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Original Research

How does Artificial Intelligence Affect Carbon Emission Efficiency? Empirical Evidence from the Pearl River Delta in China

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Abstract

In China, the Pearl River Delta (PRD) plays a leading role as not only an artificial intelligence (AI) innovation hotspot but also a pilot zone for green and low-carbon development. The Super-EBM model was used to measure the PRD's carbon emission efficiency (CEE) from 2006 to 2021. On this basis, dual fixed effect, mediation effect, and threshold effect regression estimation approaches are used to analyze the influence of AI on CEE and its internal mechanism. The results show that AI can significantly improve the CEE, and this conclusion remains true after endogenous and robustness tests such as difference-in-difference (DID), time lag effect, independent variable replacement, and split-sample tests. Mechanism analysis reveals that industrial structure upgrading and energy efficiency are two basic paths for improving CEE. The analysis of the panel threshold regression model and heterogeneity test shows that with industrial structure upgrading and energy efficiency improvement, AI has a more significant effect on promoting CEE, with that effect being more prominent in the PRD's core cities. The government should vigorously promote the deep integration of AI and the low-carbon economy, give full play to the indirect driving role of industrial structure upgrading and energy efficiency, strengthen regional cooperation, promote the coordinated development of various regions, and implement differentiated low-carbon transformation policies.

Keywords: carbon emission efficiency, artificial intelligence, super-EBM model, industrial structure upgrading, energy efficiency

Introduction

In recent years, environmental deterioration and climate problems have increasingly threatened both the survival of people and the sustainable development of human society. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), approximately 95% of global warming over the past 50 years has been caused by greenhouse gas emissions, with carbon dioxide being one of the most important greenhouse gasses. China's rapid development has also led to excessive carbon emissions. China not only promised to reduce its carbon emissions at the Copenhagen conference but also proposed at the 75th Session of the United Nations General Assembly to achieve a "carbon peak" by 2030 and be "carbon neutral"

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by 2060. At the same time, the problem of unbalanced and inadequate Chinese economic development is still prominent. Ensuring the steady development of the Chinese economy is the primary principle for solving all of the abovementioned problems. Therefore, improving carbon emission efficiency (CEE) is a feasible and effective way to coordinate economic activities with carbon emission reduction [1].

With respect to global carbon emission reduction practices, technological progress is important for green and low-carbon development and for addressing the challenges of climate change [2, 3]. As a typical representative of technological progress, artificial intelligence (AI) is the core driving force of the new round of industrial transformation, and the emerging information technology represented by AI is the engine for promoting high-quality economic and social development. With the continuous breakthrough of deep learning algorithms, the social application of AI technology has become a trend. On February 19, 2024, the State-owned Assets Supervision and Administration Commission of the State Council held a special promotion meeting on "AI enabling industry renewal". The meeting emphasized that AI development should be planned, industrial renewal should be promoted, and the layout and development of the AI industry should be accelerated. In this context, deeply exploring the correlation between AI and CEE is highly important and valuable.

At the forefront of China's reform and opening up, the Pearl River Delta (PRD) has witnessed rapid economic development, industrialization, and urbanization. As an important urban agglomeration in China, the PRD has obvious geographical advantages, which can attract foreign investment and promote regional economic development opportunities. Shenzhen and Guangzhou, in particular, are considered the "leaders" in PRD's economic development. Currently, the PRD is seen as one of the world's most important processing, manufacturing, and export hotspots, and world-class enterprises, including electronic information enterprises and appliance and furniture manufacturers, are all located in this region. However, these developments have occurred at the cost of significant energy consumption and have led to severe environmental degradation in the PRD, resulting in a significant increase in carbon emissions [4]. With prominent environmental problems, the PRD is facing increasing environmental pressure. Reduction of carbon emissions and achieving sustainable development have become important goals of the economic transformation of the PRD, requiring systematic changes and the participation of all industries [5].

In recent years, AI technology has been widely used in the PRD. On May 26, 2024, the Guangdong Provincial People's Government issued a notice on several measures to help AI empower thousands of industries; this notice proposed building a modern industrial system, enabling thousands of industries to improve quality and efficiency, and creating a new economic model, new life experience, and new ways of governance in the intelligent era. China is becoming increasingly aware of the important contribution of AI in driving the transition to a green and low-carbon future [6]. Therefore, how does AI affect CEE? In what specific ways? Is there any heterogeneity among the different regions? This paper uses the PRD as an example to discuss how AI affects CEE, aiming to provide a theoretical basis and practical guidance for realizing low-carbon development in China.

The marginal contributions of this study include the following: First, when the indirect influence of AI on CEE is studied, its nonlinear influence is mainly explored via the threshold effect test. Second, previous studies have focused mainly on the provincial level. This paper takes the PRD as the research object, which broadens the research scope of the relationship between AI and CEE, which is more targeted. In addition, the PRD is a region with unbalanced development. This study explores the heterogeneity between the core and peripheral urban agglomerations in the PRD, thus providing theoretical contributions and policy suggestions according to local conditions for ecological environment protection and high-quality development.

