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Impact of digital technology on carbon emissions: Evidence from Chinese cities

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Introduction: Promoting the development of digital technology is an important step in meeting the challenge of global climate change and achieving carbon peaking and carbon neutrality goals.

Methods: Based on panel data of Chinese cities from 2006 to 2020, this paper used econometrics to investigate the impact and mechanism of digital technology on carbon emissions.

Results: The results showed that digital technology can significantly reduce carbon emission intensity and improve carbon emission efficiency. These results remained robust after changing the estimation method, adding policy omission variables, replacing core variables, and solving the endogeneity problem. Digital technology can indirectly reduce carbon emissions by promoting green technological innovation and reducing energy intensity, and it plays a significant role in the carbon emission reduction practices of carbon emission trading policies and comprehensive national big data pilot zones. The replicability, non-exclusivity, and high mobility of digital technology help to accelerate the spread of knowledge and information between different cities, which leads to a spillover effect on carbon emission reductions. Our unconditional quantile regression model results showed that digital technology's carbon emission reduction effect continuously decreases with increases in carbon dioxide emissions.

Discussion: The results of this paper provide evidence for the potential use of digital technology in achieving the goal of carbon neutrality, which is of great significance for achieving high-quality innovation and promoting the green transformation of the economy and society.

KEYWORDS

digital technology, industrial robot, carbon reduction, green technological innovation, artificial intelligence, carbon neutrality, spatial spillover effect

1. Introduction

Reducing greenhouse gas emissions, curbing global temperature increases, and striving to achieve the goal of carbon neutrality are initiatives and shared pursuits of humanity in the face of the climate change crisis (Xiao and Peng, 2023). According to the sixth assessment report of the IPCC, "Climate Change 2021: Basis of Natural Science," increases in carbon emissions have led to the accelerated warming of the atmosphere, ocean, and land; the frequent occurrence of extreme weather events such as heat waves, heavy precipitation, droughts and typhoons; and the degradation of nature at an unimaginable speed, posing a significant threat to human survival and the ecological environment. From 2011 to 2020, which is considered the hottest decade in Earth's recent history, the global surface temperature rose by 1.09 degrees Celsius compared with the global temperature during the Industrial Revolution. The fifth assessment report of the United Nations Intergovernmental Panel on Climate Change (IPCC) outlined the scientific rationality of global warming caused by greenhouse gas emissions, among which CO_2 comprises the most significant proportion. Reducing CO_2 emissions will effectively mitigate the problem of global warming. Therefore, "carbon control" is a crucial measure taken by all countries to mitigate global climate change. Human beings and their cities need to face the challenges and opportunities brought by climate change, and they need to progress toward low-carbon transformation at all levels (Holtz et al., 2018). Climate has typical primary attributes of global public goods. In order to deal with the significant global environmental problem of climate change and effectively overcome the "tragedy of commons," it is urgent to establish an international coordination mechanism for climate change to develop low-carbon economies. The international coordination mechanism for climate change (represented by the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement) is based on the principle of "common but differentiated responsibilities" for developed and developing countries, which determines the emission responsibility and emission reduction actions of each country. The realization of the low-carbon transformation of economic development has increasingly become the consensus of the international community to deal with global climate change. As of September 2019, 60 countries have pledged to achieve net zero carbon emissions by 2050 according to the United Nations Framework Convention on Climate Change (UNFCCC).

Carbon emissions mainly come from fossil fuel consumption. Under the constraints of technology and energy structures, carbon emissions are an inevitable byproduct of economic and social development. China is highly dependent on high-carbon fossil energy consumption, and the resource and energy utilization efficiency still requires improvements (Miao et al., 2019). Statistics from the National Bureau of Statistics show that sustained and rapid economic and social development in 2021 generated a massive demand for fossil energy. The total energy consumption for the year was 5.24 billion tons of standard coal, representing a year-on-year increase of 5.2%; coal energy consumption accounted for 56%, while clean energy consumption such as natural gas, water, electricity, and nuclear power only accounted for 25.5%. With the rapid urbanization and industrialization processes, the demand for energy has remained large, and China has faced severe pressure regarding carbon emission reductions (Shi et al., 2018). Since 2006, China has become the world's largest emitter of CO_2. In 2019, China's carbon emissions accounted for 28.8% of the world's total emissions, surpassing the combined share of the United States, the European Union, and Japan (Gao et al., 2019). At the 75th UN General Assembly held in 2020, the Chinese government proposed that China will increase its independent national contributions, adopt more effective policies and measures to peak its CO_2 emissions by 2030, and strive to achieve carbon neutrality by 2060. China's "14th Five-Year Plan" also includes a proposal to "implement a system with carbon intensity control supplemented by total carbon emission control," aiming to reduce energy consumption and CO_2 emissions per unit of GDP by 13.5 and 18%, respectively. Effectively reducing urban carbon emissions has become an urgent practical problem for sustainable economic development.

For a long time, technological progress has been regarded as an essential driving force in solving the profound internal contradiction between economic growth and carbon emission reductions (Li et al., 2017; Xie et al., 2021). The Fourth Industrial Revolution, represented by digital technology (DT), is accelerating changes in the fundamental mode of global economic development and leading to changes in production and organization modes. As a strategic technology for scientific and technological revolution and industrial transformation, DT has and will play a vital role in combating climate change and brings significant opportunities for low-carbon development (Haseeb et al., 2019; Zhang and Li, 2022). Especially in the recent, critical period of rapid economic growth and high-quality development, DT has been endowed with higher green expectations (Axon, 2020; Li et al., 2021; Yang J. 2021). DT can not only reduce information asymmetry through system integration to optimize resource management and decision-making processes, improve government supervision efficiency and reduce supervision costs but also optimize the industrial structure and accelerate the GTI of enterprises through dematerialization instead of the demand for emission-intensive products, thus providing a driving force for carbon emission reductions (Tang et al., 2021). However, DT itself is based on electricity, and the development and operation of energy-intensive infrastructures such as cloud, blockchain, and data centers will lead to more carbon emissions (Yi et al., 2022). With the development of DT, the operating power, speed, and network bandwidth of computers and servers are constantly improving. This will promote the overall digital transformation of society and accelerate the growth of carbon emissions in the digital industry. The development of DT requires large-scale data generation, transmission, and processing, which increases energy consumption in the operation of the digital industry while the total amount of carbon emission exponentially increases; as such, the carbon emissions of the digital industry equal those of the aviation industry (Jones, 2018; Park et al., 2018; Zhou et al., 2019). The more that energy consumption in a data center is optimized, the more energy is consumed. The "Jevons paradox" is therefore becoming feasible.

An urgent question: can DT be used as a "Chinese solution" to reduce urban carbon emissions? If this logic holds, how does DT help reduce carbon emissions? Is there heterogeneity? Clarifying the abovementioned issues will help us better understand the relationship between DT and the low-carbon economy under current conditions. The possible contributions of this paper are as follows. First, the study was based on the facts that the industrial sector is the primary source of carbon emissions and that the manufacturing sector is becoming more automated and intelligent across the production process; this paper innovatively used robot technology to represent DT, verified its influence on carbon emission intensity at the city level, and analyzed whether modern information technology provides technical dividends in terms of the ecological environment. Secondly, based on mechanisms of green technological innovation (GTI) and energy consumption intensity, this paper explored the influence of digital empowerment on carbon emission performance, which enriches and expands the literature on the ecological benefit evaluation of DT. Thirdly, the non-linear influence of DT on carbon emissions was tested using an unconditional quantile model, and a heterogeneity test was conducted according to urban resource endowment and carbon emission control, which helps explain the heterogeneity of the influence of DT on carbon emissions in different regions. Finally, this study considered the spatial spillover effect of DT in reducing carbon emissions. The research conclusions are helpful for the joint actions of administrative departments in different regions to achieve peak CO_2 emissions and carbon neutrality as soon as possible.

2. Literature review

As a new economic form, digital economy undoubtedly has economic, societal, and environmental impacts, and this study considered the influence of DT on carbon emission reductions. In order to evaluate recent research progress, we divided the relevant literature into the following two categories for review.

