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ARTIFICIAL INTELLIGENCE AS AN ACCELERATOR FOR URBAN CARBON EMISSION EFFICIENCY BASED ON SPATIAL DURBIN MODEL

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Abstract

The explosive growth of the Artificial Intelligence market signifies the acceleration of a new phase in the industrial revolution. The challenges of global climate change and rapid technological evolution necessitate innovative approaches to improve carbon emission efficiency. While advancements in renewable energy and carbon capture technologies have been widely explored, the transformative potential of artificial intelligence in optimizing carbon emission efficiency remains underexamined. Based on the data of 285 Chinese cities from 2010 to 2022, this study examines the impact and mechanism of artificial intelligence on carbon emission efficiency through the Spatial Durbin Model (SDM). The research findings indicate that the development of artificial intelligence has effectively promoted the improvement of carbon emission efficiency, and the reduction effect remains consistent across different spatial weights. In terms of mechanism analysis, both technological research and development innovation and environmental policies have enhanced carbon emission efficiency. Finally, some suggestions are put forward to promote the development of artificial intelligence and energy conservation and emission reduction in China.

Keywords

Artificial Intelligence; Carbon Emission Efficiency; Sustainable Development; SDM Model

1. Introduction

In the context of the increasingly serious climate change and environmental pollution, an increasing number of countries are dedicated to advance low-carbon transition strategies, seeking to reconcile economic development with ecological preservation. Nevertheless, the global carbon emission efficiency has stagnated, with an annual growth of merely 1.2% to 1.5%, which is far from sufficient to reach the targets proposed in the Paris Agreement. To cope with global warming and alleviate environmental pressure, facilitating the low-carbon transformation of high-energy-consuming industries is the key to achieving carbon neutrality. Artificial Intelligence (AI), recognized as a catalytic force in green economic transformation (Qian et al. 2023), demonstrates significant potential through its capacity to optimize resource allocation and operational efficiency(Chen and Jin 2023). Hence, as a new technological factor driving industrial transformation and development and promoting technological progress, AI will undoubtedly become an important module for countries to enhance carbon emission efficiency(Ge et al. 2022; Wang et al. 2025)

Currently, artificial intelligence is growing rapidly, and all industries are developing at a fast pace, reshaping the global industrial landscape. According to statistics, it is expected to reach 190.61 billion US dollars by 2025, with an annual growth rate of 37% (Guo et al. 2025). Moreover, the scale of China's artificial intelligence industry has grown from 199.8 billion yuan in 2021 to an estimated 600 billion yuan in 2026 (Zhang et al. 2024). In terms of technological breakthroughs, generative AI has emerged as a key engine. OpenAI have significantly enhanced productivity in multiple fields through automated content generation. According to Gartner's prediction, by 2026, more than 80% of enterprises will integrate such tools (Li et al. 2025b). At the level of technology implementation, AI has deeply permeated multiple domains such as healthcare, finance, manufacturing, and education. Among them, in the healthcare field, the market size in 2023 increased by 42% , reaching 8.6 billion US dollars (Tao et al. 2024; Zhong et al. 2024). Furthermore, through the integration of intelligent computing power networks and algorithm platforms, AI enables smart cities and intelligent manufacturing, promotes industrial optimization and upgrading (Jiang and Yu 2025; Wang and Wang 2025).

Enhancing the efficiency of carbon emissions possesses distinctive advantages in attaining multiple goals, including economic growth, energy consumption reduction, and climate change response(Liu et al. 2022; Ding et al. 2023; Lee et al. 2024a). AI assumes a dual role as both an energy consumer and an enabler of efficiency. On one hand, AI technology is likely to cause a substantial increase in the power consumption and cooling resources demanded by new infrastructure, thereby generating more carbon emissions. On the other hand, in achieving the "dual carbon" goals, AI technology holds great promise. New infrastructure can lower the energy consumption per unit of data transmission through AI technology, significantly enhancing the benefits of carbon reduction. Notably, while the influence of technological advancement on carbon emissions has received considerable attention, as a biased technological progress, AI technology still has considerable scope for in-depth exploration regarding its impact on the "dual carbon" goals. In reaction to this context, numerous studies have commenced focusing on the relationship between AI and carbon emission efficiency, exploring and discussing it from perspectives such as scale effects (Zhang et al. 2024)and structural transformation (Chen et al. 2022), with providing feasible solutions for sustainable development.

