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Impact of computing infrastructure on carbon emissions in China

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The development of computing infrastructure has brought about increased productivity, but it has also brought about energy consumption and carbon emissions. Based on the panel data and business enterprise registration data of 279 prefecture-level cities from 2008 to 2021, using the econometric model system, this study investigates the relationship between computing infrastructure and carbon emission intensity, yielding several findings: First, our result finds that there is an inverse "U-shaped" pattern in the association between carbon emission intensity and computing infrastructure. According to several robustness tests, such as using IV method and PCSD model, the research conclusion still holds. Second, heterogeneity analysis indicates that our findings are particularly pronounced in central regions, hub cities and moderately digitally developed cities. Third, mechanism analysis shows that carbon emission intensity is influenced by computing infrastructure through energy consumption, green technological innovation, and servitization of the economic structure, with energy consumption also following an inverted "U-shaped" pattern. These findings contribute to understanding the environmental impact of digital infrastructure and offer insights for promoting sustainable development.

Keywords Computing infrastructure, Carbon emission intensity, Energy consumption, Green technological innovation, Economic structure servitization

The usage of fossil fuels has led to substantial carbon dioxide emissions, contributing to the rise in global average surface temperatures and intensifying the effects of global warming[1]. Global warming poses a grave threat to humanity's life, making it one of the most pressing global issues of our day[2]. There, every nation has a specific responsibility to cut back on carbon emissions, and major countries have announced carbon neutrality targets[3]. Digital economy is growing at the same time, and digital technologies like 5G and data centers are intricately entwined with the actual economy[4]. Because the amount of data is constantly increasing, computing infrastructure has gradually become a pivotal cornerstone supporting scientific advancement, societal production, and digital governance[5,6]. Computing infrastructure include data center, cloud computing center, and super computing center, mainly undertakes the function of data calculation and storage[7]. While the computing infrastructure serves as the "brain" behind internet services, its power consumption rises with data volume, placing a significant strain on the environment[8,9]. According to IEA data, data centers throughout the world used roughly 460 TWH of electricity in 2022, equivalent to 2% of total global demand. Given the relentless surge in energy demands in the digital sphere, it is critical to keep an eye on how new digital technologies - particularly computing infrastructure - affect the environment.

As an emerging economy, China gives modernizing and optimizing computing infrastructure a level of priority never seen before. In 2023, the Council of State published the 'Comprehensive Plan for the Construction of Digital China', which puts the accent on optimizing the configuration of the infrastructure computer science. In 2024, China has published an action plan to continue the project "Dong Shu Xi Suan" and accelerate the construction of a network national computing power system, which aims to channel computing demand from the eastern to the western regions through an organized approach. This initiative improves the design of data center construction and implements policies to foster collaboration between the eastern and western regions. However, according to the calculation data from the Open Data Center Committee, China's data centers used 93.9 billion kilowatt-hours of electricity in total in 2020, and they released 64.64 million tons of carbon dioxide into the atmosphere. At the same time, as the main emitter and consumer of energy at globally, China is committed to reach Carbon Peaking and neutrality carbon by 2030 and 2060. Then, does the construction of computing infrastructure increase carbon emissions? Will carbon emissions rise steadily if the growth of computing infrastructure results in higher carbon emissions? What is the process via which carbon emissions are affected by computing infrastructure? The solution of the aforementioned issues will support China's digital economy growth in addition to facilitating the enhancement of China's sustainable development plan.

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There are three primary areas where this paper's minor contributions are concentrated. First, our research specifically targets computing infrastructure as the key digital economy factor influencing carbon emissions. While previous studies have generally explored the impact of digital infrastructure on carbon emissions, our focus is on computing infrastructure as the main driver. Compared to broader digital infrastructure, the energy consumption characteristics and carbon emission patterns of computing infrastructure are more concentrated and prominent[10]. With the continuous growth in data volumes, the energy consumption associated with computing infrastructure becomes increasingly prominent, making it a critical source of carbon emissions[11,12]. Therefore, focusing specifically on computing infrastructure allows for a more precise understanding of its impact on carbon emissions, avoiding potential confounding factors introduced by other types of digital infrastructure. Second, we developed a dataset using 200 million samples of business-registered enterprise data, specifically focused on computing infrastructure. We identified relevant keywords covering data centers, cloud computing centers, and super computing centers to more accurately define computing infrastructure. Unlike many current studies that treat computing infrastructure as a homogeneous entity without examining its specific activities[6,7], our paper analyzes its impact on carbon emissions by dissecting key components like computational power, network capacity, and data storage. Third, we argue that the relationship between computing infrastructure and carbon emissions is not simply linear. While data center operations initially produce significant amounts of carbon dioxide[8,9], our findings suggest that carbon emissions decline after reaching a certain threshold, a result supported by our dataset.

Literature review

Based on an information network and using cutting-edge information technology, digital infrastructure is a new type of infrastructure system[13,14]. Building computing infrastructure and expanding processing power are the two most important factors in the development of digital infrastructure. Computing infrastructure provides the requisite physical space for the centralized processing and storage of vast data information, encompassing data centers, super computing centers, intelligent computing centers, and edge computing centers[15]. Based on digital infrastructure and computing infrastructure, some researchers have looked into how digital infrastructure affects innovation, jobs, and the economy[16,17]. Functioning as a crucial facility for data processing and energy storage, computing infrastructure has significantly propelled economic growth. Computing infrastructure engages in the refinement and processing of data elements, transforming them into valuable data products[18], after that, these products are sent to the department of R&D and the final product department, consequently diversifying product offerings and ultimately contributing to rapid economic growth[19]. Digital infrastructure development and ICT industrial innovation have the potential to stimulate creativity and increase the effectiveness of regional innovation[20].

There is less literature on the effect of computing infrastructure and carbon emission, with most of the literature focusing on digital technology and digital infrastructure. Despite the fact of previous study has looked at how digital infrastructure affects carbon emissions, there is no agreement among academics about the environmental effects of digital technology and digital infrastructure. Some scholars argue that digital infrastructure helps to reduce carbon emissions and promote sustainable development[21]. Deng and Zhong found that digital infrastructure not only mitigated carbon emissions, but also exhibited a spatial spillover effect, mitigated carbon emissions in neighboring cities[22]. Using quantile model regression, Hu et al. examined the relationship between digital infrastructure and low-carbon development, finding that digital infrastructure encouraged low-carbon growth[23]. Peng et al. represented digital infrastructure with the "Broadband China" policy, also found that the "Broadband China" policy reduced carbon emissions[24]. About the mechanism, the construction and improvement of digital infrastructure propel enterprises to incorporate data as a key element in production activities, reducing their reliance on traditional elements like capital, labor, and land, thereby enhancing resource utilization and economic efficiency for these firms[25]. Additionally, digital infrastructure leverages the shared and spillover characteristics of digital technologies to speed up knowledge transfer, allowing green technologies from leading companies to disseminate across other sectors, thus facilitating green innovation[26,27]. The application of electronic mobile devices supported by digital infrastructure for online office work, education, and entertainment, reduces residents' need for travel, while simultaneously decreasing environmental pollution associated with these activities[28].

