 1: The digital economy not only reduces local carbon emission intensity, but also radiates to decrease that of neighbouring cities, with obvious spatial spillover effect.

Hypothesis 2: Industrial structure upgrading, technological innovation and resource allocation efficiency improvement are effective channels for digital economy to exert carbon emission reduction effect.

3.2. The nonlinear effect of human capital on carbon emission reduction of digital economy

Digital economy, as a knowledge-intensive industry, requires a massive accumulation of talent to achieve technological progress; It places higher demands on labour's skills and quality (Autor & Dorn, 2013; Michaels et al., 2010). Human capital is the main body and fundamental condition of digital technology innovation. The release of digital dividends depends on the quantity and quality of users.

Labourer's necessary expertise and skills are the keys to absorbing and transforming new digital technologies. Human capital and the digital economy interact with each other. Lower human capital may constrain the role of digital economy. Higher human capital can assist in the improvement of digital economy, and healthy development of digital economy conduces to promoting human capital. Higher human capital can improve the R& D efficiency of low-carbon technology, accelerate the modernization of regional industrial structure, decreasing carbon emissions. Furthermore, a more excellent human capital also means that residents are more aware of low carbon and ecological protection. They can utilize public power to influence local governments' industrial layout and environmental policies.

Therefore, carbon emissions reductions are constrained by human capital in the digital economy, the effect of the digital economy on carbon emissions reductions can only be fully realized when human capital crosses a certain threshold. Accordingly, we propose the hypothesis:

Hypothesis 3: As human capital changes, digital economy has a nonlinear impact on carbon emissions

4. Research design

4.1. Model construction

Digital economy has further strengthened the spatial association among cities by accelerating innovation factors' flow and spillover. So, the study employs a spatial model to detect the influence of digital economy on carbon intensity. Firstly, global Moran's I is employed to examine whether there are spatial dependence of these two:

$$Moran's\ \mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j}^{n} W_{ij}} \tag{1}$$

where $S^2 = \frac{\sum_{i=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)^2}{n}$; Y_i and Y_j are observations for city i and j; $\overline{Y}$ is sample average; W_{ij} is the spatial weight matrix. When Moran's $\mathrm{I} > 0$, it indicates a positive spatial correlation.

4.1.1. Spatial model

According to Eq. (1), the space weight matrix is required to calculate the Moran index. According to the new economic geography, The closer the geographical proximity, the closer the economic ties (Krugman, 1991).In addition, digital economy has a close relationship with local economic activity. Therefore, spatial weight matrices of geographical features and socio-economic features are constructed to investigate the spatial correlation under different spatial weight matrices. The spatial matrices adopted in this paper are as follows: The spatial matrices adopted in this paper are as follows: (1) Geographic distance matrix $W1$, $W1 = \begin{cases} 0, i = j \\ 1/d_{ij}^2, i \neq j \end{cases}$ (2) Economic distance matrix $W2$, $W2 = \begin{cases} 0, i = j \\ 1/\left|GDP_i - GDP_j\right|, i \neq j \end{cases}$ (3) Nested matrix $W3$, combining geographic and economic distances: $W3 = 1 - \varphi W1 + W2$, φ ranges between 0 and 1, and 0.5 is used in this paper.

The selection of the appropriate spatial model is related to the final estimation results and explanatory power. SAR (spatial lag model), SEM (spatial error model), and SDM (spatial Durbin model) are the most commonly used spatial models. Since SDM integrates both SAR and SEM, it is more general in form, has fewer constraints, and possesses unbiased estimation (LeSage & Pac, 2009). Therefore, this paper chooses SDM to discuss the spatial effects of digital economy on carbon intensity:

$$\mathrm{CI}_{i,t} = \rho W\mathrm{CI}_{i,t} + \alpha_1 \mathrm{Dige}_{i,t} + \beta W\mathrm{Dige}_{i,t} + \alpha_k \ Control_{it} \ + \omega W Control_{it} + u_i + \nu_t + \varepsilon_{it} \tag{2}$$

where i and t denote the city and year, CI_{it} denotes the carbon intensity of the city, $\mathrm{Dige}_{i,t}$ represents the digital economy; $Control_{it}$ represents control variables, W is the spatial weight matrix, ρ is the spatial autocorrelation coefficient, and β is the spatial spillover effect from Digital economy. u_i, ν_t and ε_{it} denote city fixed effects, year fixed effects, and random disturbance terms, respectively.