The spatial panel econometric model constructed in this study has three advantages: Firstly, it can effectively capture the spatial spillover effects generated by AI through information dissemination and economic connections. AI-driven carbon efficiency improvement is characterized by increasing marginal benefits, breaking through the limitations of the traditional environmental Kuznets curve. Secondly, it can not only quantify the direct impact of local AI on regional carbon emissions but also analyze its spatial radiation effect on neighboring regions, which is in line with the reality of cross-regional transmission of economic activities. Thirdly, by embedding both individual and time fixed effects, this model can precisely handle the complex data structure of multi-city panel data with both spatial and temporal dimensions, thereby ensuring the scientific and reliability of the empirical results. In terms of method, we use the non-expected output super efficiency SBM model to measure the level of carbon emission efficiency. It overcomes the shortcomings of the traditional radial DEA models and the non-radial models. In addition, we use the spatial Durbin model (SDM) to examine the spatial effects of AI on carbon emission efficiency. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 details the research design, including the econometric model, indicators, and data sources. Section 4 presents an analysis of the empirical results, including the benchmark analysis with the spatial effect test and robustness analysis. Section 5 further discusses the mechanisms. Finally, Section 6 concludes the paper and provides policy implications.

2. Literature review

With the rise of the Industrial 4.0 revolution, AI has had a significant impact on the economy and society and has become a key research point (Dehghani et al. 2018; Goralski and Tan 2022). AI refers to the use of machine learning, computer vision, deep learning, and other technologies to imitate human behavior, thereby achieving the replacement of human or mental labor (Liu et al. 2022). AI is a technology that uses machines to replace some human functions, which can automate the production process, improve operational quality, and enhance products and services(Rammer et al. 2022). As a new general-purpose technology (Akter et al. 2024), AI has been widely applied in various aspects such as industrial production, transportation, and service industries. Many scholars have studied the impact of AI on the green economy (Zhang et al. 2024). Among them, one view holds that AI can promote technological innovation and sustainable development, and AI has replaced the market of low-skilled traditional labor, mainly reflected in the application of industrial robots (Rammer et al. 2022; Almuaythir et al. 2024). Another view is that

AI has not improved production efficiency and may lead to the productivity paradox, which is not conducive to economic growth(Kalai et al. 2024).

There is still controversy over the impact of AI on energy and the environment. On the one hand, some believe that the application of AI in the industrial sector can effectively enhance carbon emission efficiency(Chen and Jin 2023; Shan et al. 2025). Through the application of deep learning and big data technologies, energy utilization efficiency can be significantly improved(Tu et al. 2024). (Wang et al. 2023) further pointed out that AI can improve environmental quality by optimizing energy use. This conclusion has been verified in the research on the application of industrial robots in China (Zhao et al. 2024a), which shows that the use of industrial robots can achieve a marginal carbon reduction effect of about 5.44%. On the other hand, AI may also inhibit the improvement of carbon emission efficiency. Due to the large amount of data required for training AI models, this may lead to significant energy consumption (Wang and Wang 2025). Moreover, although the application of AI has improved energy efficiency, it has also reduced the unit energy cost, which may trigger a "rebound effect" (Han and Mao 2024; Lee et al. 2024b; Guo et al. 2025), that is, enterprises may expand their production scale due to the cost reduction, thereby increasing total energy consumption. However, industrial robots, with their precise operations, can significantly optimize production processes and reduce energy waste by 15% to 23%, providing important support for sustainable development(Li et al. 2025a).

As an emerging technology, AI demonstrates a significant spatial spillover effect. By facilitating the flow of factors between regions, areas with relatively backward technology can learn and imitate the innovative knowledge of advanced regions, thereby achieving a spillover effect of knowledge and technology(Mao et al. 2024; Luo and Feng 2024). Research shows that the AI patent citation network promotes cross-industry knowledge diffusion and indirectly reduces carbon emissions in related industries by approximately 10% to 12%. Moreover, AI not only enhances local carbon emission efficiency but also has a radiating effect on surrounding areas, promoting an overall improvement in carbon emission efficiency. Its technology diffusion speed is 3.2 times faster than that of traditional industries. Additionally, AI brings multiple economic benefits, such as increasing the labor income share(Dehghani et al. 2018; Goralski and Tan 2022; Cao et al. 2024), improving labor productivity (Zhou et al. 2024), and promoting economic growth and energy efficiency(Zhou et al. 2024; Zhong et al. 2024; Jiang and Yu 2025) .