The rest of the study is structured as follows: next sections review the relevant existing literature and propose the mechanism analysis and the research hypotheses. Materials and Methods section provides the model and data. The Results and Discussion sections present the empirical results, analyse the rationality of the results and make policy implications and the limitations of this paper. Conclusions section is a summary of the full study.

Literature Review

Global climate change has led many studies to pay more attention to environmental policy changes and greenhouse gas emissions, such as carbon dioxide, to achieve a win–win situation between environmental protection and economic development. Among them, improving CEE is the core of promoting carbon neutrality and the carbon peak. Generally, CEE indicators can be divided into two categories: single-factor indicators [7] and total-factor indicators [8]. The former can be simply defined as the ratio of GDP to carbon emissions. However, the single-factor index is not accurate because it can reflect only some aspects of CEE. The total factor index is a comprehensive index used to measure CEE in economic activities. All the inputs (such as capital, labor, and energy) and outputs (usually GDP or industry-added value) in the production process, as well as the carbon emissions generated from these inputs and outputs, are considered.

Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are the most commonly used methods for measuring the CEE. SFA requires assumptions about the form of the production function, which may limit its applicability. On the other hand, DEA does not require a predefined form of the production function and is applicable to analyzing datasets of various sizes [9]. Since its inception, it has been widely used in assessing CEE, helping researchers identify the causes of inefficiency and providing a scientific basis for management decisions. Zhong et al. [10], Pan et al. [11], and Shao et al. [12] confirmed the effectiveness of DEA in assessing CEE. However, the traditional Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models neglect the slack variables, and the efficiency values are only maintained within the [0, 1] interval. Tone [13] first introduced the slack-based measure (SBM) model and then the superefficiency SBM model [14], which does not need to consider the choice of orientation, and the input and output need not be strictly in accordance with the proportional change; thus, the model can solve the abovementioned defects and more accurately reflect actual efficiency values. The shortcoming of the SBM model is the lack of proportionality, which affects the accuracy of its measures. Therefore, Tone et al. introduced the epsilon-based measure (EBM) model, which combines the radial and nonradial directions, thereby greatly improving the accuracy of the measure [15].

In addition to the definition and measurement of the CEE, scholars have paid widespread attention to the factors influencing the CEE. The many examined factors include technological progress [16, 17], industrial structure [18, 19], energy efficiency [20, 21], urbanization [22, 23], the carbon emission rights trading system [24, 25], environmental regulation [26, 27], economics [28, 29], etc. With the advent of the Industry 4.0 era, AI has become a key factor in achieving global sustainable development goals [30]. Scholars have begun to focus on the impact of AI on CEE, which is believed to have dual impacts [31, 32]. On the one hand, the wide application of AI technology in various fields, such as transportation and energy production, has made a significant contribution to optimizing energy consumption and reducing waste [33], as such technology is able to collect and process information to help shape a highly integrated man–machine situation. Based on these advantages, AI can promote technological innovation [34], improve labor productivity [35], and optimize resource allocation [36] to improve CEE. On the other hand, the training and operation of AI technology require too much electricity and generate a large amount of carbon emissions [37], resulting in a "rebound effect", which offsets the improved CEE resulting from the development of AI technology and even increases the total amount of carbon emissions. For example, Liu et al. [38] studied how AI affects carbon intensity, using data from China's industrial sector from 2005 to 2016. The empirical results showed that AI significantly reduces carbon intensity, and the results remained robust even after addressing the endogeneity problem.

In conclusion, although previous studies have paid some attention to this research topic, they are still in the exploratory stage; thus, the systematic study of the impact of AI on CEE is not comprehensive enough. First, scholars have mostly used SBM models to measure the CEE, thereby ignoring proportionality, which results in measurement bias. Second, the possible nonlinear relationships are ignored when the specific mechanism is explored. Finally, most existing studies have focused on the national and provincial levels. Due to the different resource endowments, population sizes, economic development levels, employment population scales, and AI development levels of different cities, exploring the influence of AI on CEE at the city level is more practical.

Therefore, this paper first uses the superefficiency EBM (Super-EBM) model to measure the CEE of the PRD. Next, the mediation effect and threshold effect models are used to explore the influence mechanism of AI on CEE, and the possible nonlinear relationships between them are further discussed. Moreover, heterogeneity analysis is used to investigate whether regional differences exist between the core and PRD's periphery. Finally, on the basis of the findings of this paper, policy implications are made according to local conditions to promote the deep integration of AI and a low-carbon economy to provide a reference for low-carbon development in China's PRD, as well as nationwide.