On the contrary, some scholars argue that digital infrastructure itself is energy-intensive, leading to increased carbon emissions[29,30]. Che et al. used panel data from 83 countries to examine the impact of digital infrastructure on carbon emissions, finding that digital infrastructure increases global carbon emissions[31]. Tang and Yang found that digital infrastructure not only increased a city's total carbon emissions, but also increased per capita carbon emissions and boosted carbon intensity[32]. Because of competition effect, digital infrastructure changed the small firm's energy structure and expanded carbon intensity[33]. The manufacturing of electronic components and devices relied upon by the digital industry, as well as the assembly of finished products, are all energy-intensive processes, contributing to increased carbon emissions[34]. Moreover, the expansion and enhancement of digital infrastructure may result in higher carbon emissions if the local energy mix is dominated by fossil fuels. This is because digital infrastructure components, such as data centers and 5G base stations, usually need a constant power supply to function[35,36]. The potential expansion of mobility arising from the integration of digital technologies in the transportation industry could lead to increase energy consumption[37].

In summary, numerous academics have discussed, from various research perspectives, how digital infrastructure affects carbon emissions. One possible explanation for the conflicting results on whether digital infrastructure increases or reduces carbon emissions is that digital infrastructure is measured differently. Some scholars used broadband China policy and smart city policy to measure digital infrastructure[38,39], and some scholars used Internet penetration rate and telecommunication service level to measure digital infrastructure[16,40]. These indicators may not accurately measure the carbon emission effect of digital infrastructure. In addition, as a major component of digital infrastructure, computing infrastructure not only leads to high carbon emissions due to its high energy consumption and rapid growth trend, but also may have great potential to reduce carbon emissions due to technological innovation. Therefore, further evidence is desperately needed to examine the connection between computing infrastructure and carbon emissions.

Theoretical analysis and research hypothesis

Significant amounts of electricity are needed for the installation and maintenance of computing infrastructure. In many countries, natural gas and coal are two fossil fuels that are utilized to generate energy, which directly increase carbon emissions[41]. Rapid expansion of the digital economy increases the need for computing power dramatically, driving the construction of more data centers and exacerbating energy usage and carbon emissions[42]. As computing infrastructure expands, the overall carbon emissions it generates may reach a peak. This peak often occurs during periods of rapid construction, inefficient old equipment, and long upgrade cycles. At this point, carbon emissions are at their highest because so many new facilities are being built while older ones are not being maintained or kept in use. After reaching this peak, technological advancements and efficiency improvements begin to take effect. More efficient processors, optimized data center architectures, and advanced cooling technologies can significantly reduce energy consumption per unit of computing power[43]. Software-level optimizations, such as resource sharing through cloud computing, virtualization, and algorithm optimization, can reduce redundant computing and energy waste. As renewable energy sources like solar and wind power become more affordable and more efficient, more data centers are putting them to use[44]. Furthermore, the enabling effect of computing infrastructure is strong, promoting low-carbon transformations in business production methods and green, low-carbon changes in residents' lifestyles[45]. This dual benefit achieves enhanced economic efficiency and reduced energy consumption and emissions. In conclusion, this research makes the following assumptions:

H1 There is an inverted "U-shaped" nonlinear link between computing infrastructure and carbon emissions.

The energy consumption of computing infrastructure is enormous, requiring a significant amount of electricity to function. Data from China's National Energy Administration indicate that in 2022, around 3% of the country's overall electricity consumption was accounted for by the 270 billion kilowatt-hours that Chinese data centers used. With the rapid advancement of internet digitalization, it is anticipated that by 2025, China's data center electricity consumption would account for 5% of the country's overall electricity consumption. This indicates that during the initial stages of computing infrastructure development, energy usage is high because digital technologies have not yet increased capacity utilization efficiency[46].

Although the energy demand of computing infrastructure is increasing, advancements in hardware and software technology are improving energy efficiency[47]. With the rapid growth of artificial intelligence applications, data centers are transitioning from traditional models to more cloud-based, intelligent, and green approaches. Modern servers and storage systems use less energy, and sophisticated algorithms and software can cut on needless calculations and energy consumption. Computing infrastructure also facilitates the digital and flexible transformation of enterprises[48]. Businesses can enhance their conventional production methods and industrial organization structures, phase out energy-intensive and inefficient businesses, lower energy consumption per unit output, and eventually reduce the intensity of urban carbon emissions by deeply integrating digital technologies[49].

H2 The energy consumption of the computing infrastructure follows an inverted "U-shaped" nonlinear connection, and this has a nonlinear effect on carbon emissions.

Computing infrastructure, with its high penetration and cost-efficiency, promotes green technology innovation[50]. Firstly, it integrates digital technologies, such as cloud computing and big data, into enterprises' R&D and product manufacturing processes. This integration covers various nodes of the industrial chain, breaking the "information silos" between upstream and downstream entities in the green technology innovation ecosystem, thereby enabling the effective allocation of green resources[51]. Secondly, computing infrastructure offers efficient data processing capabilities and powerful computing resources, providing essential technical assistance for the development and use of green technologies. By accelerating the transformation of green technologies from theoretical research to commercial applications, high-performance computing can encourage the development and innovation of green technologies and facilitate their wider diffusion[52].

Cutting carbon emissions is largely dependent on the development of green technology[53]. It focuses on developing and applying environmentally friendly technologies and methods, providing more efficient energy utilization and alternative energy possibilities. For instance, carbon emissions are significantly reduced by renewable energy sources like geothermal, wind, and solar power, which eliminate the need for fossil fuels. Green technology innovation also enhances energy storage and transmission efficiency, making green energy more reliable[54]. In the industrial sector, green technology innovation drives enterprises to improve production processes and equipment, increasing resource utilization efficiency and reducing emissions of carbon dioxide and other pollutants. The application of the circular economy concept, through resource reuse and waste minimization, achieves ecological production processes, thereby reducing carbon emissions[55].

H3 The computing infrastructure declines carbon emissions through green technological innovation.

Computing infrastructure promotes the transition of the economic structure towards a service-oriented model by providing powerful computing capabilities and technical support. By utilizing cutting-edge technologies, businesses may improve operational efficiency and service quality by processing data, analyzing business operations, and making informed decisions more quickly[56]. Traditional manufacturing companies can achieve digital transformation of their production processes through computing infrastructure, for example, by adopting predictive maintenance and on-demand manufacturing, which reduce resource waste and inventory buildup[57]. Additionally, computing infrastructure supports the emergence of digital service models like telemedicine, online education, and e-commerce. In addition to satisfying consumer needs, these service-oriented companies promote economic diversification and modernization[58]. The economy's focus steadily moves from manufacturing to the service and high-tech sectors as more companies and industries embrace digital technologies.

Carbon emissions are greatly reduced by the economic structure's shift to a service-oriented model[59]. Compared to traditional manufacturing, service industries and high-tech industries typically have lower carbon emissions. As e-commerce has increased, the necessity for physical storefronts lessens, optimizing logistics and delivery systems, thus reducing carbon emissions from transportation. There is less need for daily travel due to the growing popularity of remote work and online learning, which further decreasing the use and emissions of transportation vehicles. Furthermore, cutting-edge technologies backed by computing infrastructure, such smart grids and intelligent transportation, can better manage and distribute energy resources, reduce energy loss during transmission, and lower peak load demand, all of which reduce the intensity of carbon emissions[60]. In addition to improving social welfare and economic gains, computing infrastructure is essential for combating climate change and supporting sustainable development since it fosters a service-oriented economic structure.