AI exerts a substantial influence on urban pollution emissions, especially through technological innovation (Chen et al. 2022) and environmental policies. AI can effectively drive green innovation and establish cleaner production technology systems via process, technological innovation, and material substitution, minimizing resource input and waste output. It has been calculated that for every additional 100 million yuan of subsidies for green technology research and development, a carbon efficiency gain of 370 million yuan can be amplified through AI(Almuaythir et al. 2024). AI also promotes the application of technological innovation. Smart urban planning and management can better foster green transportation modalities, optimize traffic flow, and alleviate congestion, thereby minimizing the impact of vehicle emissions on the urban environment. Furthermore, the government encourage enterprises to adopt more environmentally friendly production methods with tax benefits or financial subsidies (Porter and Linde 1995). Under regulatory pressure, enterprises are obligated to undertake technological innovation and implement clean production techniques, thereby enhancing resource efficiency, reducing carbon emissions, and supporting sustainable development(Cappello et al. 2022). These measures might compel enterprises to utilize AI to develop more efficient energy systems, thus improving carbon emission efficiency (Zhao et al. 2024b).

3. Research Design

3.1 Method

Given that carbon emissions exhibit externalities and that AI can improve coordination and cooperation among regions, the spatial effects of AI on carbon emission efficiency cannot be ignored. Thus, this study refers to existing research, and a spatial panel econometric model is constructed as follows:

$$\mathrm{Cee}_{it} = \alpha_0 + \rho \sum_{i=1}^{n} W_{ij}\mathrm{AI}_{it} + \beta \mathrm{AI}_{it} + \varphi \sum_{i=1}^{n} X_{it} + \theta_1 \sum_{i=1}^{n} W_{ij}\mathrm{AI}_{it} + \theta_2 \sum_{i=1}^{n} W_{ij}X_{ij} + \mu_{it} + \varepsilon_{it}$$

where i and t denote the region and year, respectively; α denotes the intercept term; X represents a set of control variables, W_{ij} denotes the spatial weight matrix, ρ, θ_1, θ_2 are the spatial correlation coefficients, μ_{it} indicates the individual fixed effects, and ε_{it} stands for the random error term.

Before conducting model estimation, this study adheres to a rigorous spatial econometric analysis process: Firstly, the global Moran's I index is calculated to test the spatial autocorrelation between AI and carbon emission efficiency. When the statistic is significantly different from zero, it indicates the existence of spatial dependence, which provides a theoretical basis for the application of spatial panel econometric models. Secondly, this study uses the Lagrange multiplier test (LM test) to compare the adaptability of the spatial Durbin model and the ordinary model. If the test result rejects the null hypothesis, it confirms the superiority of the spatial Durbin model. Thirdly, the likelihood ratio test (LR test) is used to verify the rationality of the model setting, and the Hausman test is employed to determine the choice between fixed effects and random effects.

3.2 Variable definitions

3.2.1 Dependent variable

This paper constructed a non-expected output super efficiency SBM model to measure carbon emissions efficiency. Compared with the classic DEA models, super-efficiency SBM measures relative efficiency from non-radial and non-angle perspectives. Firstly, it considers the slack of input and output. Secondly, it addresses the issue of efficiency evaluation including undesirable output. Carbon emissions efficiency consists of several input and output variables as follows:

(1) Input variables. Capital. Capital investment was measured in 2005 by calculating the capital stock for the base period. Labor, expressed by quantity of employments in each city at the year's end. Some missing data were estimated by smoothing index method. Energy, measured by the total energy consumption of each prefecture-level city.

(2) Output variables. Desirable output, actual GDP of each city over the years. Using the deflator to convert the nominal GDP of each year into constant prices based on 2010to eliminate the effect of changing prices. Undesirable output, total CO_2 emissions and environmental pollution index of each prefecture-level city. Carbon emissions are calculated according to the IPCC Guidelines for National Greenhouse Gas Inventories. Coal, coke, kerosene, gasoline, diesel, fuel oil, and natural gas are selected as the primary energy types for carbon emission accounting. Additionally, the comprehensive environmental pollution index is calculated using baseline indicators of industrial wastewater, sulfur dioxide, and soot emissions. A higher index value indicates significant environmental degradation (Ge et al. 2022).