2.1. The economic effects of digital technology

The influence of the digital economy on economic development is multi-dimensional. At the micro level, digital transformation can significantly improve the information-processing capability of enterprises, promote the flow of information elements within enterprises (Shen and Yuan, 2020), improve the innovation capability of enterprises (Manesh et al., 2020), promote EGS performance (Cheng and Zhang, 2023; Wang et al., 2023; Zhong et al., 2023), optimize organizational structures, and enhance production and operation processes (Hess et al., 2016). Boland et al. (2007) studied the influence of DT on innovation and found that enterprise-distributed technology has strong "technical penetration," which can meet the needs of the complex business–ecology relationship. Using empirical research on Chinese A-share data, He and Liu (2019) found that the digital transformation of enterprises promoted improvements in enterprise performance. At the industry level, some scholars have found that digital technologies can not only improve the efficiency of traditional industries but also trigger the interactive integration and development of multiple industries and lead to new industrial changes. Chen and Yang (2021) found that the digital economy, as a new force of economic transformation, could improve a labor-intensive and heavy industry-based industrial structure to an industrial structure with a high technology level and environmental friendliness. At the macro level, the iterative application of the new generation of information technology helps to optimize ecological systems and policy environments, stimulate the vitality of social innovation, and improve the efficiency of resource allocation. Zhao et al. (2020) found that the digital economy can enhance entrepreneurial activity and promote high-quality economic development using empirical research on the panel data of 222 cities above the prefecture level in China. In addition, several studies have analyzed the impact of DT on trade in services (Zhou L. et al., 2023), total factor energy efficiency (Fu et al., 2023; Huang et al., 2023), knowledge innovation (Orlando et al., 2020; Wang and Li, 2023), economic growth (Qu et al., 2017), air pollution (Yang Z. et al., 2023), and green total factor productivity (Guo et al., 2022; Zhao et al., 2022).

2.2. Impact of digital technology on carbon emissions

The core connotation of the "science and technology for goodness" concept is that science and technology can promote economic development and industrial transformation while enabling society to achieve sustainable development. DT not only produces huge economic benefits but also significantly impacts the current "environmental debt" and carbon emissions because the digital economy has two primary characteristics. First, the application of DT in various economic activities leads to improvements in efficiency. Second, DT leads to more energy consumption, especially the demand for electricity. The former lowers carbon emissions, while the latter increases carbon emissions. Therefore, scholars' conclusions regarding DT's effects on carbon emissions are not consistent. The carbon emission reductions enabled by DT are mainly discussed from two angles: optimizing industrial structures and improving energy efficiency. In optimizing industrial structures, DT has continuously penetrated the service industry, becoming a new engine of service trade and promoting the formation of new green industries. The integrated development of emerging and traditional industries based on data elements and the application and promotion of DT in production practice will promote the transformation of industrial structures into technology-intensive and environment-friendly forms (Zhang and Wang, 2023). Choi (2010) used panel data from 151 countries to investigate the impact of the Internet on service trade and found that the digital economy improved the "non-long-distance trade" of traditional services with the help of DT and information technology and promoted the rapid development of service trade. Furthermore, as an important production factor, data are clean and efficient, which can reduce the dependence on and destruction of natural resources, as well as promote the digital transformation of traditional enterprises. Dong F. et al. (2022) empirically tested the panel data of 60 countries and found that the digital economy had significantly reduced carbon emission intensities by upgrading industrial structures. Technological progress is the main source of economic development, and it often leads to improvements in resource allocation efficiency and production efficiency (Zhou P. et al., 2023). Some studies have also discussed the relationship between digital technologies, energy consumption intensity, and total factor energy efficiency. The rapid development of the digital economy based on digital technologies effectively reduces carbon emissions, which aids the promotion energy saving and emission reductions across the whole production life cycle and provides a new research perspective for our sustainable development and carbon emission reductions (Sahoo et al., 2021; Zhao et al., 2021). DT will reduce power consumption, especially the energy consumption of industrial sectors (Wang J. et al., 2022). Digital transformation is essential to improve energy consumption and reduce carbon emissions. Other studies have pointed out that digital technologies can reduce carbon emissions by promoting manufacturing agglomeration (Li X. et al., 2022), ease the financing constraints of enterprises (Yang G. et al., 2023), improve public awareness (Wang Q. et al., 2022b), and strengthen environmental regulation (Liu et al., 2023).

Zhang et al. (2021) argued that the digital economy has broken the restrictions of geography, time, and space while promoting efficiency improvements in all aspects from production to sales. Based on the panel data of 278 cities in China, Yu et al. (2022) found that when green energy efficiency is low, the digital economy promotes carbon emissions and that when green energy efficiency is high, the digital economy reduces carbon emissions. Green energy efficiency has a threshold variable effect in the relationship between the digital economy and carbon emissions. However, not all researchers believe that DT has a positive effect on the environment. Dhar (2020) pointed out that DT also consumes a large amount of energy, resulting in significant electricity costs. Zhang Q. et al. (2022) pointed out that due to the rebound effect, the scale expansion of DT will increase energy demands and have adverse effects. Hittinger and Jaramillo (2019) found that while smart devices bring convenience to life, the large amounts of data transmission and remote processing supported by data centers consume significant amounts of energy. Sun et al. (2021) found that data centers in the United States consume about 2% of the country's electricity. Jiang et al. (2021) used simulations to show that, without any policy interventions, the bitcoin industry in China is expected to generate 130.5 million tons of carbon emissions in 2024, which will become a major obstacle to China's carbon neutrality goal.

Researchers have explored the digital economy's economic effects and application value from the perspectives of the macro-economy, structural transformation, and environmental governance, engaging in the valuable exploration of the relationship between information and communication technology and carbon emissions. However, the existing literature ignores an important question: Can DT improve carbon emission performance? If so, what path can be used to implement this impact? In this paper, we attempted to integrate DT and carbon emissions into a unified framework, and we studied the realization of the strategic goal of carbon emission reductions under digital empowerment at the city level.

3. Theoretical analysis and research hypothesis

Economic growth is the most important factor of carbon emissions, and reducing carbon emissions is the key to achieving green growth (Chen and Golley, 2014). On the basis of endogenous growth theory, we introduce data, energy input and environmental pollution as input elements to conduct mechanism analysis. According to the framework of endogenous growth, digital technology has direct carbon reduction effect and indirect carbon reduction effect through green technological innovation and energy intensity reduction.

3.1. Direct impact of digital technology on reducing carbon emissions

DT is defined as a combination of information, computing, communications, and connectivity technologies (Bharadwaj et al., 2013). It converts various kinds of information into binary numbers that computers can identify and use to perform operations, processing, storage, transmission, dissemination, and restoration.

According to endogenous growth theory, DT can be seen as a new type of high-quality capital product of enterprises that has resulted in remarkable technological progress by reducing the marginal cost of production. As in typical Schumpeterian patterns of technological progress, DT can break through the time and space constraints of traditional knowledge and technology exchange to a significant extent and spawn new technologies, industries, and formats that are closely related to energy production and consumption—such as energy storage technology, smart grids, new energy industries, intelligent transportation, and distributed energy use systems—that affect urban energy-use efficiency. The high-efficiency integration of AI, distributed energy production and utilization technology, and energy storage technology enables the measurement, control, and prediction of energy from production and transmission on the supply side to consumption and service on the demand side, thus realizing the intensification and refinement of the energy supply. Furthermore, DT can shorten clean energy's research and development cycle through the accurate three-dimensional modeling of natural and geographical conditions to continuously reduce the cost of renewable energy power generation. Clean power generation, such as wind and photovoltaics, will gradually replace fossil fuels (Schulte et al., 2016).

As capital goods, DT can replace other input factors such as energy input, directly reducing the input of high energy consumption factors and reducing carbon intensity; DT can also change the configuration of the production function $F(\bullet)$, i.e., improve the efficiency of resource allocation. DT's function is to improve the information and intelligent operation level of society and the allocation efficiency of production factors in the market (Wang et al., 2021; Wu, 2021). As has been found in some literatures, DT can digitally transform the energy production process and improve total factor energy efficiency (Xu W. et al., 2022), promoting the transition to the green economy.