H4 The computing infrastructure declines carbon emissions through economic structure servitization.

The theoretical framework is illustrated in Fig. 1.

Methodology, variables and data

Model construction

This study aims to assess the influence of computing infrastructure on carbon emission intensity. To achieve this, we build upon the theoretical analysis discussed in the preceding sections and establish a bidirectional fixed effects model, as formulated below:

$$CEI_{it} = \alpha_0 + \alpha_1 CI_{it} + \alpha_2 X_{it} + \delta_i + \sigma_t + \varepsilon_{it} \tag{1}$$

In this model, CEI_{it} shows the city i's carbon emission intensity in period *t*, while CI_{it} shows the city i's computing infrastructure development indicator in period *t*. Control variables are present in vector *X* that capture other city-level characteristics influencing carbon emission intensity, such as economic development, financial development, population density, and environmental regulation. δ_i represents city fixed effects, σ_t represents time fixed effects, and the random disturbance term is denoted by ε_{it}. α_0 is the intercept term, and α_1 is the coefficient for the computing infrastructure variable.

In order to assess the possible nonlinear link between computing infrastructure and carbon emission intensity, this study expands Model (1) by incorporating the squared term of the main explanatory variable, computing infrastructure. The resulting fixed effects model is structured as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 CI_{it} + \alpha_2 CI_{it}^2 + \alpha_3 X_{it} + \delta_i + \sigma_t + \varepsilon_{it} \tag{2}$$

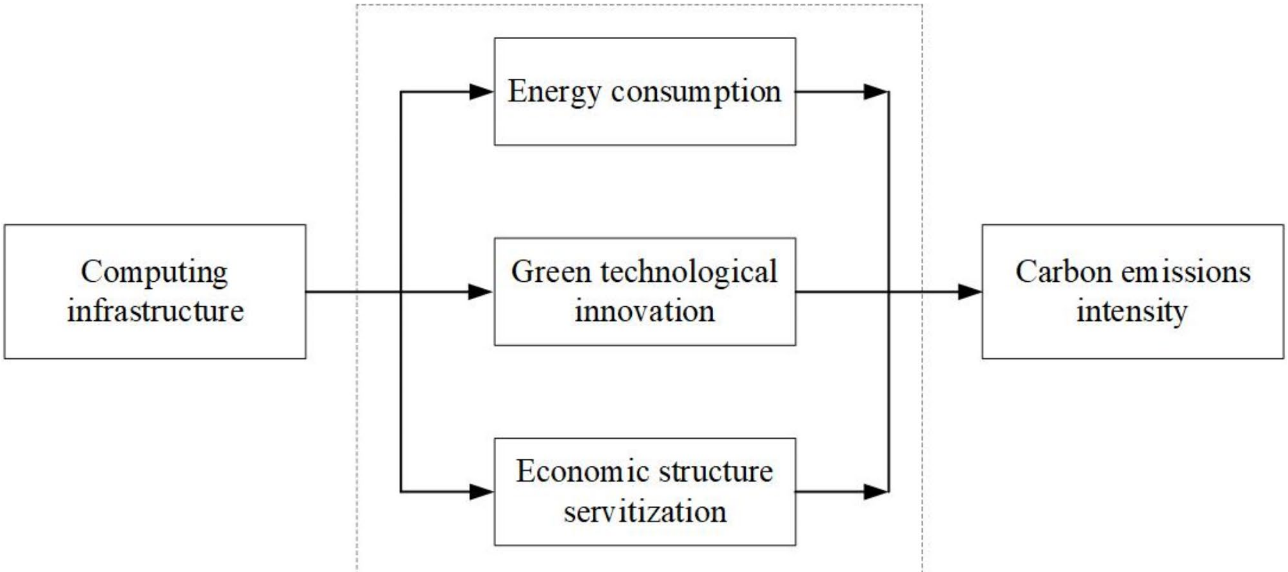

Fig. 1. A theoretical framework of computing infrastructure on carbon emission intensity.

To further clarify the process by which computing infrastructure influences the intensity of urban carbon emission, this study adopts the method and employs a mediation analysis model. Specifically, using Model (2) as a foundation, the study develops two mediation models as outlined below:

$$med_{it} = \beta_0 + \beta_1 CI_{it} + \beta_2 CI_{it}^2 + \beta_3 X_{it} + \delta_i + \sigma_t + \varepsilon_{it} \tag{3}$$

$$CEI_{it} = \lambda_0 + \lambda_1 CI_{it} + \lambda_2 CI_{it}^2 + \lambda_3 med_{it} + \lambda_4 X_{it} + \delta_i + \sigma_t + \varepsilon_{it} \tag{4}$$

In Eqs. (3) and (4), the mediating variables are represented by med_{it}, which cover urban energy consumption, green technology innovation, and economic structure servitization. The examination of the mediation model involves three steps. Firstly, estimating the coefficients α_1 and α_2 in Model (2) to test the effects of computing infrastructure and its square term on urban carbon emission intensity. Secondly, estimating the coefficients β_1 and β_2 in Model (3). Finally, estimating the coefficients λ_1 and λ_2 in Model (4). If all these coefficients are significant, it implies that the impact of computing infrastructure on urban carbon emission intensity is somewhat mediated by the mediating variable.

Variables measurement

Explained variable

Carbon emission intensity (denoted by *CEI*). Gas emissions, liquefied petroleum gas consumption, electricity generation, and heat generation are all included in the category of urban carbon emissions[61]. To illustrate the scope of urban carbon emissions, prior research frequently used statistics on overall carbon emissions[62]. However, this study emphasizes efficiency considerations by focusing on carbon emission intensity. Following Shao et al.[63], The ratio of carbon emissions to the gross regional product is used in this study.

Core explanatory variable

Computing infrastructure (expressed by *CI*). Given the scarcity of research on measuring computing infrastructure levels and the absence of direct data on this topic, this study leverages insights from the "Action Plan for High-Quality Development of Computing Infrastructure". It defines computing infrastructure as a modern information system integrating computational power, network capacity, and data storage, primarily serving computing needs in society. Building on a thorough examination of the "Action Plan for High-Quality Development of Computing Infrastructure", the study identifies keywords related to computational power, network capacity, and data storage, as detailed in Table 1. It then filters business-registered entities, preserving those with relevant keywords within their business scope as computing-related enterprises. These computing-related enterprises are subsequently aggregated by city and year, providing the total and newly added counts for each period. For the analysis in this chapter, the count of newly added computing-related enterprises is utilized to gauge the level of computing infrastructure in each city. The spatial distribution of CI from 2008 to 2021 is displayed in Fig. 2. In the descriptive statistical and empirical analysis that follows, we divide the computing infrastructure data by 10,000.