Considering that the carbon intensity is influenced by the previous period, that is, there is 'time inertia', the study builds a dynamic spatial Durbin model (DSDM):

$$\begin{aligned}\mathrm{CI}_{i,t} = {} & \alpha_0 + \tau \mathrm{CI}_{i,t-1} + \rho W\mathrm{CI}_{i,t} + \varphi W\mathrm{CI}_{i,t-1} + \alpha_1 \mathrm{Dige}_{i,t} \\ & + \beta W\mathrm{Dige}_{i,t} {}_{+\alpha_k \ Control_{it} + \omega W Control_{it} + u_i + \nu_t + \varepsilon_{it}}\end{aligned} \tag{3}$$

where $\mathrm{CI}_{i,t-1}$ is the lagged one-period carbon emission intensity, τ is the time-−lagged term coefficient, which reflects the path − dependent characteristics of carbon emissions, φ denotes the time and space lagged term coefficient.

4.1.2. Threshold model

To explore the effect of human capital on carbon reduction of digital economy, with reference to Hansen (1999), the panel threshold model can be constructed as follows:

$$\begin{aligned}\mathrm{CI}_{it} = {} & \eta_0 + \eta_1 \mathrm{Dige} * \mathrm{I}(Z \le \delta_1) + \eta_2 \mathrm{Dige} * \mathrm{I}(\delta_1 < Z \le \delta_2) \ \cdots \\ & + \ \eta_n \mathrm{Dige} * \mathrm{I}(\delta_{n-1} \\ & < Z \le \delta_n) + Control_{it} + u_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{4}$$

where Z denotes the threshold variable, and I denotes the indicator function, and δ is the specific threshold value.

4.2. Variables selection

4.2.1. Explained variable

Carbon emissions intensity (CI) refers to carbon dioxide emissions per unit of GDP (CO_2/GDP). Since it takes into account both economic activities and the quantity change of carbon emissions, it provides a more accurate representation of the level of carbon emissions in a city. Refer to Hao and Wei (2015), the formula for measuring CO_2 emissions is as follows:

$$\mathrm{CO}_2 = \mathrm{C}_n + \mathrm{C}_p + \mathrm{C}_e = k\mathrm{E}_n + \gamma \mathrm{E}_p + \phi(\eta \times \mathrm{E}_e) \tag{5}$$

In Eq. (5), C_n, C_p, C_e denote carbon emission from natural gas, liquefied petroleum gas, and electricity, respectively. E_n, E_p, E_e denote the consumption of that, and η is the proportion of coal-fired power in total electricity generation. k, γ and ϕ are carbon dioxide emissions factors.

4.2.2. Explanatory variable

Digital economy (Dige). Digital economy measurements are not standardized in academic circles. Referring to Zhao et al. (2020), considering the data availability and integrity, digital economy in this paper includes digital industrialization and inclusive digital finance. In this paper, we standardize the data and adopt PCA to measure the digital economy development. Digital industrialization includes four indicators: telecommunications business volume, mobile phone users, Internet broadband users, and employees in Information transmission, computer services and the software industry.

4.2.3. Control variables

Since urban carbon emissions intensity is affected by a number of factors, by reference to previous literature, the study employs the following control variables to mitigate interference from omitted variables: government regulation (gov) is denoted by the proportion of fiscal spending in GDP of that year; economic development is denoted by the logarithm of GDP per capita(lnpgdp); level of opening (open) is denoted by the logarithm of total trade; Foreign direct investment (FDI) is denoted by the logarithm of the amount of foreign direct investment actually utilized; Financial development (fina) is denoted by the logarithm of the loan balance of financial institutions.