An important aspect of carbon emission reductions is the real-time supervision, disclosure, and control of carbon emissions (Zeng et al., 2021). According to transaction cost theory, in cases of information asymmetry, both parties may face high transaction costs that will affect the daily business decisions of enterprises. Improvements in the digital infrastructure will lower the cost of information acquisition and dissemination. The rapid dissemination of a large amount of enterprise production and operation data brings new opportunities for the development and efficiency improvements of various industries, effectively improving resource utilization efficiency and reducing carbon emissions (Luo and Yuan, 2023). DT comprises real-time data collection technologies such as the Internet of Things, intelligent sensors, and edge computing. It can sense, analyze, act, and provide feedback on carbon information and is a crucial vehicle for improving the disclosure of carbon information (Zheng et al., 2021). As transaction costs are reduced, according to multi-dimensional sensors, DT enables different enterprise departments and production operations to form connections, communicate across different networks, and dynamically collect various elements, energy, and other information related to enterprise sewage discharge activities in real time. The effective monitoring and accurate predicting of carbon emissions can be used to reduce the costs of monitoring carbon information and improve monitoring efficiency to optimize the carbon emission reduction decisions of governments and enterprises. DT has also facilitated the public's access to information on environmental pollution and assisted government departments in improving environmental governance and reducing corporate carbon emissions through informal environmental regulation channels. In addition, AI has facilitated the sharing of data elements; it can be used to construct intelligent management systems for energy interconnection and global energy distribution networks utilizing element circulation and knowledge and technology spillovers. Traditional chimney-style independent system and island-style management frameworks have evolved into a unified framework management, with comprehensive applications used to realize the overall planning, coordination, and optimization of the whole chain in order to promote the low-carbon development of society and improve energy-use efficiency. Most importantly, carbon trading and finance operations must be connected to DT.

A final important step in reducing total carbon emissions is accelerating the transformation of the emerging technology, advanced manufacturing, and modern service industries (Yang, 2021). Relying on "Metcalfe's Law" of digital networks, DT is reshaping the traditional production model and has produced strong economies of scale, scope, and long tails. It has achieved good results in cross-industry emission reductions (Koomey et al., 2013; Beier et al., 2018; Weigel and Fischedick, 2019). DT is deeply integrated with key carbon emissions areas such as power, industry, transportation, construction, and agriculture. With the gradual popularization of digital carbon reduction applications in these areas, DT can effectively promote energy consumption reductions throughout the life cycle in key carbon emission industries and release the carbon reduction potential of technology. DT can effectively empower enterprises with intelligent green manufacturing and energy management, lead the innovation of green processes and services, and further promote the development of the industry toward intelligent and green practices while increasing the industry's added value and reducing energy consumption and carbon emissions (Lyu and Liu, 2021). For example, in the industrial field, DT optimizes production processes, improves production efficiency, and saves production costs by enhancing the intelligent interconnections of factories, information integration, data-driven decision making, and human–computer collaboration. The automation of the production process and the intelligence of the decision-making process will drive significant changes in the manufacturing process, improve the efficiency of the use of resources such as energy and capital, realize simultaneous improvements in production and carbon efficiency, and significantly reduce the overall social energy consumption.

Based on the above analysis, the following two research hypotheses are proposed.

> H1: DT has emission reduction effects and can significantly reduce urban carbon intensity.
>
> H2: DT can reduce carbon emissions by reducing the energy intensity.

3.2. Indirect channel of green technological innovation

According to the definition of green growth, economic green growth results from technological progress and technological efficiency improvements (Chen and Golley, 2014). As a special kind of environmentally biased technological progress, GTI is essential to reducing energy consumption and controlling carbon emissions (Liu et al., 2020). DT changes A(t) in the production function and promotes GTI. DT also has a strong technology spillover effect, which drives technological innovation in other industries through the change of A(t) to improve the sustainability of green growth.

The three essential ways to promote the peaking of carbon emissions and the goal of carbon neutrality are to continuously reduce the proportion of fossil energy consumption, improve energy efficiency, and develop clean energy, all of which require the support of advanced technological progress, especially the development of GTI. The low carbonization of industries and consumer terminals continuously uses green technologies to transform or replace carbon-based energy technologies that result in high levels of energy consumption and pollution. GTI promotes the deepening adjustment and two-way optimization of energy and industrial structures, encourages green product R&D and market competition, significantly reduces carbon emissions per unit GDP, and ensures economic efficiency improvements and green low-carbon transformation in terms of energy conservation and power conversion. GTI is also widely used in enterprise production and citizens' lives. It can boost cleaner enterprise production, enhance energy efficiency, promote green energy consumption, reduce resource consumption from the production and consumption sides, spawn new energy consumption patterns, and reduce carbon emissions from enterprise production and resident consumption to realize the source prevention and control of carbon emissions. The use of GTI in the energy field can accelerate the development of photovoltaic, wind power, and renewable energy sources and effectively promote the transformation of energy consumption structures to green, low-carbon, and clean energy structures that can directly reduce carbon emissions. Finally, GTI can effectively control the cost of decarbonization and provide corresponding technical support for the research, development, and large-scale application of CO_2 utilization, capture, and storage technology, leading to the "technology dividend" effect and promoting improvements in carbon emission performance.

GTI requires massive R&D investment. R&D innovation activities are characterized by high adjustment costs, uncertain results, and sunk input, making enterprises less willing to take initiatives to carry out GTI. DT can effectively reduce the cost of information search and social transaction costs, as well as promote the agglomeration of innovation resources, which is conducive to realizing technology innovation with high efficiency and low energy consumption (Xing et al., 2019). Generally speaking, digital networks not only promote the healthy and efficient development of digital industrialization with the help of universal and enabling technologies and network connection effects but also bring new production factors such as information, technology, and data to industrial development. This process improves comprehensive technical efficiency and R&D innovation efficiency. Digital networks can strengthen the diffusion effect of digital low-carbon technologies, help accelerate the efficiency of information flow, reduce the cost of knowledge transfer, alleviate information asymmetry in the technology market, promote the green technology spillover of knowledge to other industries and sectors, and facilitate the digital and low-carbon transformation of traditional enterprises. With the help of DT, enterprises can quickly shift toward intelligent and flexible directions, gradually change their energy consumption modes in actual operation, reduce redundancy and intermediate consumption in the production process, stimulate the vitality of scientific research and innovation, and improve carbon emission performance (May et al., 2016). Additionally, DT will force enterprises to develop and apply clean technologies and to promote the formation of DT-based green raw material procurement strategies, low-carbon product production and transformation, intelligent logistics warehousing and sales circulation, and carbon emission reductions.

Technological progress will also drive "learning by doing." DT has a technology spillover effect on production and innovation activities, therefore optimizing internal production processes and management organization forms through learning by doing and reducing some variable costs (Zhu et al., 2022). When DT reduces the cost of production, it can compensate for the green production behavior of industrial enterprises. Generally speaking, through technical progress and learning by doing driven by its technology spillover effect, DT has promoted green economic growth.

Based on the above analysis, this paper proposes the third research hypothesis.

> H3: DT can reduce carbon emissions through the channel mechanism that promotes GTI.

4. Research design

4.1. Variables design

4.1.1. Dependent variable

The dependent variable was carbon emissions (CE). Because of the lack of CO_2 monitoring data at the city level in China, this paper used the apparent emission accounting method to measure carbon emissions. The carbon emission sources of cities were set as direct and indirect energy consumption. Direct energy includes liquefied petroleum gas, coal, and natural gas, and indirect energy includes electricity and heat (Zha et al., 2022). Carbon emissions from direct energy sources were mainly calculated based on the carbon emission conversion coefficients of various energy sources published in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Indirect energy carbon emissions were mainly calculated using the corresponding carbon conversion factor to calculate the carbon emissions generated by electricity and heat consumption. It was assumed that there is only one carbon emission factor for the same local power grid (Glaeser and Kahn, 2010), so the calculation of electric energy carbon emissions was mainly based on the baseline emission factor and urban electric energy consumption of the six major power grids in China. It was also assumed that heat energy is generated by different supply modes, mostly the use of raw coal. In this paper, referring to Wu and Guo (2016), the thermal efficiency value was selected as 70%, the average low calorific value of raw coal was selected as 20,908 kJ/kg, and the total amount of heating was converted into the required amount of raw coal. Finally, direct energy consumption and indirect energy consumption carbon emissions were added together to obtain the total carbon emissions of each city.