Mechanism Analysis and Research Hypotheses

Direct Impact of AI on CEE

Endogenous growth theory holds that technological progress is the basis of promoting sustainable economic growth. As a typical representative of a new round of scientific and technological revolution, AI has gradually become an important engine for promoting the high-quality development of China's economy [39]. Improving CEE is key to promoting green and low-carbon transformation and achieving high-quality economic growth. On this basis, many studies have discussed the role and impact of AI in CEE improvement from different perspectives [40]. Most studies have argued that AI can promote CEE improvement, and some studies have concluded that the relationship between AI and CEE presents an inverted U-shaped curve [41]. AI, as one of the core technologies used to promote green and low-carbon development, has the ability to monitor and analyze corporate carbon emission data and identify potential emission reduction possibilities. Moreover, AI can analyze trends in carbon trading markets and help companies and governments develop more effective carbon reduction strategies, thus improving CEE. Huang et al. [42] built a theoretical model including industrial robots and energy input, showing that industrial robots can enable urban industrial carbon emission reduction. Sun et al. [43] tested the impact of AI innovation on regional carbon emissions based on panel data of Chinese provinces from 2006 to 2021. The results show that AI innovation has significantly improved CEE. Therefore, this paper proposes Hypothesis 1 as follows:

Hypothesis 1: AI can improve CEE.

Indirect Impact of AI on CEE

It is widely believed that industrial structure upgrading and energy efficiency are the key paths in the strategic goal process of low-carbon economic transformation [44]. On the one hand, in terms of the path of industrial structure upgrading, the PRD, China's industrial and manufacturing center, has experienced a particularly significant transformation driven by AI. AI applications promote the orderly flow of production factors among industries, avoid the mismatch of resources, and contribute to industrial structure rationalization. Moreover, AI empowerment has promoted service innovation in traditional industries and has also given rise to emerging service sectors such as smart healthcare and online education. This has enriched the diversity of the tertiary industry and propelled the PRD's third sector to continuously advance towards a high-quality and intelligent direction. Therefore, AI is conducive to industrial structure upgrading [45]. Most scholars agree that a reasonable industrial structure is conducive to improving CEE. The share of secondary industry in all industries has a general and direct effect on CEE [46]. Therefore, industrial structure upgrading can help reduce the proportion of secondary industries characterized by energy intensity, which is conducive to green and low-carbon development [47].

On the other hand, in terms of the path to energy efficiency, the PRD faces substantial and complex energy demands. AI facilitates real-time monitoring, analysis, and feedback of energy consumption data, thereby effectively identifying potential wastage and optimization opportunities within the energy usage process and proposing corrective measures [48]. In areas such as manufacturing and transportation, AI can predict equipment failure and performance decline and conduct maintenance in advance, thereby reducing energy waste and downtime. Furthermore, the application of AI in smart grids has enabled more intelligent supply and demand management. Through automated control and dynamic adjustments, it achieves optimized allocation of electrical resources, preventing the over-supply or shortage of energy, thereby enhancing the overall efficiency of the power system. Therefore, AI is conducive to improving energy efficiency. Energy is the main driver of carbon emissions [49]. The less energy is consumed, the less carbon emissions are generated. Improving energy efficiency will help countries achieve environmental benefits at a lower cost [50]. In conclusion, the present study proposes Hypothesis 2a and Hypothesis 2b as follows:

Hypothesis 2a: AI can improve CEE through industrial structure upgrading.

Hypothesis 2b: AI can improve CEE through energy efficiency.

Nonlinear Effects of AI on CEE

AI empowers a wide range of industries, improves automation, connectivity, and flexibility in production, manufacturing, and consumption processes, and promotes industrial structure upgrading and energy efficiency. However, in the primary stage of AI, the ability of intelligent equipment to combine information and data is limited, and AI has difficulty fully meeting the demand for high-skilled labor [39]; this means that AI is unable to adequately promote industrial structure upgrading and improve energy efficiency at this stage, resulting in a nonsignificant improvement in CEE. However, with the development of AI and its deep integration into big data, blockchain, and other information technologies, the forefront of industrial technology continues to move forward so that enterprises can automatically adjust their production methods according to the energy supply and cost conditions and minimize energy loss [51]. AI is starting to play an active role in optimizing production processes and improving energy efficiency, thus driving CEE. At this time, AI has become a key force driving the transformation of the low-carbon economy. Therefore, this paper proposes Hypothesis 3 as follows:

Hypothesis 3: With industrial structure upgrading and the improvement of energy efficiency, there are obvious nonlinear characteristics of the effects of AI on CEE.