4.3. Data source

Research samples are the cities of China's Mainland during the period of 2011–2018, and exclude cities with seriously missing data. In the end, 275 cities were retained in the panel data. Among them, the data mainly come from the Institute of Digital Finance of Peking University, *China Patent Database of the State Intellectual Property Office*, *China Statistical Yearbook*, *China Urban Statistical Yearbook*, *China*

Table 1. Moran's I test results.

	W1		W2		W3	
Year	Dige	CI	Dige	CI	Dige	CI
2011	0.071***	0.192**	0.242***	0.384***	0.010**	0.023***
2012	0.064***	0.156***	0.243***	0.356***	0.007***	0.019***
2013	0.051***	0.120**	0.199***	0.297***	0.002*	0.014***
2014	0.043***	0.128**	0.183***	0.334***	0.017**	0.018***
2015	0.036***	0.264**	0.163***	0.414***	0.017**	0.040***
2016	0.034***	0.098**	0.162***	0.301***	0.012**	0.018***
2017	0.042***	0.110***	0.187***	0.231***	0.009**	0.033***
2018	0.047**	0.218***	0.208***	0.372***	0.014*	0.044***

Note.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

Environmental Statistical Yearbook, National Research Network, China Economic Net database and so on. A small amount of missing data was completed by interpolation. Table 1 shows the descriptive statistical results of variables.

5. Results and discussion

5.1. Spatial correlation analysis

First, we examine the global spatial correlation of the explanatory and explained variables. Table 1 reports the Moran's I under several different matrices. As shown in Table 1, from 2011–2018, a majority of Moran's I index of digital economy and carbon intensity are significant at the 1% or 5% levels, demonstrating that these two variables both are spatially correlated.

We next depict Moran Scatter Plots (MSP) to analyze the local spatial correlation of the digital economy and carbon intensity. Figures 1 and 2 show the local Moran scatter plots only of 2018 for lack of space. It can be seen that these spots are mostly located in quadrants one and three, with just a few in quadrants two and four. Hence, the carbon intensity and digital economy are characterized by China's spatial clustering.

5.2. Spatial spillover effect analysis

Drawing from Elhorst (2014), this paper adopts Wald and LR tests to make the model selection. As Table 2 indicates, first, Hausman test results reject the original hypothesis at 1% level, implying that fixed effects models should be employed rather than random effects. both the Wald spatial lag test and the LR spatial lag test reject the original hypothesis at the 1% level, indicating that the model is not degradable to SAR; likewise, both the Wald spatial error test and the LR spatial error test significantly reject the original hypothesis, indicating that the model is not degradable to SEM. there may be errors in using SEM and SAR to investigate the spatial spillover effect of digital economy on carbon intensity, the spatial Durbin model (SDM) is more reasonable and robust.

In Table 3, columns (1), (3), and (5) are estimates of static spatial models, and columns (2), (4), and (6) are that of dynamic spatial models. It is pretty obvious that

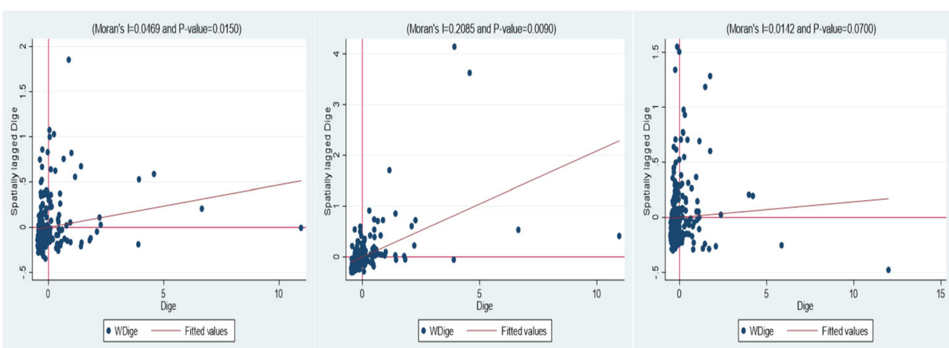

Figure 1. MSP of digital economy in 2018.
Source: Calculated by the author.