4.1.2. Core explanatory variable

The core explanatory variable of this study was digital technology (DT). Industry results in high energy consumption and emission levels, and it is the main source of greenhouse gases (Dong M. et al., 2012). According to the International Energy Agency, the Chinese industrial sector's share of carbon emissions from all sources rose from 71% in 1990 to 83% in 2018, and according to the Cady research report, China's industrial sector accounts for about 70% of all industrial emissions in the country. Given the industry's high energy and high emission characteristics, this paper mainly considered the impact of the introduction of DT to the industrial sector on carbon emissions. With the successive proposal and deepening of "Industry 4.0" and "Made in China 2025," the global industrial system is developing toward automation, integration, intelligence, and green practices. In the field of intelligent manufacturing, industrial robots (as a kind of automation equipment that integrates a variety of advanced technologies) reflect the characteristics of modern industrial technology, such as high efficiency and the combination of software and hardware, and have become essential parts of modern manufacturing systems such as flexible manufacturing systems, automated factories, and intelligent factories. Robots are known as a priority of manufacturing. Therefore, this study used the density of industrial robot installations in each city to represent DT.

Acemoglu and Restrepo (2020) constructed an index of robot density at the regional level in the United States based on the idea of the "Bartik instrumental variable" when studying the impact of robot applications on the labor market in the United States. This method has been widely used in subsequent studies on the social effects of robots (Paul et al., 2020). Based on the common practice of the literature (Wang and Dong, 2020; Dauth et al., 2021; Chen et al., 2022; Xu J. et al., 2022; Ge and Zhao, 2023; Yang and Shen, 2023), this paper constructed a robot density index at the level of prefecture-level cities in China. First, International Federation of Robotics (IFR) industry classification data were matched with 14 two-digit industries in the industry classification of China's national economy. Then, based on each industry's robot and employment data, this paper calculated the industrial robot density index at the industry level. Finally, this paper selected the initial year of the statistical sample as the benchmark year to calculate the weight of robot density in each industry in each city in China. The specific calculation formula is

$$DT_{it} = \sum_{s=1}^{14} \frac{employ_{s,i,t=2006}}{employ_{i,t=2006}} \times \frac{Robot_{st}}{employ_{s,t=2006}} \tag{1}$$

In Eq. (1), DT represents digital technology, $Robot_{st}$ represents the number of industrial robots installed in industry's in year t, $employ_{s,i,t=2006}$ represents the number of people employed in industry s in City i in 2006, $employ_{i,t=2006}$ represents the total number of people employed in City i in 2006, and $employ_{s,t=2006}$ represents the total number of jobs in industry s in 2006.

4.1.3. Mechanism variable

The mechanism variable of this study was green technology innovation (GTI). The quantity and quality of green technology patents can significantly reflect the level of green technology in a region (Zhang and Bai, 2022). In 2010, the World Intellectual Property Organization (WIPO) developed the IPC Green Inventory based on the UNFCCC guidelines linked to the existing IPC classification system and divided green technologies into seven specific areas. This paper used the number of green invention patents to measure GTI. We established the patent type, IPC classification number, announcement date, and application address from the website of China Patent Publication and Announcement of the State Intellectual Property Office through advanced inquiry, and we considered this information along with the patent database of listed companies in China to identify the number of green invention patents authorized by each city in each year.

4.1.4. Control variables

In order to alleviate the endogeneity problem caused by the omission of important variables to the model as much as possible and to obtain more accurate estimation results, this paper selected six control variables according to the existing literature on the influencing factors of carbon emissions (Lenonard, 1984; Valérie, 1999; Dong B. et al., 2012; Bernauer and Koubi, 2013; Danlami et al., 2017; Sapkota and Bastola, 2017; Sheraz et al., 2022). Population density was measured as the ratio of urban area to the resident population at the end of the year, the level of economic development was measured as GDP *per capita*, financial support was measured as loan balance *per capita*, industrial structure was measured as the ratio of the secondary industry's added value to GDP, foreign direct investment was measured as the amount of foreign direct investment utilized by each city, and the intensity of fiscal expenditure was measured as the ratio of government public general budget expenditure to GDP measures.

4.2. Econometric model

To test the impact of DT on carbon emissions, we constructed the following econometric model.

$$\begin{aligned} CE_{it} = \theta_0 + \alpha_1 DT_{it} + \alpha_2 PD_{it} + \alpha_3 LED_{it} + \alpha_4 FS_{it} \\ + \alpha_5 IS_{it} + \alpha_6 FDI_{it} + \alpha_7 FEI_{it} + \nu_t + \lambda_i + \varepsilon_{it} \end{aligned} \quad (2)$$

In Eq. (2), i and t represent city and time, respectively; ε_{it} represents the random disturbance term subject to the white noise process; θ_0 represents the constant term; α represents the regression coefficient; λ_i represents the individual fixed effect; and ν_t represents the time fixed effect.

In order to alleviate the endogeneity of the channel test and the defects of the mediating effect test as much as possible, this paper focused on explaining the influence mechanism of GTI on carbon emissions as part of theoretical analysis and research hypothesis by referring to the idea of the mediating test proposed by Jiang (2022); as such, only the influence of DT on GTI was tested here, and a significantly positive DT regression parameter on GTI indicates that DT can reduce carbon emissions through the channel mechanism of promoting GTI. Classical panel data models only consider individual fixed effects and point-in-time fixed effects to reveal time differences that do not vary across individuals and individual differences that do not vary over time in a sample. Considering the impact of various uncertain factors on entire economies, there is heterogeneity in the response of different individuals to these shocks. In order to overcome the endogeneity and inherent defects of the mediation test method as much as possible, this paper expanded the traditional two-way fixed effect model into an interactive fixed model to establish a mediating effect test equation because an interactive fixed effect model could better fit the data (Bai, 2009). The equations expressing the influence of DT on GTI are

$$GTI_{it} = \theta_0 + \beta_1 DI_{it} + \beta_2 Control_{it} + \nu_t + \lambda_i + \delta_i^{'} F_t + \varepsilon_{it} \quad (3)$$

$$EI_{it} = \theta_0 + \beta_1 DI_{it} + \beta_2 Control_{it} + \nu_t + \lambda_i + \delta_i^{'} F_t + \varepsilon_{it} \quad (4)$$

In Eqs. (3) and (4), the meaning of each code symbol is consistent with that for Eq. (2). Control represents the information set for the control variable, β is the regression coefficient, $\delta_i^{'} F_t$ represents interactive fixed effects (which can be regarded as the product of multidimensional individual effects and multidimensional time effects), F_t is the common factor, and δ_i is the factor load.

4.3. Data sources and descriptive statistics of variables

Following the principle of data availability, this paper used the panel data of 269 Chinese cities from 2006 to 2020 as statistical samples. The original data of the relevant variables involved in the econometric model were mainly sourced from the China Statistical Yearbook, China City Statistical Yearbook, China Energy Statistical Yearbook, China Electric Power Yearbook, National Intellectual Property Office, National Bureau of Statistics, International Federation of Robotics and EPS Database. For very few missing values, we used an interpolation method. The descriptive statistical analysis of each variable is shown in Table 1.

TABLE 1 Descriptive statistics of variables.