3.2.2 Independent variable

AI. This study selects the sum of AI application level and AI innovation level. Based on industrial robot data released by the International Federation of Robotics (IFR), covering six industries: electricity, gas and water supply; agriculture, forestry, and mining; manufacturing; animal husbandry and fishery; construction; and education, the industrial robot installation density at the prefecture-level city was calculated. The number of patents was used to measure AI innovation level. Following the methodology of Hu et al. (2021), Python was employed to crawl AI patent data for each prefecture-level city, with original data sourced from the Chinese Patent Database. The AI industry chain was divided into upstream, midstream, and downstream, corresponding to three categories: the basic layer (software and hardware infrastructure), the technical layer (general products and platforms), and the application layer (applied products and scenarios). These were classified at the city level to obtain AI patent data across different cities. Finally, the entropy method was applied to calculate the comprehensive AI index.

3.2.3 Mediation variables and Control variables

In this study, R&D innovation (inno) and environmental regulation (Env) are selected as mediating variables. Research and development innovation is represented by the proportion of R&D expenditure to GDP, while environmental regulation is measured by the proportion of environmental governance investment to GDP.

The control variables selected in this study are operationalized as follows: (1) Urbanization level (City), measured by the ratio of urban population to the national total; (2) Economic development (Indu), represented by the logarithm of per capita GDP; (3) Labor force size (Labor), quantified through the logarithm of the number of employed individuals; (4) Government intervention intensity (Gov), calculated as the proportion of municipal fiscal expenditure relative to GDP; (5) per capital carbon emission(Ce), measured by per capita carbon dioxide emissions of prefecture-level cities; and (6) Industrial Structure(Str), represented by the ratio of added value of tertiary industry to GDP.

3.3 Data

This paper analyzes 3705 observations panel data from 285 prefecture-level cities in China period 2010-2022, excluding Hong Kong, Macau, and Taiwan, as show in *Table 1*. The data AI on originates from the International Federation of Robotics and the Chinese Patent Database. Other data are collected from the official websites of authoritative institutions such as the Ministry of Science and Technology, the National Bureau of Statistics, and the People's Bank of China. Due to the lack of information for specific cities and years, interpolation was used to generate the required data additions.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
CEE	3,705	0.606	0.284	0.161	5.740
AI	3,705	4.922	4.164	0.0629	25.91
inno	3,705	0.0028	0.0027	0.00012	0.063
gov	3,705	0.0743	0.0393	0.00395	0.257
indu	3,705	10.74	0.594	8.576	13.06
labor	3,705	3.604	0.853	1.611	7.042
city	3,705	4.025	0.175	3.121	4.495
env	3,705	0.0123	0.00493	0.00157	0.0335
str	3,705	45.52	11.15	10.68	89.75
ce	3,705	2.198	0.742	0.0864	5.372

4. Analysis of empirical results

4.1 Analysis of spatial econometric model testing

Spatial autocorrelation is assessed using the global Moran's I index to examine whether AI exerts a synergistic local neighborhood effect on carbon emissions efficiency. As shown in *Table 2*, there is a significant positive relationship between AI development and carbon emission efficiency across different cities, as evidenced by a positive Moran's I value at the 1% significance level. Importantly, the geographical spillover effects of AI on carbon emission efficiency between regions should be considered.

Table 2 Global Moran's I index of AI and carbon emission efficiency

Year	AI			Carbon emission efficiency		
	Moran'I	p-value*	z	Moran'I	z	p-value*
2010	0.080	0.003	2.792	0.026	4.570	0.000
2011	0.136	0.000	4.563	0.030	5.053	0.000
2012	0.124	0.000	5.024	0.033	6.593	0.000
2013	0.178	0.000	5.909	0.041	6.743	0.000
2014	0.185	0.000	6.130	0.043	6.968	0.000
2015	0.241	0.000	7.962	0.043	7.036	0.000
2016	0.239	0.000	7.883	0.051	8.188	0.000
2017	0.219	0.000	7.487	0.034	5.816	0.000
2018	0.154	0.000	5.357	0.020	3.668	0.000
2019	0.194	0.000	6.432	0.037	6.174	0.000
2020	0.160	0.000	5.309	0.028	4.830	0.000
2021	0.175	0.000	5.798	0.028	4.755	0.000
2022	0.219	0.000	7.340	0.037	6.246	0.000

Following the research approach, the LM test, LR test, hasusman test are sequentially employed to select the optimal spatial econometric model. The test results are provided in *Table 3*. First, the null hypothesis (the spatial Durbin model degenerates into a general model) can be rejected because both the LM and LR tests are passed at the 1 % significance level, suggesting that the spatial econometric model is superior to the ordinary model. Second, the Hausman test results show that fixed effects outperform random effects. In summary, to eliminate the influence of time factors and individual differences across cities, the spatial Durbin model is adopted.