Control variables

Based on prior literatures[64,65], we choose six control variables: Economic Development Level (*agdp*), assessed through urban per capita GDP; Population Density (*density*), derived from the population count per square kilometer; Financial Development Level (*fin*), determined by dividing year-end bank loan balances by GDP; Government Intervention Level (*gov*), determined by deviding local government spending by GDP in the region; Technological Progress Level (*tech*), signified by the proportion of local scientific expenditure to the general budget; and Environmental Regulation Level (*envir*), assessed by the amount of terms to the environment in government work reports.

Mechanism variable

Energy Consumption (*ec*): Following Chen[66], 10,000 tons of standard coal equivalent (tce) are used in this study to quantify energy consumption. Green Technology Innovation (*gti*): Following existing research, this study looks at the quantity of green patent applications. Economic Structure Servitization (*esc*): In order to quantify the degree of economic structure servitization in cities, this study compares the added value of the tertiary sector to that of the secondary industry.

Computing infrastructure	Keywords
Computational power	Server, Processor, CPU (Central Processing Unit), GPU (Graphics Processing Unit), FPGA (Field-Programmable Gate Array), ASIC (Application-Specific Integrated Circuit), Computer Technology, Cloud Computing, Edge Computing, Intelligent Computing, Supercomputing, Stream Computing, Graph Computing, In-Memory Computing, Secure Multi-Party Computation, Neuromorphic Computing, Green Computing, Cognitive Computing, Distributed Computing, Blockchain, Data Center, Intelligent Computing Center, Supercomputing Center, Edge Computing Center, Computing Layer
Network capacity	Switch, Router, Optical Transport Network, Internet of Things (IoT), IPv4 (Internet Protocol Version 4), IPv6 (Internet Protocol Version 6), SRv6 (Segment Routing over IPv6), Network Architecture, Network Bandwidth, Network Latency, Optical Fiber Deployment
Data storage	Storage Array, Distributed Storage, Exabyte (EB) Storage, All-Flash Storage, Blu-ray Storage, Storage Medium, Storage Chip, Storage System, Storage Device, Storage Component, Storage Layer

Table 1. Identification of key terms in computing infrastructure.

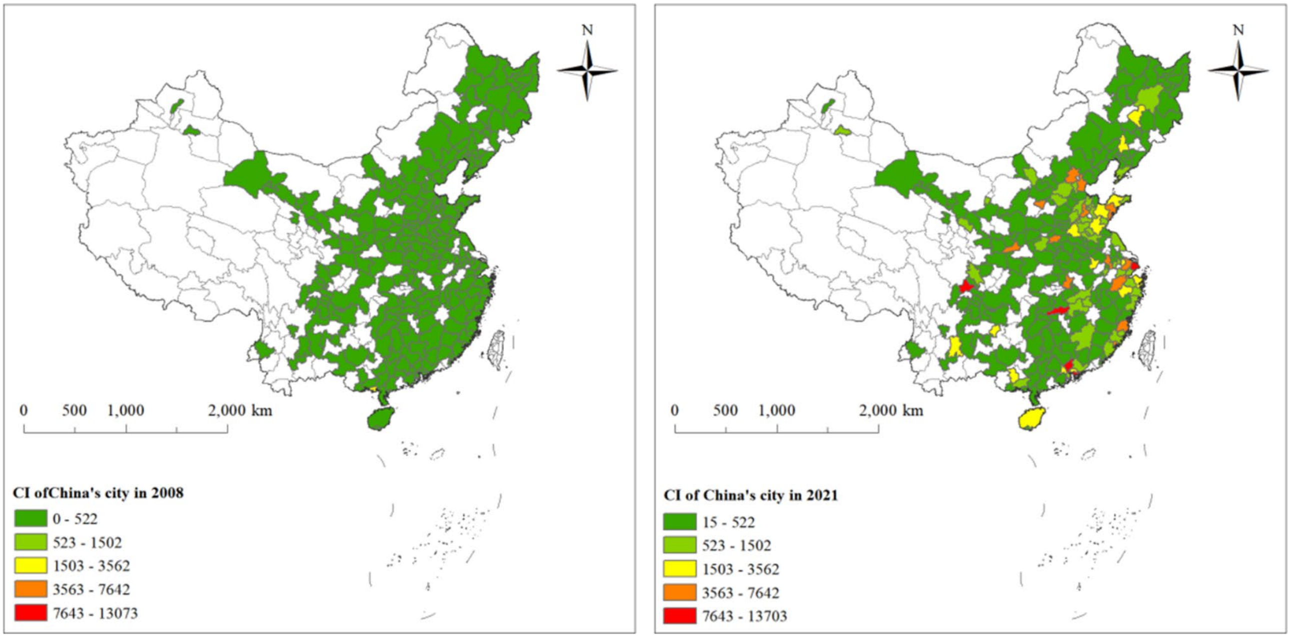

Fig. 2. Spatial distribution of China's CI for selected years (this map was created by authors using ArcGIS 10.8. Source: GS(2019)1822).

Variable name	Symbol	Obs.	Mean	Std. dev.	Min.	Max.
Carbon emission intensity	*CEI*	3906	2.1351	2.3567	0.0424	33.0491
Computing infrastructure	*CI*	3906	0.0359	0.1702	0	4.0141
Economic development	*agdp*	3906	5.0022	3.4083	0.0099	46.7749
Population density	*density*	3906	0.0474	0.0527	0.0005	0.8892
Financial development	*fin*	3906	0.9864	0.6212	0.0753	9.6221
Government intervention	*gov*	3906	0.1911	0.1020	0.0426	1.4852
Technological progress	*sci*	3906	0.0164	0.0164	0.0006	0.2068
Environmental regulation	*envir*	3906	0.0034	0.0014	0	0.0124

Table 2. Descriptive statistics.

Data sources
The study's empirical analysis sample data covers the years 2008 through 2021. We manually collected and processed data on computing infrastructure from nationwide business-registered enterprises. Data on the intensity of urban carbon emissions were taken from the "China Energy Statistical Yearbook", and estimation was performed using the IPCC (2006) reference method along with relevant parameters officially published by China. Energy consumption data for the mechanism variable indicators were taken from the "China Energy Statistical Yearbook", environmental regulation level data were extracted from government work reports. The IPC Green Inventory and the national intellectual property database were cross-referenced to obtain information on green technology innovation via WIPO. Any missing data was collected from city statistical bulletins, the "China Urban Statistical Yearbook" and other city statistical yearbooks were the sources of additional data not specifically specified. Table 2 provides a statistical description of the sample variables.

Table 3 shows the correlation coefficients of the major variables. It can be seen that the correlation coefficient between computing infrastructure and the mean carbon emission intensity is 0.1153, which is significant at 1% level.