Variables	Code	Standard error	Mean	Min	Max
Digital technology	DT	1.2774	0.3821	0.0001	21.6515
Carbon emission	CE	1.1448	6.0509	2.0189	9.5846
Green technology innovation	GTI	1.6087	9.9619	4.2047	15.5293
Population density	PD	0.8815	5.8079	1.5476	7.9155
Level of economic development	LED	0.7055	10.4686	4.5951	13.0557
Financial support	FS	1.1129	10.2185	7.5835	13.8749
Industrial structure	IS	0.2521	3.8248	2.3684	4.4502
Foreign direct investment	FDI	1.8439	9.9179	1.0986	14.9413
Financial expenditure intensity	FEI	0.9361	14.5539	11.72107	18.24054
Energy intensity	EI	−9.6284	0.5735	−11.2660	−7.5322

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5. Empirical analysis

5.1. Baseline regression analysis

Commonly used fitting models for panel data include the Pooled OLS (POLS), fixed effects (FE), and random effects (RE) models; deciding which method was most suitable for sample data in this study required further testing. As seen in Table 2, the results of the F-test rejected the original hypothesis at the level of 1%, indicating that the FE model was better than the POLS model. Furthermore, the results of the Hausman test rejected the original hypothesis at the level of 1%, indicating that the FE model was superior to the RE model. Therefore, this paper mainly analyzed how DT affects carbon emissions according to the regression results of the FE model. As Ozokcu and Ozdemir (2017) stated that Pesaran cross-sectional dependence (Pesaran CD) test is be used here in order to test whether residuals are correlated across countries or not. A Wooldridge test is used to detect serial correlation in panel data. As can be seen from Table 2, the serial correlation and cross-sectional dependence of panel data needed to be alert. Hoechle (2007) stated that it is better to use Driscoll-Kraay (DK) standard errors, if the model is heteroskedastic, autocorrelated, and cross-sectionally dependent. Therefore, considering that there may be heteroscedasticity, cross-section correlation, and sequence correlation in panel data estimation, this paper uses DK standard error for correction by referring to the ideas of existing literature (Driscoll and Kraay, 1998; Dabbous and Tarhini, 2021; Zakari et al., 2022).

In Table 2, column (1) shows the results of not adding any control variables, column (2) shows the results of adding all control variables and not adding individual fixed and time fixed effects, column (3) shows the results of adding individual fixed and time fixed effects but not adding control variables, column (4) shows the results of including all control variables and fixed effects, but the common standard error is used, and column (5) reports the result of DK standard error. The results without individual and time effects showed that the impact of DT on carbon emissions was significantly positive; that is, the digital transformation of enterprises and the use of modern DT may increase carbon emissions. However, the POLS model was the result of uncontrolled factors that change with time, and the reliability of its regression results was low. The results of the two-way fixed effect model in columns (3) and (4) show that the DT regression parameters on carbon emissions were −0.0081 and −0.0102, respectively, and both of them were significant at the level of 1%; these results indicated that DT can reduce carbon emissions, which preliminarily confirmed the research hypothesis 1. In addition, to test whether DT can improve carbon emission efficiency while reducing carbon emissions, this paper replaced carbon emission intensity in formula (2) with carbon emissions per unit of gross domestic product. The results in column (5) of Table 2 show that the DT regression coefficient of carbon emission efficiency was −0.0301, which was significant at the level of 1%; these results indicated that DT can not only reduce carbon emission intensity but also reduce CO_2 emissions per unit of GDP and improve carbon emission efficiency, so DT is essential in dealing with climate change and promoting carbon emission reductions. The main role of DT in emission and carbon reductions is to provide real-time carbon information, and the deep application of DT in the carbon footprint and carbon sink fields can aid the promotion of the digital monitoring, accurate emission measurement and prediction, planning, and implementation efficiency of the energy industry, thus significantly improving energy-use efficiency and directly or indirectly reducing the carbon emissions. Additionally, the DT embedded in the production and development of energy can promote the transformation of energy and the transformation of the energy industry, thus constantly promoting the development of renewable energy, accelerating the substitution of traditional fossil energy consumption, enabling the optimization and upgrading of energy production and consumption structures, and significantly reducing the total amount of urban carbon emissions. Finally, DT can improve traditional industries by reducing their carbon emissions and improving their carbon emission efficiency through technology and management innovation.

TABLE 2 Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.3256*** (11.25)	0.0227*** (2.83)	−0.0081* (−1.67)	−0.0102*** (−2.07)	−0.0102*** (−10.18)	−0.0301*** (−8.43)
LED		−0.0291 (−0.68)		0 0.0845*** (3.72)	0.0845*** (2.97)	−0.1450* (−2.06)
PD		0.2061*** (13.02)		0.7716*** (5.65)	0.7716*** (7.54)	0.5267*** (7.03)
FS		0.4968*** (19.39)		0.0597** (2.32)	0.0597* (1.88)	−0.0131 (−0.32)
IS		0.3940*** (6.24)		0.1559*** (3.11)	0.1559 (1.65)	−0.2947*** (−5.21)
FDI		0.1373*** (14.54)		0.0054 (0.92)	0.0055 (0.72)	−0.0095 (−0.87)
FEI		0.1097*** (4.99)		0.1550*** (4.13)	0.1550*** (3.26)	−0.1196** (−2.60)
Individual effect	No	No	Yes	Yes	Yes	Yes
Time effect	No	No	Yes	Yes	Yes	Yes
R-squared	0.1320	0.5868	0.3665	0.3906	0.3906	0.4512
Hausman test				Prob>chi2 = 0.000		
F-test				Prob > F = 0.000		
Pesaran CD test				49.772***		
Wooldridge test				189.95***		

***, **, and * indicate significance at 1, 5, and 10%, respectively; t-statistics are reported in parentheses.

5.2. Robustness test

The benchmark regression results shown in Table 2 demonstrate that the impact of DT on carbon emissions was found to be significantly negative, which initially confirmed the research hypothesis that DT can reduce carbon emissions. In order to verify the robustness of this conclusion, we used four methods. We first used the robust regression of the S-estimation method to deal with outliers. There may be a small number of outliers in a conventional dataset, and the fair value obtained by FE estimation is not an unbiased estimator. Robust regression modifies the objective function in ordinary least squares regression to fit most data structures while also identifying potential outliers, strong influence points, or structures that deviate from the model assumptions. We secondly increased the number of policy omission variables because the impact of DT on carbon emission is affected by policies related to carbon emission management and digital infrastructures. During the sample period, Chinese government implemented a carbon emission trading policy and a national comprehensive big data experimental zone policy in 2011 and 2016, respectively. The former quantifies and capitalizes carbon emissions, endows them with the attributes of carbon-emitting commodities, and guides enterprises to control and reduce greenhouse gas emissions using market mechanisms. The latter is used to carry out systematic experiments in areas with relatively complete digital infrastructures, focusing on tasks such as data resource management and sharing, data center integration, data resource applications, and big data industry agglomeration. By constantly summing up practical experiences that can be used for reference, replicated, and popularized, the radiation-driven and demonstration-leading effect of the experimental area could finally be formed; considering the importance of policy variables in China's economic operation, this paper incorporated two policies into its model. We thirdly replaced the number of explanatory variables. It takes some time for industrial robots to be installed and constructed over introduction, installation, and production to large-scale application, and the optimization of industrial technology and production processes also needs practical exploration. The influence of DT on carbon emissions may have a specific time lag. This paper used the time lag of DT to replace the original variable. Finally, feasible generalized least squares (FGLS) substitutes the residual vector of each cross-section individual into the covariance matrix of cross-section heteroscedasticity, and the generalized least squares (GLS) method is used to decompose the population variance matrix, and the regression residuals are transformed into residuals satisfying the classical assumptions, and then the ordinary least squares (OLS) method is used for regression. FGLS can correct heteroscedasticity, cross-sectional dependence, and serial correlation caused by panel data and improve the consistency and effectiveness of parameter estimation.

According to the robustness test results shown in Table 3, the DT fitting coefficients of carbon emissions of the four tested methods were −0.0101, −0.0099, −0.0109, and −0.2228, respectively. All of them passed the significance test, indicating that the conclusion that DT reduces carbon emissions was still valid in all models. This, in turn, proved that the benchmark regression results were robust and H1 was valid.

5.3. Endogenous test

Although more control variables were added to the model to alleviate the endogenous problem of missing variables, the endogenous problem caused by measurement errors and reverse causality was still an unavoidable obstacle for causal inference in this paper. For example, in the process of improving the new digital infrastructure, information technologies such as big data, 5G communication, and AI are constantly developing, the public's attention to environmental pollution and greenhouse gases is constantly increasing, and the cost of obtaining environmental information is gradually decreasing, which will make local governments pay more attention to the ecological environments of cities, strictly regulate high-energy-consuming enterprises, and urge enterprises to pay attention to improvements in cleaner production technology for a long time with the help of administrative powers. At the same time, the level of mature intelligence and DT is constantly increasing and the sustainable development and application of clean technologies and industries will eventually produce carbon emission reduction effects. Accordingly, extensive economic development modes are dominant in areas with high carbon emission levels even though technical levels and total productivity are still relatively low. Furthermore, the GDP assessment mechanism forces administrative departments to pay more attention to economic growth and pay less attention to ecological environments. The path of DT in promoting technological innovation and industrial structure upgrading is challenging, and the digital infrastructure in these areas may need to be revised.