Table 3 Selection test of spatial econometric models

Inspection type	LM-lag	Robust-LM-lag	LM-error	Robust-LM-error	LR-lag	LR-error	Hausman
Inspection results	83.31	58.06	32.37	7.12	21.05	15.97	103.10
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

4.3 Benchmark analysis with the spatial effect test

This research adopts the Durbin model based on the spatial economic geographic weight matrix to dissect the relationship between AI and carbon emission efficiency. The outcomes are presented in *Table 4*. The first column shows the regression results of the double fixed-effect model without incorporating the spatial weight matrix, revealing that AI significantly boosts urban carbon emission efficiency. This is predominantly attributed to the proliferation of applied AI, which empowers various industries, elevates production efficiency, and curbs the increase in carbon emissions. Columns 2 to 4 respectively exhibit the regression results of the spatial fixed effect models under the geographic economic weight matrix. In all the fixed-effect models, the influence of AI on urban carbon emission efficiency is significantly positive at the 1% significance level, indicating that AI continuously promotes the enhancement of urban carbon emission efficiency in the spatial dimension and further validates the positive relationship between AI and carbon emission efficiency.

Regarding the control variables, the coefficient of government governance and economic development are significantly positive at the 1% significance level, indicating that contributes to the improvement of carbon emission efficiency. Especially in the nascent stage of the development of AI technology, the support and guidance of government policies play a crucial role. Nevertheless, the labor factor demonstrates a significant inhibitory effect to a certain extent, which might be ascribed to the shortage of high-skilled talents in the current human capital structure of China. Low-skilled laborers lack of competitiveness, thereby resulting in a certain lag in the development process.

Table 4 Benchmark analysis with the spatial effect test

	POOLEDOLS CEE	Time fixed CEE	Individual fixed CEE	Individual and time fixed CEE
AI	0.012***	0.00772***	0.00240***	0.00747***
	(6.32)	(3.60)	(-1.41)	(3.50)
gov	0.105**	0.0717***	0.309*	0.0810***
	(1.11)	(0.78)	(-2.44)	(0.89)
indu	0.118***	0.175***	0.217***	0.179***
	(5.62)	(6.29)	(12.90)	(6.50)
labor	-0.126***	-0.131***	-0.0161*	-0.130***
	(8.04)	(-8.46)	(-2.47)	(-8.39)
city	0.0002**	0.00307	-0.00217	-0.00204
	(0.02)	(0.19)	(-0.09)	(-0.13)
ce	-7.356***	-7.610***	-12.11***	-7.319***
	(7.48)	(-8.11)	(-10.97)	(-7.82)
str	-0.0034**	-0.00183*	-0.00688***	-0.00186*
	(0.43)	(-2.11)	(-12.64)	(-2.15)
W*AI		0.00637**	0.0136***	0.00726*
		(2.77)	(4.80)	(2.25)
W*gov		0.224***	0.172***	0.149***
		(-1.16)	(0.64)	(-0.77)
W*indu		-0.194***	-0.144***	-0.164***
		(-6.00)	(-5.23)	(-4.17)

W*labor		0.0599*	-0.0118	0.0818*
		(2.20)	(-1.06)	(2.52)
W*city		-0.0162	-0.0235	-0.0301
		(-0.51)	(-0.45)	(-0.85)
W*ce		-2.699	-8.919***	-1.407***
		(-1.34)	(-3.92)	(-0.68)
W*str		0.00332**	-0.00210*	0.00485**
		(2.82)	(-2.10)	(3.17)
ρ		0.264***	0.314***	0.160***
		(9.41)	(11.31)	(5.24)
σ^2	0.66***	0.0273***	0.0615***	0.0267***
		(42.99)	(42.96)	(43.00)
N	**3705**	**3705**	**3705**	**3705**