Results and discussion
Baseline estimates
We first examine the linear regression results of computing infrastructure on urban carbon emission intensity, and then we analyze the findings from the nonlinear regression. City-level clustering is observed in the baseline estimation outcomes. As shown in Table 4, without control variables, the linear regression results were shown in column (1), with control variables included in column (2). It is observed that the construction of computing infrastructure increases urban carbon emissions, regardless of the inclusion of control variables, which means that computing infrastructure serves as an "accelerator" for carbon emissions. Existing studies generally

	CEI	CI	agdp	density	fin	gov	sci	envir
CEI	1.0000							
CI	0.1153***	1.0000						
agdp	− 0.2436***	− 0.3669***	1.0000					
density	− 0.1420***	− 0.3684***	0.3935***	1.0000				
fin	− 0.0884***	− 0.2821***	0.3034***	0.1638***	1.0000			
gov	0.1217***	0.0635***	− 0.3729***	− 0.2931***	0.1261***	1.0000		
sci	− 0.2165***	− 0.3701***	0.5741***	0.4957***	0.2687***	− 0.3110***	1.0000	
envir	− 0.0095***	0.0195	0.0697***	− 0.0447***	0.0845***	0.0411**	0.0373**	1.0000

Table 3. Correlation coefficient of main variables. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)
CI	0.2685***	0.4073***	0.5617**	0.9271***
	(0.0894)	(0.0961)	(0.2354)	(0.2380)
CI^2			− 0.1082*	− 0.1864***
			(0.0584)	(0.0632)
agdp		− 0.0479		− 0.0515
		(0.0312)		(0.0318)
density		3.1648		2.8996
		(2.4108)		(2.3139)
fin		0.2463**		0.2404**
		(0.1111)		(0.1098)
gov		1.9634*		1.9880**
		(0.9988)		(1.0013)
sci		− 6.3260**		− 6.6651***
		(2.4762)		(2.5102)
envir		− 20.9332*		− 19.0027
		(12.2190)		(11.9816)
Constant	3.0878***	2.7797***	3.0865***	2.7972***
	(0.0603)	(0.2286)	(0.0597)	(0.2286)
City fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	3906	3906	3906	3906
R^2	0.3066	0.3486	0.3069	0.3498

Table 4. Baseline regression results. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

suggest that digital infrastructure promotes carbon reduction and lowers carbon emission intensity. However, considering existing research, this study posits that there may be a nonlinear relationship between computing infrastructure and carbon emissions. Thus, a squared term of computing infrastructure is added to re-examine its impact on urban carbon emission intensity.

Without control variables, the nonlinear regression results are displayed in column (3), control variables are included in column (4). It is found that the coefficient of computing infrastructure is positive, its squared term is negative, respectively, suggesting an inverse "U" shape relationship between computing infrastructure and urban carbon emission intensity. Thus in the early phases of computing infrastructure development, computing infrastructure acts as an "accelerator" for carbon emissions, whereas in the later stage, it works as a "speed bump" for carbon emissions. Additionally, the nonlinear effect passes the U-test, with a value of 2.6871 for the inverted "U" shape's turning point. According to the findings, most cities are at a point where computing infrastructure has a greater carbon-increasing impact than a carbon-reducing one. This study performs a multicollinearity test on the baseline regression results. There is no multicollinearity in the baseline regression, as indicated by the variance inflation factor's mean value of 2.58 that was found, which is less than the critical threshold of 10.

We do a dimensional analysis of the impact of computer infrastructure on urban carbon emission intensity in order to offer a more thorough representation of the link between the two variables. Referencing the "High-Quality Development Action Plan for Computing Infrastructure", computing infrastructure is categorized into computational infrastructure, carrying capacity infrastructure, and storage infrastructure. We investigate each of the nonlinear impacts on the intensity of urban carbon emissions. Table 5 displays the regression findings.

Variable	(1)	(2)	(3)
CI	1.1479***	2.5465***	0.6188**
	(0.2794)	(0.6268)	(0.3077)
CI^2	− 0.2494***	− 2.3455***	− 0.0615*
	(0.0791)	(0.6464)	(0.0320)
Constant	2.7844***	2.8022***	2.7789***
	(0.2278)	(0.2309)	(0.2299)
Control variable	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	3906	3906	3906
R^2	0.3489	0.3496	0.3466

Table 5. Regression results by dimension. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Substituting variables		Modifying sample scope		Changing empirical models	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
CI	0.2901*	0.2006***	0.7011**	1.0097***	0.3745*	0.9100***
	(0.1717)	(0.0547)	(0.3376)	(0.2917)	(0.2224)	(0.2200)
CI^2	− 0.0675*	− 0.0073***	− 0.1381*	− 0.2054***	− 0.0661*	− 0.1837***
	(0.0411)	(0.0025)	(0.0794)	(0.0697)	(0.0461)	(0.0595)
Constant	0.2313***	2.7958***	2.4462***	2.4244***	6.8315***	2.8388***
	(0.0249)	(0.2298)	(0.2179)	(0.2650)	(0.5564)	(0.2792)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3906	3906	3850	3780	3906	3906
R^2	0.2670	0.3504	0.3580	0.3643		

Table 6. Robustness check. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Columns (1) displays the nonlinear effects of computational infrastructure on urban carbon emission intensity. It is evident that, the quadratic term's coefficient is negative and the linear term's coefficient is notably positive in relation to computational infrastructure, which indicates that the impact of computational infrastructure on urban carbon emission intensity is inverted-U shaped. Columns (2) present the nonlinear effects of carrying capacity infrastructure on urban carbon emission intensity. Similarly, the coefficient of the linear term and the quadratic term of the carrying capacity infrastructure are equivalent to the computational infrastructure. Columns (3) outlines the nonlinear effects of storage infrastructure on urban carbon emission intensity. The linear term's coefficient is significantly positive, and the quadratic term's coefficient is notably negative, also demonstrating an inverted-U shape effect. The above results indicate that, whether it is computational infrastructure, carrying capacity infrastructure, or storage infrastructure, the impact on urban carbon emissions initially rises and then falls.

Validity tests

To guarantee the accuracy of the results, we do several validity tests. These checks include substituting the explanatory and dependent variables, modifying sample scope, changing the empirical model, with results presented in Table 6.

Substituting variables

This study conducts robustness checks by substituting both the explanatory and explained variables. First, we replace the explained variable with the total carbon emissions. Columns (1) displays the outcomes. After substituting the dependent variable, there is a notable inverted "U" shape in the relationship between computing infrastructure and urban carbon emissions, indicating that computing infrastructure increases urban carbon emissions in the initial stages of development but decreases them as development matures. Next, we replace the explanatory variable with the total number of computing enterprises providing computing services. The results are shown in columns (2). An inverted "U" shape is still seen in the relationship between computing infrastructure and urban carbon emission intensity, with emissions rising initially and falling afterward.

Modifying sample scope

In the previous baseline regression analysis, it included four municipalities directly under the central government. However, the four cities differ significantly from other prefecture-level cities in terms of economic size and administrative management. Therefore, based on the initial regression sample, this study excluded these four municipalities and then examined the relationship between computing infrastructure and urban carbon emission intensity, with results shown in columns (3). The quadratic coefficient is negative and the linear coefficient is positive, indicating an inverted "U-shaped" impact of computing infrastructure on urban carbon emissions. After excluding the municipalities, this study also removed the sub-provincial city samples, with results presented in columns (4). The data indicates that the impact of computing infrastructure on urban carbon emissions is inverted.