This paper used two-stage least squares (2SLS) regression to eliminate endogenous problems. Regarding the setting of tool variables, this paper continued to refer to Bartik's concepts and used the interaction of the first-order lag and difference terms of DT as the first tool variables. In order to prevent the problem of weak tool variables, this paper used the lagging second order of DT as the second tool variable. According to the endogenous test results shown in Table 4, the DT regression parameters of the two kinds of instrumental variables were −0.1115 and 1.4820, respectively, and both of them passed the significance test, which indicated that the influence of instrumental variables on DT was significant and met the principle of correlation. The instrumental variable validity test results

TABLE 3 Results of robust test.

Variable	Method 1	Method 2	Method 3	Method 4
DT	−0.0101* (−1.69)	−0.0099*** (−8.93)	−0.0109*** (−6.06)	−0.2228** (−2.31)
Control variable	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

TABLE 4 Results of endogenous tests.

Variable	First stage	Second stage	SYS-GMM
DT		−0.0115** (−2.05)	−0.0109*** (−3.00)
IV 1	−0.1115* (−1.71)		
IV 2	1.4820*** (112.37)		
Control variable	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes
Time effect	Yes	Yes	Yes
F-test		6353.943	
AR(1)			0.000
AR(2)			0.696
Sargan test			0.397

***, **, and * indicate significance at 1, 5, and 10%, respectively.

showed that the LM statistic rejected the unidentifiable original hypothesis at the 1% level; the F-statistic was 6353.94, much larger than 19.93 of the 10% critical value, indicating that there was no weak tool variable problem. According to the second stage results, the DT regression coefficient of carbon emissions was −0.0015, and it passed the 5% significance test. In addition, in order to further reflect the rigor of the causal inference relationship in this paper, we also convert the static panel data model into a dynamic panel model, and then use the generalzed method of moments (GMM) to eliminate the endogeneity. By introducing the lag term with two or more lag periods as the instrumental variable and satisfying all the moment conditions as far as possible, the GMM estimation method obtains a better estimator. In essence, GMM is also an instrumental variable method. Traditional econometrics estimation methods, such as the ordinary least square method, instrumental variable method, and maximum likelihood method, have their own limitations. That is, its parameter estimator can only be reliable when it satisfies some assumptions, such as when the random error term of the model follows normal distribution or a known distribution. However, GMM does not need to know the accurate distribution information of the random error term, allowing the random error term to exist in heteroscedasticity and sequence correlation, so the obtained parameter estimator is more effective than other parameter estimation methods. The estimation methods of the dynamic panel data model include differential GMM and system GMM. Since the former will generate errors under the influence of weak instrumental variables in the estimation process, while the latter has the advantages of solving the unrecognized individual differences, the influence of variables not taken into account, and the correlation between variables and random items in the estimation, we use system GMM for empirical analysis. According to the results of SYS-GMM in Table 4, the regression coefficient of digital technology is 0.0109 and significant at the 1% level. Meanwhile, the results of AR (1) and AR (2) show that there is no sequence correlation, and the results of the Sargan test show that there is no overidentified problem. These results show that the SYS-GMM model constructed in this paper is effective, and the conclusion that digital technology can reduce carbon emissions is still valid.

To sum up, the results showed that DT's carbon emission reduction effect was still valid after eliminating endogenous problems.

5.4. Mechanism analysis

In order to reveal DT's carbon emission reduction mechanism according to the intermediary effect test equation constructed for research hypotheses 2 and 3, this paper used the interactive fixed effect model for regression calculation.

According to the mechanism analysis test results shown in Table 5, the DT regression coefficients of energy intensity and GTI were −0.0243 and 0.0699, respectively, and both were significant at the 1% level, indicating that DT can promote carbon emission reductions through the channel mechanisms of promoting GTI and reducing energy intensity. H2 and H3 were therefore verified. Under the background of increasingly scarce raw materials (represented here by energy) and worsening environmental pollution, GTI can improve production efficiency, promote sustainable growth, and be a critical link in reducing carbon intensity and carbon emissions, which mainly come from burning fossil energy in high-carbon-emission industries. Therefore, GTI will improve the total factor energy efficiency while promoting the transformation and upgrading of high-energy-consuming enterprises and indirectly affect urban carbon emissions. DT has a strong technology spillover effect that can strengthen the diffusion range, degree, and speed of advanced energy-saving and emission reduction technologies in the field of cleaner production, promote the rapid popularization and application of advanced technologies, further bring about iterative innovation of energy-saving and emission reduction technologies, promote smart industrial clusters, and expand the ecological scene of cleaner industry application, thus reducing carbon emissions. Digital networks, which rely on the Internet, can significantly reduce the social transaction and information search costs, effectively reduce barriers to the flow of production factors between regions, and therefore accelerate the flow of factors, which is conducive to enterprises' access to innovative resources in the value network, thus promoting the overall GTI capability of a city. The development of DT enables enterprises to analyze users' environmental protection needs in real time, which helps enterprises to arrange innovation and production activities according to users' differentiated and dispersed needs (Peng and Tao, 2022). Therefore, DT can reduce carbon emissions through the channel mechanism of promoting GTI.

5.5. Heterogeneity tests

Our benchmark regression results showed that the development of the DT is generally conducive to reducing regional carbon emission intensity. So, does this carbon emission reduction effect have a general rule in different regions? In order to test the heterogeneous regional effect of DT on carbon emissions, this paper classified urban samples according to the classification standard of carbon emission regulation intensity and the development degree of DT facilities. For robustness, this paper added carbon emission trading and comprehensive big data experimental zone policies to control the impact of carbon emission control and digital infrastructure perfection on carbon emissions. Pilot cities and non-pilot cities were divided into two categories by using the pilot status of the two policies in cities. According to the regression results of the carbon emissions trading pilot and comprehensive big data experimental zone policies shown in Table 5, the DT pilot city regression parameters of the two types of policies

TABLE 5 Mechanism and heterogeneity test results.

Variable	Mechanism test		Carbon emission trading policy		Comprehensive big data experimental zone policy	
	EI	GTI	Pilot cities	Non-pilot cities	Pilot cities	Non-pilot cities
DT	−0.0243*** (−4.31)	0.0699*** (4.06)	−0.0217*** (−7.96)	0.0189* (2.10)	−0.0265*** (−7.49)	0.0193*** (2.78)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
N	4,035	4,035	1,365	2,670	1,005	3,030

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

TABLE 6 Regression results of unconditional quantile model.

Variable	10%	25%	50%	75%	90%
DT	−0.0811*** (−3.46)	−0.0524*** (−3.54)	−0.0394*** (−3.41)	−0.0211* (−1.79)	0.0618*** (3.50)
Control variable	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

were −0.0217 and −0.0265, respectively, and both of them passed the significance test of 1%. However, the DT regression parameters in non-pilot cities were 0.0189 and 0.0193, respectively, and both of them passed the significance test. The results showed that DT can significantly reduce the total carbon emissions in pilot cities but significantly increase the carbon emissions in non-pilot cities. A possible reason is that the economic development model of non-pilot cities mainly depends on energy-intensive industries that are more dependent on natural resources, so the pace of industrial structure upgrading lags. The characteristics of industrial structure also have an important influence on the pressure of the urban ecological environment (Zhang B. et al., 2022). For example, in a non-pilot city with a carbon emissions trading policy, the economic development process has not been affected by the carbon market price and the intervention of administrative forces. The primary characteristics of such a city are a high industrial proportion, low total factor energy efficiency, and low level of green technology, and it still faces high pressure regarding carbon emission reduction. Furthermore, non-pilot cities are mainly areas with low economic development levels in the central and western regions; these areas have gradually become “pollution shelters” for transferring energy-intensive industries to developed regions in recent years. The path dependence caused by the “resource curse” makes it difficult for DT and environmental policies to quickly and significantly change the original industrial structure (Li and Zhan, 2022). The dependence on production technology also prevents these areas from adopting cleaner production technology in a short time, and the use of DT is often accompanied by specific energy consumption and carbon emission trends that lead to the significant positive impact of DT on carbon emissions in non-pilot cities (Shi and Li, 2020).