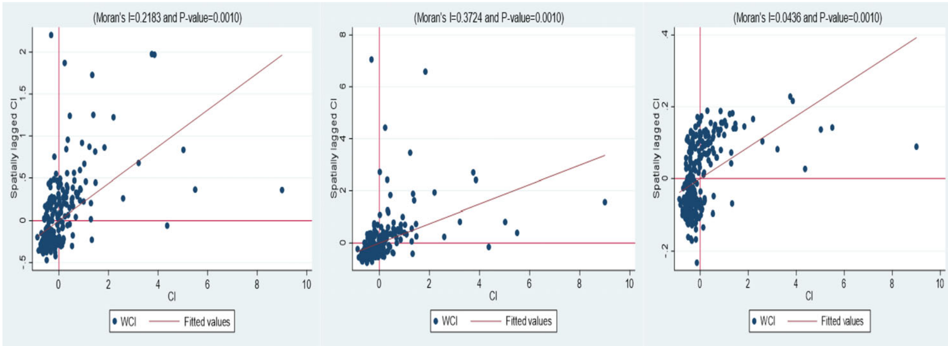

Figure 2. MSP of carbon intensity in 2018.
Source: Calculated by the author.

Table 2. Model comparison.

	W1	W2	W3
Wald spatial lag	11.48***	11.24***	5.21***
	(0.0007)	(0.0008)	(0.0012)
LR spatial lag	11.47***	13.93***	4.62***
	(0.0007)	(0.0002)	(0.0032)
Wald spatial error	9.11**	8.23***	4.85***
	(0.0025)	(0.0041)	(0.0007)
LR spatial error	9.10***	12.30**	3.10***
	(0.0026)	(0.0005)	(0.0078)
Hausman test	25.23***	7.34**	21.26**
	(0.0000)	(0.0005)	(0.0000)

Note. Standard deviations in parentheses, similarly hereinafter.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

Table 3. Spatial effects of digital carbon intensity.

	W1		W2		W3	
	(1)	(2)	(3)	(4)	(5)	(6)
L.CI		0.0539**		0.0305**		0.0849***
		(0.0225)		(0.0224)		(0.0224)
LWCI		−0.398***		−0.211***		−0.592**
		(0.0627)		(0.0359)		(0.202)
Dige	−0.104**	−0.106*	−0.154**	−0.134*	−0.0977**	−0.0760*
	(0.0519)	(0.0642)	(0.0548)	(0.0654)	(0.0518)	(0.0628)
W. Dige	−0.874**	−0.231**	0.0133*	−0.0302*	−0.859**	−0.340**
	(0.355)	(0.225)	(0.0908)	(0.109)	(0.324)	(0.708)
ρ	0.784***	0.266***	0.263***	0.198***	0.780***	0.119**
	(0.0381)	(0.0484)	(0.0240)	(0.0276)	(0.0378)	(0.131)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
W. Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N R2	2200 0.283	1925 0.350	2200 0.240	1925 0.315	2200 0.355	1925 0.388

Note.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

Table 4. Spatial effect decomposition.

	W1			W2			W3		
	Static	Dynamic Short	Long	Static	Dynamic Short	Long	Static	Dynamic Short	Long
Direct effect	−0.120*	−0.103*	−0.109**	−0.155**	−0.129*	−0.131*	−0.113*	−0.0698**	−0.0752**
	(0.050)	(0.0616)	(0.0650)	(0.0542)	(0.0628)	(0.0646)	(0.0508)	(0.0600)	(0.0658)
Indirect effect	−4.431***	−0.319**	−0.184**	−0.0345*	−0.0562**	−0.0203**	−4.240**	−0.312**	−0.168**
	(1.499)	(0.296)	(0.206)	(0.108)	(0.128)	(0.109)	(1.347)	(0.808)	(0.507)
Total effect	−4.550**	−0.422*	−0.287**	−0.190*	−0.185**	−0.151**	−4.353**	−0.382**	−0.243**
	(1.491)	(0.309)	(0.210)	(0.115)	(0.148)	(0.120)	(1.338)	(0.810)	(0.505)