Changing empirical models

This study employs the Panel Corrected Standard Errors model and the Random Effects model to examine the impact of computing infrastructure on urban carbon emission intensity in columns (5) and column (6). According to column (5), the coefficient of computing infrastructure is significant positive and the squared term of computing infrastructure is significant negative. This implies that, in line with the baseline regression results, the relationship between computing infrastructure and urban carbon emissions has an inverse "U-shaped" pattern. The findings of the Random Effects regression on the relationship between computing infrastructure and urban carbon emission intensity are shown in Column (6). Both the first-order and the second-order term of computing infrastructure have coefficients that are consistently significant. As computing infrastructure develops, urban carbon emissions are "accelerated" firstly and "braked" in the end.

Endogeneity analysis

Given the numerous factors influencing urban carbon emission intensity, the current control variables may not encompass all relevant factors, potentially leading to omitted variable bias and endogeneity issues. Consequently, this study introduces instrumental variables to conduct an endogeneity test. Specifically, we use the minimum distance from the centroid of each province to the "Eight Vertical and Eight Horizontal" optical cable backbone cities as an instrumental variable for computing infrastructure to address potential endogeneity issues[67]. Since distance data is cross-sectional, we use the lagged one-period international internet user count to construct panel data for the instrumental variable. This is seen by the interaction term that results from lagged one-period international internet user count and the minimum distance between each city's centroid and the optical cable backbone cities.

Furthermore, we use the methodology of Xie et al.[68] to confirm the reliability of the nonlinear impact estimates of computing infrastructure on urban carbon emission intensity. This involves introducing the first-order and second-order interaction terms between the minimum distance from each city's centroid to the "Eight Vertical and Eight Horizontal" optical cable backbone cities and the lagged one-period international internet user count as instrumental variables for the computing infrastructure and its squared term.

Table 7 displays the results of the instrumental variable estimation. The results, which do not include the computing infrastructure quadratic term, are displayed in columns (1) and (2). The instrumental variable's regression coefficient is significantly negative, indicating that the greater the distance from the "Eight Vertical and Eight Horizontal" optical cable backbone cities, the lower the operational efficiency of the computing infrastructure. After accounting for endogeneity, the impact coefficient of computing infrastructure on the intensity of urban carbon emission intensity stays notably positive. Additionally, there was no weak instrument difficulty in the estimate procedure and the validity of the instruments is confirmed.

<table>
<tr><th>Variable</th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th></tr>
<tr><td rowspan="2">IV</td><td>− 0.0219***</td><td></td><td>− 0.2189***</td><td>− 0.0257***</td><td></td></tr>
<tr><td>(0.0022)</td><td></td><td>(0.0022)</td><td>(0.0071)</td><td></td></tr>
<tr><td rowspan="2">IV^2</td><td></td><td></td><td>− 0.0002</td><td>− 0.0101**</td><td></td></tr>
<tr><td></td><td></td><td>(0.0012)</td><td>(0.0039)</td><td></td></tr>
<tr><td rowspan="2">CI_IV</td><td></td><td>5.0858***</td><td></td><td></td><td>7.8560***</td></tr>
<tr><td></td><td>(0.7902)</td><td></td><td></td><td>(1.2601)</td></tr>
<tr><td rowspan="2">CI^2_IV^2</td><td></td><td></td><td></td><td></td><td>− 2.3391***</td></tr>
<tr><td></td><td></td><td></td><td></td><td>(0.8685)</td></tr>
<tr><td>Control variable</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>City fixed effects</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Time fixed effects</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>N</td><td>3906</td><td>3906</td><td>3906</td><td>3906</td><td>3906</td></tr>
<tr><td colspan="3">Kleibergen-Paap rk LM statistic: 95.134 (0.0000)</td><td colspan="3">Kleibergen-Paap rk LM statistic: 12.509 (0.0004)</td></tr>
<tr><td colspan="3">Kleibergen-Paap rk Wald F statistic: 97.158 (8.9600)</td><td colspan="3">Kleibergen-Paap rk Wald F statistic: 6.240 (6.0300)</td></tr>
</table>

Table 7. Endogeneity analysis. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Columns (3) to (5) present the instrumental variable test results with both the linear and quadratic terms of computing infrastructure. Column (3) demonstrates that the instrumental variable's first-order order term's coefficient is significantly negative. Column (4) reveals that both the first-order term coefficient and the quadratic term coefficient of the instrumental variable are considerably negative. Column (5) indicates that under the instrumental variable estimation, the coefficient of computing infrastructure is positive, the quadratic term coefficient of computing infrastructure is negative, which means that even with endogeneity taken into account, the impact of computing infrastructure on urban carbon emission intensity exhibits an inverse "U" shape, initially increasing and then decreasing. Furthermore, there was no weak instrument issue during the estimating procedure and the validity of the instruments is confirmed.

Heterogeneous analysis

Heterogeneity effects by region

Based on the National Bureau of Statistics of China's classification system, this study divides China into four primary economic areas: Eastern, Central, Western, and Northeastern. Every region's impact of computing infrastructure on urban carbon emission intensity is examined independently, and Table 8 displays the findings of the regression analysis. The findings indicate that computing infrastructure significantly affects urban carbon emission intensity, albeit it varies with geographic location.

As indicated by the regression findings in column (1) and (2), the Eastern region's computing infrastructure has a notable linear impact on urban carbon emission intensity, whereas its nonlinear impact is minimal. This implies that the Eastern region's continuous expansion of computing infrastructure has raised urban carbon emissions without reaching a saturation point. In columns (3) and (4) of the regression findings, both the linear and nonlinear impacts of computing infrastructure on urban carbon emissions are substantial in the Central region. To be more precise, the quadratic term coefficient in column (4) is − 2.6991, which is significantly negative, whereas the linear term coefficient for computing infrastructure is 4.0714, which is notably positive. These results suggest that during the initial developmental stages, computing infrastructure contributes to higher urban carbon emissions, whereas as digital technology advances, it reduces urban carbon emissions during the mature phase. Columns (5) and (6) highlight the significant linear effect of computing infrastructure on urban carbon emission intensity in the Western region, with an insignificant nonlinear effect, demonstrating a rise in carbon emissions from cities as a result of expansion of computing infrastructure. Lastly, in contrast to other regions, the Northeastern region has a significant linear relationship between computing infrastructure and urban carbon emission intensity, as demonstrated by columns (7) and (8), wherein the expansion of computing infrastructure has resulted in a decrease in urban carbon emission intensity. It is determined that the nonlinear effect of computing infrastructure on the intensity of urban carbon emissions is negligible.

The possible cause for the aforementioned outcomes is that the eastern region serves as the primary site of computing infrastructure. As the demand for computing power keeps rising, it directly gives rise to an increase in energy consumption, thereby escalating carbon emissions. Although the western region can take advantage of abundant renewable energy, the technology dissemination is low, and it will lead to an increase in carbon emissions in the short term. The initial construction of data centers in the central region raised carbon emissions, but with efficient equipment, the energy efficiency gradually improved and carbon emissions decreased. The northeastern region has a lower population density, making it more feasible to achieve a low-carbon transition.