Note：t statistics in parentheses，*p<0.05,**p<0.01,***p<0.001

The results of the effect decomposition are shown in Table 5. The carbon emission reduction effect of the variable AI presents multi-dimensional spatial characteristics. Specifically, the direct effect coefficient of the development of artificial intelligence technology reached 0.0076 (p<0.01), indicating that it has a significant driving effect on the improvement of carbon emission efficiency in this region. This direct impact mainly stems from the iterative upgrading of intelligent manufacturing systems, the intelligent optimization of energy management systems, and the precise development of carbon emission monitoring technologies. In terms of spatial interaction effects, the research found that the development of artificial intelligence has significant indirect effects (0.0098, p<0.01), which verified the spatial spillover mechanism of artificial intelligence technology. This cross-regional transmission may be achieved through three channels. First, the gradient transfer of the artificial intelligence industrial chain in core cities forms a technology diffusion effect; Secondly, the network radiation effect generated by the construction of new infrastructure; Thirdly, the institutional demonstration effect of the construction of green innovation alliances in urban agglomerations. This corroborates the spatial interaction theory of new economic geography, indicating that the development of artificial intelligence not only reshapes the efficiency of local factor allocation but also reconstructs regional green development through spatial correlation networks. It is worth noting that the negative spatial effect of the economic development level in the control variables (-0.062, p<0.05) exposes the potential risk of the emergence of a row growth pattern. This pollution diffusion effect may stem from two contradictory transmission mechanisms: On the one hand, the expansion of economic scale triggers a rigid increase in energy consumption, forming a carbon lock-in effect; On the other hand, the phenomenon of "pollution havens" during the process of industrial transfer has exacerbated the negative externalities of the environment. This verifies the phased characteristics of the environmental Kuznets curve, that is, the current development stage has not yet crossed the critical threshold of carbon emission**s.**

Table 5 Impact of AI on local neighbor carbon emission efficiency

Variables	Local effects	Neighbor effects	Total effect
AI	0.0764***	0.00978**	0.0174***
	(3.51)	(2.74)	(5.38)
gov	0.0759***	0.142***	0.0656***
	(0.87)	(0.63)	(0.27)
indu	0.181***	-0.161***	0.0191***
	(6.92)	(-3.67)	(0.54)
labor	-0.130***	0.0707	-0.0591**
	(-8.67)	(1.91)	(-1.56)
city	-0.00222	-0.0326	-0.0348
	(-0.14)	(-0.74)	(-0.72)
ce	-7.293***	-3.166	-10.46***
	(-7.80)	(-1.32)	(-3.79)
str	-0.00185*	0.00547**	0.00363*
	(-2.12)	(3.13)	(2.19)

Note：t statistics in parentheses，*p<0.05,**p<0.01,***p<0.001

4.3 Robustness analysis

Table 6 presents the regression results with the dependent variable replaced by per capita capital emissions and the matrix altered. Replacing the dependent variable with per capita capital emissions indicates that AI has an inhibitory effect on per capita carbon emissions. Meanwhile, the spatial econometric model's matrix was changed. This weight was calculated by squaring the reciprocal of the distance between two regions to analyze the impact of AI on carbon emissions through a geographical distance matrix rather than an economic geographical matrix. The sign of each explanatory variable is consistent with that in the previous section, further confirming the synergy effect of AI on carbon reduction between local and neighboring regions.

Table 6 Robustness test

	Per capita emissions			Geographic distance		
Variables	Direct	Indirect	Total	Direct	Indirect	Total
AI	-0.951***	-1.149***	-2.100***	-0.00183	0.183***	0.181***
	(11.58)	(6.52)	(-1.08)	(-1.05)	(4.59)	(4.56)
gov	-30.52***	-120.4***	-150.9***	0.211***	7.002***	6.791***
	(5.23)	(6.82)	(7.86)	(1.69)	(1.83)	(1.77)
indu	-16.60***	6.193***	-10.41***	0.195***	-0.201***	-0.00667
	(22.31)	(-3.86)	(8.11)	(17.02)	(-1.11)	(-0.04)
labor	-8.209***	-5.518***	-13.73***	-0.0131*	-0.295*	-0.308*
	(-28.19)	(-7.70)	(-18.87)	(-2.18)	(-2.39)	(-2.52)
city	0.259***	5.131	5.390	-0.00142	0.317***	0.316
	(0.23)	(1.39)	(1.33)	(-0.06)	(0.38)	(0.37)
ce	-381.5***	-309.4*	72.10	-12.36***	-230.1***	-242.4***
	(-7.31)	(-2.24)	(0.48)	(-10.87)	(-4.53)	(-4.75)
str	-0.0598***	-0.547***	-0.607***	-0.00752***	-0.0584***	-0.0659***
	(-2.41)	(-8.86)	(-9.86)	(-14.57)	(-3.85)	(-4.35)