Note.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

under different matrices, spatial autoregressive coefficient ρ of the dynamic, or the static spatial models, all pass the significance level at 1% or 5%, showing that there exists strong spatial dependence in urban carbon intensity, the two conclusions are generally consist. The time-lagged term (L.CI) is significant at 1% or 5% level, indicating that there are obvious path-dependent features of carbon intensity, i.e., higher carbon intensity in the previous period can lead to higher carbon intensity in the next period, thus inducing the 'snowball' effect of environmental pollution. Therefore, the dynamic spatial panel model is preferred, since it can simultaneously take into account endogeneity, time and space. The spatial autoregressive coefficients of the dynamic spatial model are relatively small in comparison with the static model, because the dynamic spatial model can separate the geographical factors, spatial effects and lagged effects from the spatial factors, so as to correct the bias of the above models due to the overestimation of the carbon reduction effect.

The estimation results of the dynamic spatial Durbin model show that the estimates of the spatial lag coefficient (ρ) and the time-lagged term (L.CI) of the dependent variable are both significant at the 1% level, indicating that the carbon emission intensity not only has a spatial spillover effect, but also has a correlation in time; and the coefficient of time and space lag term (L.WCI) is also significant at the 1% level, indicating that the current carbon intensity of cities is influenced by carbon emissions from neighbouring regions. The spatial lagged term of the explanatory variable (W. Dige) is significantly negative, indicating that the digital economy development not only reduces the local carbon intensity, but also has a significant inhibitory effect on the carbon intensity of neighbouring cities.

However, bias exists in the estimated coefficients due to spatial lagged terms for the independent and dependent variables in the spatial Durbin model. According to LeSage and Pac (2009), we decompose the effects into direct effect and indirect effect (spatial spillover effect).

In Table 4, the majority of the direct, indirect and total effect coefficients pass the significance test, suggesting that the digital economy can inhibit the local carbon intensity, and decrease the carbon intensity of surrounding regions via spatial spillover effects. Hypothesis 1 is verified. A comparative analysis of the estimation results under these spatial matrices reveals that the long-term and short-term direct effects do not differ much. While the time variation of the indirect effect is larger. Specifically, the indirect effect under geographical matrix is larger than that of

Table 5. Robustness tests.

	SAR			Data tailing		
	(1) W1	(2) W2	(3) W3	(4) W1	(5) W2	(6) W3
L.CI	0.0648**	0.0349*	0.0931***	0.153***	0.118***	0.191***
	(0.0224)	(0.0225)	(0.0223)	(0.0229)	(0.0228)	(0.0228)
L.WCI	−0.228***	−0.159***	−0.248***	−0.572***	−0.372***	−1.085***
	(0.0380)	(0.0302)	(0.0452)	(0.0637)	(0.0350)	(0.193)
Dige	−0.112	−0.138*	−0.0910***	−0.0839***	−0.126*	−0.0749***
	(0.0645)	(0.0658)	(0.0627)	(0.0586)	(0.0603)	(0.0568)
W. Dige	−0.112**	−0.138*	−0.0910**	−0.0839**	−0.126*	−0.0749**
	(0.0645)	(0.0658)	(0.0627)	(0.0586)	(0.0603)	(0.0568)
ρ	0.475***	0.250***	0.802***	0.333***	0.313***	0.0572***
	(0.0354)	(0.0257)	(0.0412)	(0.0496)	(0.0264)	(0.147)
Controls City FE	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes	Yes	Yes
Year FE R2	Yes	Yes	Yes	Yes	Yes	Yes
	0.224	0.219	0.333	0.465	0.4473	0.564
N	1925	1925	1925	1925	1925	1925

Note.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

economic matrix, revealing that the spatial spillover effect is more 'sensitive' to changes in geographical distance, geographical interaction between cities is relatively important for the spatial correlation effect. From the time dimension, the direct, indirect and total effects of long-term are smaller than short-term ones. This means that digital economy is only in its infancy, its long-term effects are yet to come, and the actual medium- and long-term equilibrium has yet to be reached.