5.6. Non-linearity test

Considering that quantile regression can be used to eliminate extreme interference and describe a conditional distribution in an overall way (Han et al., 2021), five representative quantiles (10, 25, 50, 75, and 90%) were selected to correspond to regions with different carbon emission levels in order to investigate the nonlinear influence of DT on regional carbon emission levels. Table 6 shows that the DT regression parameters from the 10 to 75% quantiles were all significantly negative and that the fitting parameters showed a downward trend, indicating that the emission reduction effect of DT continued to decline with the increase in carbon concentration. In particular, at the 90% sub-site, we found that the DT regression parameter was 0.0618, and it passed the significance test at the level of 1%, indicating that DT does not reduce carbon emissions at this subsite but increase the carbon emissions of similar cities.

Regions with higher concentrations of CO_2 use more energy, and economic development is more dependent on high-carbon natural resources. These regions often have a single industrial structure, and resource-intensive industries dominate. Therefore, it is challenging for DT to generate technology dividends in these regions, and it even generates carbon emissions due to excessive electricity consumption. In 2010, the eastern coastal areas of China launched a policy to transfer energy-intensive industries to developed areas. The economic development model of the eastern coastal areas has achieved a qualitative leap through the industrial gradient transfer, and the high-end manufacturing and modern service industries have rapidly developed; this has lowered the carbon emission concentrations in regions with higher economic development levels. Following these developments, DT can play a better primary role in economic production and a more significant role in carbon emission reductions.

5.7. Empirical analysis of the spatial effect

With its technical advantages of network distribution and decentralization, DT breaks geographical space and time constraints and deepens the correlation degree of economic activities between regions. If the spatial correlation between economic variables is ignored, estimation results will be biased. According to the first law of geography, the correlation between regions is related to distance; the farther the distance, the less the correlation. Since geographic distance factors, regional economic development levels, and other non-geographic factors may affect DT's spillover effect, this paper adopted the weight matrix of economic and geographic distance to depict spatial correlations. As seen in Table 7, the global Moran index (Moran's I) results based on the weighted matrix of economic distance and geographical distance showed that the coefficient of carbon emission and DT was significantly positive, indicating a positive spatial correlation. In order to verify whether the impact of DT on carbon emissions has a spatial spillover effect, this study incorporated a standard two-dimensional panel econometrics model into the spatial location information for verification. However, the regression coefficient value of the spatial econometric model cannot directly reflect the spatial spillover of DT, so this paper adopted the spatial regression with partial differential method to decompose the spatial spillover effect of DT on carbon emissions. The results of correlation diagnostic tests showed that the optimal model of sample data in this study was a two-way fixed effect spatial autoregressive (SAR) model.

Due to the strong dependence of the spatial econometric model on the weight matrix, this paper also calculated the economic distance weight matrix results for the sake of robustness. Table 8 shows the total effect decomposition results of the SAR. The effect decomposition results show that under the two cases of economic distance, the economic and geographic nested matrix, the direct spillover effect, and the total effect of DT on carbon emissions passed the significance level test; furthermore, the influence coefficients were negative, indicating that the estimated results were robust. The results in Table 8 show that carbon reductions in a given region can be achieved with local DT and surrounding cities' DT. In other words, DT has a positive spatial spillover effect on carbon reduction. A possible reason for the spatial spillover effect of DT in reducing carbon emissions is that the rapid development of DT has realized the cross-regional integration and synergistic effect of resources. An essential feature of modern DT is that it weakens the physical space–time distances and enhances the relevance and permeability of regional economic activities using efficient information transmission (Huang et al., 2023). Digital technologies have accelerated the free flow of labor, capital, and knowledge factors of production. Through digital networks, the business, logistics, and capital flow of enterprises operate at high speeds, promoting the innovation of relevant technical knowledge and the adjustment of industrial layouts and bringing digital dividends to realize carbon emission reductions in different regions. At the same time, surrounding cities can take the application of DT as the starting point, the development of a low-carbon economy as the entry point, green and low-carbon industrial clusters as the approach, and local digital infrastructure and resource endowment as the basis to form a green digital economy development mode with the close division of labor, high-efficiency and energy-saving practices, and carbon emission reductions. Therefore, the high-speed transmission of digital information can be used to realize the mutual sharing of carbon emission monitoring data between regions and help the joint prevention and control of carbon emissions between regions.

6. Conclusions and policy implications

6.1. Conclusions

The Index Climate Action Roadmap released by the Global Climate Action Summit in 2020 states that DT solutions in the fields of energy, manufacturing, agriculture, land, construction, services, transportation, and traffic management can help the world reduce carbon emissions by 15%. DT has profoundly changed the habits and motivations of producers, consumers, and investors, and it has provided technical support for enterprises in digital production sectors to reduce emissions and consumption and for non-digital sectors to reduce emissions. This research focused on the digital and intelligent transformation of the manufacturing industry. It innovatively used industrial robots as a proxy variable of DT to investigate its impact on carbon emissions. This paper also evaluated the role of digital infrastructure and carbon emission control systems in the DT process to reduce carbon emissions. Unlike previous nonlinear studies, this paper used unconditional quantiles to test the

TABLE 7 Moran's I of DT and CE.

Year	DT	CE	Year	DT	CE
2006	0.283*** (8.827)	0.415*** (12.50)	2014	0.163*** (5.34)	0.460*** (13.84)
2008	0.327*** (10.30)	0.409*** (12.27)	2016	0.231*** (7.30)	0.472*** (14.17)
2010	0.307*** (9.58)	0.435*** (13.09)	2018	0.241*** (7.65)	0.455*** (13.67)
2012	0.183*** (6.12)	0.439*** (13.20)	2020	0.241*** (7.65)	0.429*** (12.91)

*** denotes significance at the 1% level. z-statistics are reported in parentheses.

TABLE 8 Spatial effect decomposition of SDM.

Variable	Economic distance			Economic and geographical distance		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
DT	−0.0011** (−2.04)	−0.0012* (−1.74)	−0.0112** (−2.04)	−0.0098** (−2.01)	−0.0011* (−1.70)	−0.0109** (−2.01)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes

** and * are significant at the 5 and 10% levels, respectively. *z*-statistics are reported in parentheses.

nonlinear relationship between DT and carbon emissions to make the regression results more consistent with objective reality. Finally, this study used SAR to verify the spatial spillover effects of digital technologies to reduce carbon emissions. Considering the rapid development of DT in China, the urgent task of carbon emission reductions, and the data of 269 cities in China from 2006 to 2020, this paper used the installation density of robots to represent DT according to robot technology use information in the industrial production sector. The influence mechanism of DT development on regional carbon emissions and its heterogeneous effects were empirically tested in multiple dimensions. The major conclusions of this study are as follows.

1. The real-time monitoring provided by digital technologies can significantly reduce urban CO_2 intensity while improving carbon emission efficiency. In other words, DT can significantly reduce carbon emissions. This conclusion was still found to be valid after changing the estimation method, adding policy omission variables, substituting variables, and solving the endogeneity problem, which had strong robustness.
2. The results of the channel test showed that DT reduces the defects of risk uncertainty, limited technical conditions, and asymmetric market information in the process of R&D innovation; stimulates the willingness and ability of enterprises to engage with GTI; and can effectively reduce CO_2 emission intensity. That is, DT can promote carbon emission reductions through the channel mechanism of promoting enterprises' GTI. In addition, digital technologies can enable the digital transformation of energy management and improve overall energy efficiency. In other words, DT can achieve energy conservation and emission reductions.
3. The impact of DT on carbon emissions is characterized by heterogeneity. The carbon emission reduction effect of DT was found to be more significant in regions with solid carbon emission control and better DT facilities. In regions without carbon trading policies and weak DT facilities, DT increases carbon emissions and does not pay technological dividends. Our unconditional quantile regression results showed that DT has had a significantly positive impact on carbon emissions at 90% of the studied loci, which means that DT cannot reduce carbon emission in areas with high CO_2 concentrations. The spatial econometrics model results showed that DT has a spatial spillover effect on carbon emission reductions. That is, the carbon emission of a certain region will be affected by not only the local DT but also the DT of the surrounding cities.