Heterogeneity effects by policy

To advance data center planning, optimize supply and demand, promote eco-friendly development and connectivity, and bolster the nation's general computing capacity, the National Development and Reform Commission has sanctioned the establishment of eight national computing hub nodes in key regions. The comprehensive launch of the "Dong Shu Xi Suan" initiative has received approval. Consequently, this study categorizes the 279 cities in its sample into hub cities participating in the "Dong Shu Xi Suan" project and

	Eastern		Central		Western		Northeastern	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI	0.1307***	0.2732	1.7090***	4.0714**	0.8417*	0.3671	− 5.3585*	− 1.2867
	(0.0470)	(0.1766)	(0.6107)	(1.9616)	(0.4867)	(0.9992)	(2.9281)	(6.2740)
CI^2		− 0.0453		− 2.6991*		0.5562		− 21.8166
		(0.0424)		(1.6061)		(1.0677)		(32.2592)
Constant	1.8446***	1.8513***	2.9963***	3.0852***	1.7591	1.7379	2.3831**	2.3258**
	(0.0840)	(0.0838)	(0.3954)	(0.4047)	(1.4878)	(1.5181)	(0.9960)	(1.0566)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1204	1204	1120	1120	1134	1134	448	448
R^2	0.5479	0.5482	0.5053	0.5073	0.4925	0.4922	0.2542	0.2532

Table 8. Heterogeneity effects by region. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	Participating cities		Non-participating cities	
	(1)	(2)	(3)	(4)
CI	0.3359***	0.8971***	1.0069***	1.8352**
	(0.0885)	(0.2460)	(0.3784)	(0.9295)
CI^2		− 0.1828***		− 1.1289
		(0.0609)		(0.8624)
Constant	2.7990***	2.8209***	2.3146***	2.3352***
	(0.2159)	(0.2145)	(0.2652)	(0.2638)
Control variable	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	1442	1442	2464	2464
R^2	0.3987	0.4009	0.3545	0.3548

Table 9. Heterogeneity effects by policy. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	Low-level		Medium-level		High-level	
	(1)	(2)	(3)	(4)	(5)	(6)
CI	0.1133**	0.2115	1.2519***	3.0953**	0.0871	− 1.3198
	(0.0541)	(0.2206)	(0.3949)	(1.2958)	(0.8848)	(3.2814)
CI^2		− 0.0322		− 2.2869*		4.8058
		(0.0545)		(1.2640)		(9.4463)
Constant	2.0787***	2.0841***	2.4278***	2.4907***	3.1098***	3.0863***
	(0.2570)	(0.2591)	(0.2890)	(0.2930)	(0.4306)	(0.4284)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1540	1540	1596	1596	770	770
R^2	0.2053	0.2049	0.5179	0.5196	0.4524	0.4520

Table 10. Heterogeneity effects by the level of urban digital development. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

those not involved, conducting separate analyses on the varied impact of computing infrastructure on carbon emission intensity in different sorts of cities. Table 9 presents the results of the empirical regression in detail.

According to the regression results, computing infrastructure exhibits statistically and economically significant linear and nonlinear effects on carbon emission intensity in the "Dong Shu Xi Suan" project's cities. This indicates an inverted "U-shaped" pattern of computing infrastructure's impact on carbon emission intensity in these hub cities, with an inflection point at 2.4538 as confirmed by the U-test. In contrast, computing infrastructure significantly increases carbon emission intensity along a straight path in non-hub cities of the project, with no nonlinear effects. This outcome can be attributed to the concerted efforts in developing computing infrastructure and enhancing digital technology and product innovation, particularly in regions targeted by the "Dong Shu Xi Suan" project.

The "Dong Shu Xi Suan" project aims to optimize the distribution of data processing and storage capacity across the country. When the "Dong Shu Xi Suan" project is implemented, the construction of new data centers will bring a lot of energy consumption and carbon emissions increase in the short term; As the project progresses, these hub node cities gradually increase the proportion of renewable energy used, thereby reducing their dependence on fossil energy and reducing carbon emissions. For other cities, which have been slower to embrace renewable energy, carbon emissions will continue to increase as the demand for computing power grows.

Heterogeneity effects by the level of urban digital development

In order to investigate the impact of computing infrastructure on urban carbon emission intensity across different levels of digital development, this study draws upon the research by Mao et al.[69] and the Digital Transformation Index. Based on the locations of the firms' digital maturity, the sample is divided into cities with high, medium, and low levels of digital development. The effect of computing infrastructure on each of these cities' carbon emission intensity is then examined separately; the results are shown in Table 10.

The regression analysis reveals that computing infrastructure's influence on cities' carbon emission intensity with lower levels of digital development is solely characterized by a linear effect, devoid of any nonlinear impact. The impact of computing infrastructure on carbon emission intensity exhibits both nonlinear and linear features in cities with moderate degrees of digital development. This observation indicates an inverted "U-shaped" trend in moderately digitally developed cities, where the effect initially rises and then declines. Moreover, the presence of the nonlinear effect is confirmed by the U-test, with an inflection point value of 0.5918 for computing infrastructure's influence on carbon emission intensity. On the other hand, there are no statistically significant linear or nonlinear effects of computing infrastructure on carbon emission intensity in cities with higher degrees of digital development.

One possible cause of these outcomes is that cities with a low digital level are prone to adopt more conventional construction and operation approaches when they initially commence building their computing infrastructure, thereby leading to higher carbon emissions. As the digital economy expands, the demand for computing power in cities with a medium level of digitalization also surges rapidly, and new data centers will be constructed in the short term, causing an increase in carbon emissions. In the later phase, with the advancement of technology, efficient liquid cooling technology will be employed, renewable energy will be gradually introduced, and ultimately dependence on fossil energy will be reduced and carbon emissions will be mitigated. Cities with a higher degree of digitalization already possess a superior green energy system and can better regulate the growth of carbon emissions.

Mechanism test

The empirical result in the baseline analysis shows that there is an inverted "U-shaped" pattern in the relationship between computing infrastructure and urban carbon emission intensity, where emissions are first promoted and then inhibited. The theoretical part clarifies how energy consumption, green technological innovation, and economic structure servitization all affect metropolitan carbon emission intensity in relation to computing infrastructure. To empirically verify whether computing infrastructure affects urban carbon emissions through these mechanisms, this study employs stepwise regression for analysis.