5.3. Robustness tests

To verify the robust and trustworthy of the study, firstly, we re-estimate with the spatial lag model (SAR). Second, in the interest of data robustness, we rerun the regression with data winsorized by 1% to minimize the effects of possible outliers on the regressions. Columns (1)–(3) of Table 5 are the result of SAR regression, and the results of the reduced-tailed data regressions are shown in columns (4)–(6). Most spatial autoregressive and spatial interaction term coefficients are significant, whether the SAR model or the regression after data processing is employed. This proves that the conclusions in the previous section are robust and trustworthy.

5.4. Analysis of impact mechanisms

According to the previous theoretical analysis, industrial structure upgrading, technological innovation and resource allocation efficiency improvement are possible channels. In the study, industrial structure is denoted by the ratio added value of tertiary sector to added value of secondary sector (indst); Technological innovation is denoted by the quantity of patents granted per 10,000 persons (tech); resource allocation efficiency is denoted by the total factor productivity (TFP) of city (Hsieh & Klenow, 2009).

Table 6. Analysis of impact mechanisms.

	(1) CI	(2) indst	(3) CI	(4) tech	(5) CI	(6) TFP	(7) CI
L.CI	0.0539**		0.0527**		0.0506*		0.0539*
	(0.0225)		(0.0220)		(0.0231)		(0.0225)
L.WCI	−0.398***		−0.211***		−0.378***		−0.397***
	(0.0627)		(0.0612)		(0.0660)		(0.0627)
Dige	−0.106*	0.00974**	−0.095*	−0.774***	−0.0577*	0.0605**	−0.102
	(0.0642)	(0.0198)	(0.0626)	(0.0245)	(0.0701)	(0.0255)	(0.0642)
indst			−0.757***				
			(0.0712)				
tech					−0.0565**		
					(0.0448)		
TFP							−0.00535*
							(0.0568)
W. Dige	−0.231*	0.128**	−0.205*	1.263***	−0.215	0.457***	−0.217
	(0.225)	(0.0700)	(0.222)	(0.0884)	(0.250)	(0.0899)	(0.228)
W. indst			−0.0826**				
			(0.227)				
W. tech					−0.00421**		
					(0.207)		
W. TFP							−0.00947*
							(0.0683)
ρ	0.266***	0.149**	0.269***	0.131*	0.263***	1.101***	0.266***
	(0.0484)	(0.0571)	(0.0479)	(0.0564)	(0.0492)	(0.0210)	(0.0484)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE R2	Yes 0.350	Yes 0.479	Yes 0.3503	Yes 0.549	Yes 0.316	Yes 0.261	Yes 0.314
N	1925	1925	1925	1925	1925	1925	1925

Note.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.
Source: Calculated by the author.

In view of space constraints, just mechanism test results under the geographic matrix *W1* are displayed. As shown in columns (2), (4), and (6) of Table 6, the coefficients of *Dige* on the intermediary variables are all significant, suggesting that the digital economy development has a positive impact on industrial structure, technological innovation and resource allocation efficiency. In columns (3), (5), and (7), the significance and absolute value of the coefficient of digital economy on urban carbon intensity decrease when the mediating variables are included in the regression, indicating that industrial structure (Lin & Zhou, 2021), technological innovation and resource allocation efficiency are effective channels, verifying hypothesis 2.

Several previous studies have identified similar channels (Ai et al., 2015; X. Zhang et al., 2020). Upgrading industrial structure is an important means of reducing emissions and conserving energy (Tian et al., 2019; Wen et al., 2022). Technological innovation is crucial for environmental pollution prevention (Irandoust, 2016), as well as energy saving and emission reduction (Shahbaz et al., 2020). Internet development is a powerful medium for introducing, spreading, and innovating new technologies. Furthermore, through information sharing and resource sharing, digital technologies such as the Internet provides efficiency and effectiveness in resource utilization (Acemoglu & Restrepo, 2018; Y. Cao & Shen, 2019). The influence of resource allocation on carbon reduction is rarely mentioned, which can be regarded as a small contribution of this paper.