Our study using panel data of Chinese cities showed that DT has a carbon reduction effect, which is consistent with the conclusions of some studies that use provincial-level data from China, such as Meng et al. (2022) and Wang Q. et al. (2022a). Of course, our results are also consistent with some conclusions using transnational panel data analysis, such as Choi (2010), Dong F. et al. (2022), Li Y. et al. (2022). According to endogenous growth theory, DT is a creative destructive force (Aghion and Howitt, 1992). Therefore, according to the theory, we identified mechanisms of promoting GTI and reducing energy intensity, which extends the discussion on carbon reduction mechanism of DT in the existing literature.

Of course, our results are different from those of Dhar (2020), Noussan and Tagliapietra (2020), Dong K. et al. (2022), and others who think that the impact of DT on the environment will be intensified with the expansion of DT scale. The difference in the existing research conclusions is due to differential proxy variables selected for measuring DT and the different measuring of carbon emissions. Unlike Stanford H A I (2019), who built the index system of DT in terms of R&D, technical performance and industrial development, we use industrial robots as a proxy variable of DT, because industrial robots directly reflect the development degree of DT. In China, R&D spending on DT is difficult to clarify. Using industrial robots as proxy variables also reduces the problem caused by the linearity of the index. We use the carbon emission coefficient method to calculate the carbon emission level at the city level, which is more scientific than the input–output method. Because China compiles an input–output table every 5 years, the input–output method is difficult to reflect the real impact of DT on CO_2, especially in recent years, DT has shown explosive growth. In addition, the conclusion of the study may also be influenced by regional heterogeneity. For example, estimates based on developed countries may differ from estimates based on emerging countries, where DT is still in rapid development (Dong K. et al., 2022); In regions with environmental incentives, DT is more likely to promote GTI, and the estimated value should be different (Aghion et al., 2021). DT in China is in the stage of rapid development, and the creative destruction of DT has improved the traditional energy-dependent industrial structure and technological innovation path. At the same time, China is also actively responding to the global climate change mitigation action and reducing carbon emissions in many cities. This is also in accordance with the results of nonlinear analysis in our paper, that is, DT, as a general-purpose technology, is in a rapid development stage. It can promote the innovation of manufacturing production processes and stimulate the second innovation. Under the regulation of green development policies such as the government's carbon trading policy, it will exert the carbon reduction effect.

6.2. Policy implications

Based on the above research conclusions, this paper proposes the following policy recommendations.

1. The development of DT and boost the transformation of low-carbon cities should be accelerated. Administration should vigorously promote the construction of digital technologies such as 5G, cloud computing, the Internet of Things, and related digital infrastructure, as well as guide social and democratic capital to invest in the high-quality development of the digital industry. Relevant administrative departments can guide the in-depth integration and innovative application of digital technologies such as blockchains, industrial robots, and AI with the energy and environment fields and traditional departments through the promulgation of laws and regulations or incentive measures, and they can promote the continuous emergence of new technologies, industries and formats related to low-carbon fields. These practices will accelerate the transformation and upgrading of DT-enabled energy industry departments, optimize the allocation of energy resources, and promote the large-scale utilization of clean energy and

improvements in energy efficiency. Enterprises should pay attention to the technical dividend of digital development, speed up digital investments, actively use DT to optimize resource allocation and management change, improve energy utilization efficiency and reduce carbon emissions. Finally, relevant authorities should promote the transformation of traditional industries toward digitalization and intelligence. With the help of DT, the development potential of urban green transformation should be improved and the role of advanced technology in reducing carbon emissions and improving carbon performance should be given full play.

2. Authorities should correctly handle the relationship between DT and carbon emission by implementing DT according to local conditions to promote carbon emission reduction strategies. In areas with inadequate digital infrastructures and a strong dependence on natural resources, the development of DT may increase carbon emissions. However, the role of DT in energy saving and emission reduction cannot be denied. Developing DT requires an excellent digital infrastructure and more application scenarios. Administrative departments should speed up the digital transformation of industrial bases and resource-based cities according to their resource endowment and economic development advantages, relying on regional resource endowment and industrial development realities. Cities with poor economic development should establish digital industries according to their development characteristics, as well as make full use of DT to transform traditional industries in an overall and whole-chain way while enhancing the suitability of DT to urban industrial structure adjustment with different industrial attributes and resource endowments. Based on new digital technologies, urban development should accelerate the cultivation of new business forms and models and speed up the technological progress and GTI of enterprises. We should strengthen low-carbon technological innovation and digital transformation in resource-based industries, break the curse of structural energy and resources, and constantly unleash the vitality of low-carbon transformation in cities empowered by digital construction. In regions with vital digital infrastructure and carbon emission control, it is necessary to continuously optimize the industrial structure, continuously promote the high-quality integration of DT and the real economy, constantly realize the convergence and multiplier effects of digitalization and industrialization, improve energy efficiency, and stimulate the carbon emission reduction effect of DT.
3. As digital and real integration enters the deep-water zone, because of the mismatch between the skills of current digital talents and the needs of industrial enterprises, digital talents with high levels of integration and strong professionalism should be actively cultivated. It is necessary to cultivate not only senior professional talents who focus on DT development and digital enterprise operation but also first-line technical talents who operate and maintain digital production lines. We should build a digital talent training system that combines academic education, vocational education, and vocational practice, and we should forge a "main force" of multi-level and overall digital transformation. Furthermore, in view of the lack of confidence and capital shortage of enterprises in digital transformation, it is necessary to build a policy system of digital–real integration that conforms to the actual situation and facilitates development and to propose practical measures to support the R&D and introduction of DT to help enterprises overcome difficulties and overcome risks in the process of digital transformation.
4. New infrastructure should be the strategic resource and base for economic and social development. With the acceleration of digital transformation, DT and critical industries are constantly infiltrating and merging. Although the energy consumption and carbon emissions of communication networks and data centers continue to increase, these organizations can promote economic growth and carbon emission reductions of society to a significant extent and promote the low-carbon and harmonious development of the digital economy of society as a whole. We should accelerate digital transformation; constantly carry out technological innovation and industrial structure optimization; promote the development of communication infrastructure toward low-carbonization, digitalization, and intelligence; and promote the coordinated development of DT and "double-carbon" strategy in the communication industry. We should make use of its network advantages, increase cooperation and integration among industries, promote reductions in energy consumption, slow down the growth rate of carbon emissions, and realize the win–win cooperation of leading development and the goal of "double carbon."

6.3. Limitations

1. Measuring the level of digital development in cities can be challenging. In future studies, based on the pilot list of smart manufacturing demonstration factories and digital economy industrial parks, it will be helpful to use regression discontinuity design (RDD), difference-in-differences (DID), and synthetic difference-in-differences (SDID) for the policy evaluation of carbon reduction effects of digital technologies. Similarly, how to accurately measure urban carbon emissions remains a challenging task. Although the study included as many sources of urban carbon emissions as possible, it still faced the problem of inaccurate measurement of carbon emissions. In future studies, it is necessary to consider more carbon sources in assessing carbon emissions. It will be beneficial to use remote sensing data of luminous lamps and GDP data to correct carbon emissions in cities with remote sensing data repeatedly.
2. An essential feature of DT is that it is not constrained by spatial distance. The spatial econometric models used in this study were not cutting edge. In future studies, a semi-parametric spatial model and geographically and temporally weighted regression can be used to estimate the spatial effect.
3. As a typical large-sample research paradigm, this paper reveals the impact of DT on carbon emissions, which can provide a more reliable theoretical basis for policymaking. However, this paper cannot provide detailed guidance for enterprises to introduce and install industrial robots to reduce carbon emissions and environmental pollutants, and relevant case studies must be urgently supplemented.

4. This paper mainly used two variables to explain the channel mechanism of DT to reduce carbon emissions: energy intensity and GTI. Because DT is extensive and inclusive, future research can further elaborate the relationship of DT and carbon emissions from cities through the channels of virtual industrial agglomeration, factor price distortion, and supply chain effect.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XZ conceived and designed the experiments, project administration, and funding acquisition. ZY performed the formal analysis and wrote sections of the manuscript. YS conceptualization, resources, data curation, methodology, software, validation, formal analysis, and writing—original draft and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

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

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