Note：t statistics in parentheses，*p<0.05,**p<0.01,***p<0.001

4.4 Endogenous analysis

In this study, the lagged 1-period AI (L. AI) was selected as a key instrumental variable, to address the potential issue of endogeneity, the two-step least squares instrumental variable (IV-2SLS) regression analysis was utilized. The results of the endogeneity test are presented in *Table 7*. In the first stage results, it is evident that the coefficient of the lagged 1-period AI (L.AI) is 0.006 which is statistically significant at the 1% level. This confirms that the lagged 1-period AI (L.AI) is appropriate as an instrumental variable and can effectively represent AI. In the outcomes of the subsequent phase, the parameter associated with AI stands at 0.023, which is likewise significant at the 1% level. This suggests that, after addressing concerns regarding endogeneity, AI persistently exerts a beneficial influence on the carbon emission efficiency.

Table7. Endogeneity test results

	(1) phase I	(2) phase II
L.AI	0.006*** (2.78)	
AI		0.023*** (8.57)
Controlvariable	Yes	Yes
Year	Yes	Yes
Non-identifiability	636.728	
Weak instrumental variable	32960	

5. Conclusions and policy implications

Based on the panel data of 285 municipalities in China from 2010 to 2022, this article empirically researches the influence and mechanism of AI on the efficiency of carbon emission. The consequences exhibit the following.

(1) China's carbon emission efficiency level is not high. The carbon emission efficiency presents obvious heterogeneity. By regions, the carbon emission efficiency of the eastern area was larger than that of the central area and larger than that of the western area. (2) The development of AI has significantly promoted the improvement of the collaborative efficiency of pollution reduction and has a positive spatial spillover effect. The conclusion is still valid after the replacement space weight matrix, the tail-tail treatment of continuous variables, and the robustness test of excluding the sample of municipalities. (3) The mechanism analysis results show that the development of AI can reduce environmental pollution and carbon emissions by improving the level of regional technology innovation and the advanced level of industrial structure. This development can also promote the improvement of the carbon emission efficiency, that is, the intermediary effect between the level of technology innovation and the advanced level of industrial structure. Based on the above conclusions, this study proposes the following policy recommendations:

(1) The government should enhance its support for technological innovation, especially in the field of AI. To promote the development of AI, the government needs to increase investment in education and science and technology, providing sufficient human and material resources for technological research and development and infrastructure construction. Additionally, the government should actively promote the deep integration of AI technology with industrial scenarios, facilitating the optimization and upgrading of the industrial structure and high-quality economic development.

(2) Implement spatial differentiation strategies. In regions such as the Yangtze River Delta and the Pearl River Delta, explore an AI technology and carbon linked trading mechanism, combining the application of AI technology with carbon emissions trading to incentivize enterprises to adopt more efficient energy conservation and emission reduction measures. For the western energy bases, implement the policy with computing power for energy consumption to achieve efficient resource allocation and green development goals across regions.

(3) Through the triple innovation of technology, market and policy, China is expected to achieve the carbon peaking goal before 2030. The in-depth application of AI technology can increase the emission reduction efficiency of key industries by 30% to 50%, but it is still necessary to be vigilant against the carbon lock-in effect and regional development imbalance risks that may be caused by digital technology. It is suggested to establish an AI Carbon Neutrality Development Index to dynamically assess the sustainability and long-term impact of various technological paths.

(4) Issues such as technological transparency, data privacy protection, and employment structure adjustment remain key challenges for future development. Policy makers and technology developers need to work together to balance the potential and risks of AI technology. The academic and industrial sectors should deepen cooperation, not only promoting the application of technology but also building a more resilient social ethical framework to ensure that technological progress is in line with social development.

Author Contributions

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Declarations

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