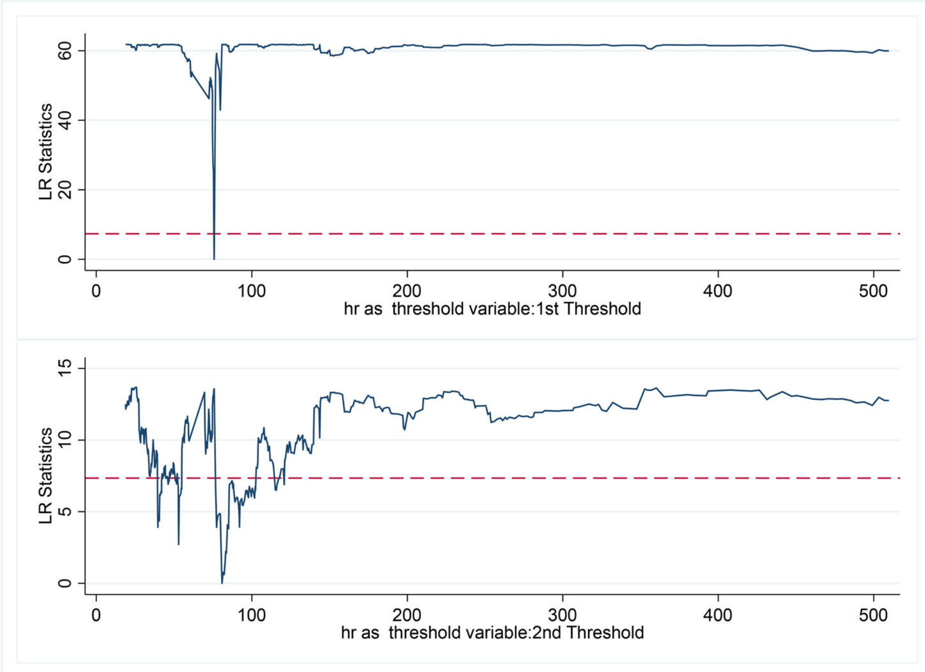

Figure 3. Threshold and confidence interval of threshold variables.
Source: Calculated by the author.

Table 7. Threshold effect test and threshold value estimation results.

	Models	F-value	P-value	Threshold value	95% confidence interval	Threshold value (%) 10	5	1
hr	Single threshold	4.92	0.7900	65.2000	[64.8800 65.4150]	18.2829	27.1965	46.3652
	Double threshold	59.48***	0.0000	75.8100	[75.5400 76.7400]	18.0309	22.3155	49.5004
				80.8400	[80.8400 81.0600]			

Note.
***$p < 0.01$.
Source: Calculated by the author.

Table 8. Regression results for threshold effects.

	(1) CI
hr $\le$75.8100	−0.267 (0.18)
75.8100 $<$ hr $\le$ 80.840	−4.061*** (0.52)
hr $>$ 80.8400	−0.180*** (0.06)
Controls	YES
N	2200

Note.
***$p < 0.01$.
Source: Calculated by the author.

5.5. Threshold effect analysis

To test hypothesis 3, we adopt human capital as a threshold variable for threshold model analysis. The study adopts college students per 10,000 people to measure human capital (hr); Bootstrap is employed to do the threshold effect test. As shown in Figure 3, human capital passes the double-threshold test. As human capital varies, the impact of digital economy on urban carbon intensity shows a nonlinear dynamic change. Table 7 shows the specific test results of the threshold effect.