Table 11 presents the results of energy consumption as the mediating variable. Specifically, column (1) examines how the coefficients of computing infrastructure's linear term and computing infrastructure's quadratic term affect urban energy consumption levels after controlling for other variables influencing energy consumption. It is found that the linear term coefficient of computing infrastructure is notably positive and the quadratic term coefficient is considerably negative, which indicates a nonlinear effect where computing infrastructure initially increases and then decreases urban energy consumption. One plausible explanation could be that the digital economy's backbone, computing infrastructure, has a high energy consumption. Early on in development, computing infrastructure operations use a significant amount of energy due to inefficient capacity utilization, which raises carbon emissions. However, when green computing technologies advance and are used more frequently, computing infrastructure can promote digital transformation in enterprises. Big data and cloud computing technologies are being incorporated into business operations to enhance manufacturing processes and phase out energy-intensive businesses, which lowers energy use and carbon emissions. The mediating variable, energy consumption level, is used in Column (2). It is noted that, computing infrastructure linear term's coefficient is still highly positive, and its value decreases compared to column (4) of Table 3. Additionally,

	ec	CEI	gti	CEI	esc	CEI
Variable	(1)	(2)	(3)	(4)	(5)	(6)
CI	7.8539***	0.6274***	0.2480***	0.9207***	0.2352***	0.9101***
	(1.1722)	(0.2351)	(0.0646)	(0.2384)	(0.0730)	(0.2477)
CI^2	− 1.5412***	− 0.1276**		− 0.1827***		− 0.1768***
	(0.2977)	(0.0621)		(0.0639)		(0.0671)
ec		0.0382**				
		(0.0152)				
gti				− 0.0968**		
				(0.0442)		
esc						− 0.2996***
						(0.0594)
Constant	1.0786***	2.7560***	− 0.0209**	2.9860***	1.6154***	3.2850***
	(0.3173)	(0.2254)	(0.0095)	(0.2657)	(0.0841)	(0.2440)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3906	3906	3882	3882	3906	3906
R^2	0.4557	0.3528	0.3932	0.3508	0.4660	0.3642

Table 11. Mechanism test. Values in parentheses are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the coefficient of the computing infrastructure's quadratic term is considerably negative, with an absolute value smaller than that in column (4) of Table 3. The energy consumption level has a considerable favorable impact on urban carbon emission intensity. The initial mechanism by which computing infrastructure influences urban carbon emissions is confirmed by these results, which show that energy consumption level influences the nonlinear effect of computing infrastructure on urban carbon emission intensity.

The effect of computing infrastructure on the degree of green innovation is examined in column (3). It is evident that the computing infrastructure's coefficient is notably positive, indicating that computing infrastructure promotes green technological innovation. This may be due to the rapid diffusion and strong penetration characteristics of computing network technology, which can integrate with energy-saving technologies to promote the green innovative products' dissemination, thereby enhancing levels of green technological innovation. Column (4) incorporates the green innovation mechanism variable. It is observed that the coefficient of the linear term for computing infrastructure remains significantly positive, the quadratic term's coefficient is notably negative. Both coefficients are lower than those in column (4) of Table 3. Additionally, there is a significant negative correlation between the intensity of urban carbon emissions and the amount of green technical innovation, suggesting that higher levels of green technological innovation are associated with lower levels of urban carbon emission intensity. These findings validate the second mechanism.

The effect of computing infrastructure on economic structure servitization is examined in Column (5), where a statistically significant positive coefficient is found. This effect is probably caused by the way computing infrastructure empowers traditional industries, making it easier to modernize and transform important industries like manufacturing and transportation, which in turn creates new low-carbon industries like intelligent manufacturing and smart transportation. These new industries help to overcome the low-end lock-in effect of industrial structures, thereby promoting traditional industrial structures servitization through computing infrastructure. Column (6) incorporates the economic structure servitization mechanism variable. The quadratic term's coefficient is still negative, the linear term's coefficient of computing infrastructure is still positive. This demonstrates that even with the inclusion of the economic structure servitization mechanism variable, computing infrastructure continues to exhibit a reverse "U-shaped" effect on urban carbon emission intensity, where the impact initially increases and then decreases. Additionally, the linear and quadratic factors' coefficients are smaller than those in Table 3's column (4), suggesting that economic structure servitization lessens the impact of computer infrastructure on the intensity of urban carbon emissions.

Conclusions and recommendations

Conclusions

Computing infrastructure has become a key factor in the evolution of the digital economy and a major generator of new economic expansion. However, it has also contributed to substantial carbon emissions and environmental pollution. Investigate the ways in which computing infrastructure influences urban carbon emission intensity is crucial for China's pursuit of sustainable growth and high-quality development. This paper utilizes data on computing infrastructure and urban carbon emission intensity from Chinese cities between 2008 and 2021, establishing a static panel data model to thoroughly examine the underlying effects of computing infrastructure on urban carbon emission intensity. The study explores the relationship between the two variables, conducts a set of robustness tests, and examines the heterogeneity base on urban characteristics. Finally, it investigates the mechanism through which computing infrastructure influences urban carbon intensity, leading to the following conclusions:

Firstly, an inverse "U-shaped" pattern describes how computing infrastructure affects the intensity of carbon emissions in urban areas, and according to the "High-Quality Development Plan for Computing Infrastructure", when computing infrastructure is divided into computational infrastructure, carrying infrastructure, and storage infrastructure, all the three categories have an inverse "U-shaped" impact. Secondly, heterogeneity analysis indicates that our findings are particularly pronounced in central regions, the "Dong Shu Xi Suan" project's cities and moderately digitally developed cities, while its nonlinear characteristic are not significant in other cities. Thirdly, by considering energy consumption level, green technological innovation level, and economic structure servitization level as mechanism variables, the empirical tests reveal that computing infrastructure influences these variables. The study finds that computing infrastructure affects carbon emission intensity through its impact on energy consumption, promoting green technological innovation, and upgrading industrial structures. Specifically, computing infrastructure initially increases and then decreases carbon emission intensity through energy consumption, while through the promotion of green technical innovation and economic structure servitization, it lowers carbon emission intensity.

Recommendations

Based on the aforementioned research findings, the subsequent three policy recommendations are suggested:

Firstly, develop a environmentally friendly, and low-carbon industrial structure system by accelerating the penetration of digital technologies into traditional industries, optimizing the energy consumption structure, and promoting the evolution of industries in the direction of digitalization, intelligence, and low carbonization. Facilitate the advancement of the low-carbon digital industry, taking data center efficiency and smart energy as the starting points, enhance the energy utilization efficiency of data centers, mitigate carbon emissions, and establish a more ecological model for the development of the digital economy.

Secondly, we intend to enhance the impact of green technological innovation and a service-oriented economic structure on the reduction of carbon emissions. Increased environmental regulations on businesses and subsidies for digital low-carbon development are two ways to encourage the development of green technology. The public should be encouraged to travel in a low-carbon manner, select digital low-carbon products, create demand for digital goods and services, support businesses that produce low-carbon and green products, and encourage the upgrading of industries to low-carbon intensification.

Lastly, allow the "Dong Shu Xi Suan" process to have its full impact. This will hasten the construction, upkeep, and alteration of the green data center in the west, force motion data to pass through the prime, and direct the calculation power to shift in a sequential manner. Promote the deep integration of computing infrastructure and energy infrastructure, improve energy efficiency, lay a solid foundation for development, and fully release the carbon emission potential of energy conservation and efficiency. Reaching carbon neutrality and the carbon peak can be accomplished in part by extending the digital industrial chain upward and downward.

Limitations and future research

There are certain limitations to this study that merit additional research: This paper mainly focuses in the impact of computing infrastructure on carbon emissions. Future research could focus on how the integration of computing infrastructure and network infrastructure affects urban carbon emissions. The "Dong Shu Xi Suan" project is similar to a state policy, future research could use the DID model to assess economic and environmental effects of the policy. Regarding the research content, this paper investigates the nonlinear impact of computing infrastructure on urban carbon emissions, future research could focus on whether there exists a spatial effect and the attenuation boundary of such spatial spillover effect.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Declarations

Competing interests
The authors declare no competing interests.

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