The estimation of Table 8 suggests that urban carbon intensity is reduced by the digital economy, but the effect is insignificant when human capital level is lower than 75.8100. In the presence of human capital levels beyond 75.8100, the carbon reduction effect becomes significant at the 1% level. That means that only when human capital reaches a specific threshold value will digital economy be able to reduce emissions more effectively. The digital economy takes information networks as the carrier and communication technology as the driving force, all of which are based on specific human capital. In human capital-rich cities, technological advancement can be more easily applied, low-carbon and clean production technologies can be developed and applied more quickly, and energy-intensive industries to be transformed.

When human capital exceeds 80.84, the carbon intensity coefficient decreases in absolute value. This means that the carbon reduction effect has been weakened. This may be because the current training model does not match the demand for talents, resulting in a certain amount of idle human capital. Generally speaking, the quality of human capital affects the carbon reduction effect of the digital economy, and digital economy development places higher demands on human capital under the 'dual carbon' target.

6. Conclusion and recommendations

Achieving the 'double carbon' goal requires not only a transformation of the energy system, but also a broad and profound systemic change of the current economic system. Digital economy will transform economic growth patterns, is one of the major driving forces for achieving energy savings and emissions reduction and promoting green transformation. Analysing the urban panel data in China, we investigate the impact of digital economy on urban carbon intensity, spatial effects and mechanism. Meanwhile, we introduce the panel threshold model to further detect the moderating effect of human capital on this impact. The findings show: First, because there is an interaction between economic activities and carbon emissions over time and space, digital economy not only reduces local carbon intensity, but also radiates to decrease that of neighbouring cities, with obvious spatial spillover effect. Second, digital economy upgrades the industrial structure effectively, facilitates technological innovation, and actualizes efficient allocation of resources, which are crucial for reducing carbon emissions. These are effective channels through which digital economy contributes to carbon reduction. Third, the function of the digital economy in curbing carbon emissions intensity is influenced by human capital, showing a threshold effect, that is to say, the effect of the digital economy on carbon emissions reductions can only be fully realized when human capital crosses a certain threshold. Accordingly, we propose the following recommendations.

Firstly, we must advance the digital infrastructures, consolidate the foundation, and optimize the environment for digital economy development. By strengthening digital connectivity and information sharing for green development, we will provide the hardware and software foundation for achieving 'carbon neutrality' by improving information infrastructure construction, accelerating the popularization of the Internet, and fostering a more robust interconnection of digital technology facilities and information sharing.

Secondly, improve the regional collaborative governance model. On the one hand, we need to strengthen interregional links and build a digital industrial system with an orderly market and consistent goals. Pay attention to the exchange and sharing of talents, information and technology across regions, departments and institutions, build a cooperation platform for cross-organizational interconnection and collaborative innovation and cooperation platforms for inter-organizational connectivity and collaborative innovation. On the other hand, we should build inter-regional joint prevention and control mechanisms and plan the industrial layout from an overall national perspective to avoid pollution transfer caused by regional industrial adjustment. Build an open and unified market system to smooth the spatial spillover channels, maximize the advantages of digital economy in integrating resources across regions and forming a green growth synergistic development network.

Thirdly, strengthen technology innovation, optimize industrial structure and resource allocation, and create a long-term mechanism for carbon emissions reduction. Using digital technology to create diverse innovation platforms, we will intensify technology innovation and create a favourable environment. Increase the research, development, application and popularization of pollution control technology and resource-saving technology. Ensure the transformation of traditional industries with high technology, guide the healthy development of new industries and models, and contribute to forming new industrial systems. The city should improve its business environment, reform its institutional systems, facilitate the flow of digital factors, rationalize resource distribution, and reduce carbon emissions.

Fourthly, establish a sound talent system. Digital talents are the key to improving the speed and quality of digital economy development. We need to promote human resources reform and stimulate the technological innovation effect of innovative human capital. We should train talents in a demand-oriented way, reduce the idleness and mismatch of human capital, and accelerate the digital construction and low-carbon process. In addition, we should expand the knowledge spillover and collective learning effect of human capital, enhance the public's green concept and low-carbon awareness, and guide green consumption and green living.

Disclosure statement

No potential conflict of interest was reported by the authors.

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