Heterogeneity in the Effects of AI on CEE

Owing to the different geographical locations and policy orientations of the core and peripheral cities of the PRD, there are significant regional differences in AI development. First, core cities possess strong research and development capabilities, hosting a multitude of high-tech enterprises and research institutions that continuously drive innovation and the application of AI in energy conservation and emission reduction. Second, owing to rapid economic development and increasing demand for energy efficiency and environmental protection, core cities offer a vast market for the widespread application of AI across industries, thereby promoting energy optimization and industrial upgrading. Last, compared to peripheral cities, cities such as Shenzhen and Guangzhou attract numerous technological talents, providing abundant human resources for AI research and innovation. In contrast, peripheral cities exhibit a relatively slower economic structure and development pace. In the context of the unbalanced development of AI, differences in the development level of AI itself and its various subdimensions may also have heterogeneous impacts on CEE. Therefore, this paper proposes Hypothesis 4 as follows:

Hypothesis 4: Due to the different levels of development of the core and peripheral cities in the PRD, the impact of AI on CEE is different throughout the region.

Materials and Methods

Model Building

The Superefficiency EBM Model

The EBM hybrid distance function is a hybrid model proposed by Tone and Tsutsui that contains both radial and SBM distance functions, which Tone refers to as EBM because of the use of ε parameters in the model. The input-oriented EBM model is expressed as Equation (1):

$$\begin{aligned} &\min \theta - \varepsilon \frac{1}{\sum_{i=1}^{m} w_i^-} \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_k} \\ &s.t. \quad X\lambda - \theta x_k + s^- = 0 \\ &\qquad Y\lambda \geq y_k \\ &\qquad \lambda \geq 0, s^- \geq 0 \end{aligned} \tag{1}$$

The efficiency value of the evaluated DMU is the optimal solution of the objective function, which is shown in Equation (2):

$$\theta^* - \varepsilon \sum_{i=1}^{m} \frac{w_i^- s_i^{-*}}{x_k} \tag{2}$$

There are $m + 1$ parameters in the model: ε and w_i^-($i = 1, 2, ..., m$). w_i^- represents the relative importance of each input index, and ε is a key parameter. The value range is [0, 1]. It represents the importance of the nonradial part in the calculation of the efficiency value, i.e., 0 for the radial model and 1 for the SBM model. Using this model, this paper will measure the CEE in the PRD.

Benchmark Regression Model

Based on the above mechanism analysis, the panel benchmark regression model is first established for empirical analysis of the impact of AI and CEE in the PRD, which is shown in Equation (3):

$$CEE_{i,t} = \alpha + \beta AI_{i,t} + \sum \varphi Control_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

The subscripts i and t are region and time, respectively; $CEE_{i,t}$ represents the explained variable CEE; $AI_{i,t}$ represents the AI application level; $Control_{i,t}$ represents a series of control variables; α, β, φ represent the parameters to be estimated; u_i and λ_t represent individual and time fixed effects, respectively; and ε represents random disturbance items.

Mediation Model

According to the above mechanism analysis, AI may affect CEE through industrial structure upgrading and energy efficiency; thus, the following mediation model is constructed to conduct the identification test.

A mediation model is a statistical analysis technique used to study how an independent variable can ultimately affect the dependent variable by affecting another mediating variable. There are general steps taken when testing a mediation effect [52].

First, three regression equations need to be developed to analyze the relationships among the independent, mediating, and dependent variables. These are expressed as Equations (4), (5), and (6):

$$Y = cX + \varepsilon_1 \tag{4}$$

$$M = aX + \varepsilon_2 \tag{5}$$

$$Y = c' + bM + \varepsilon_3 \tag{6}$$

The regression coefficient c in Equation (4) is the effect of the independent variable X on the dependent variable Y; the regression coefficient a in Equation (5) is the effect of the independent variable X on the mediating variable M; and the regression coefficient b in Equation (6) is the effect of M on Y after controlling for the effect of X. The coefficient c' is the effect of X on Y after controlling for the effects of M, and ε_1, ε_2, ε_3 are the residuals.

Next, by analyzing the results of these three regression equations, we can judge whether there is a mediating effect. Specifically, if a, b, c' are significant ($p<0.05$), there is a mediation effect. If a, b are significant but c' is not significant, then there is a complete mediation effect; however, if c' is significant, then there is a partial mediation effect.

Panel Threshold Regression Model

To test whether there is a nonlinear relationship between AI and CEE, this panel threshold model is set as Equation (7):

$$\begin{aligned} CEE_{i,t} &= \varphi_0 + \varphi_1 AI_{i,t} I(TH_{i,t} \leq h1) + \varphi_2 AI_{i,t} \\ &\bullet I(TH_{i,t} > h1) + \sum \varphi Control_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $TH_{i,t}$ represents threshold variables, including industrial structure upgrading and energy efficiency. I(·) is an indicator function with a value of either 1 or 0, where 1 indicates that it meets the parenthesis condition; otherwise, it is 0. Equation (7) is a single threshold situation, which can be extended to multiple threshold cases according to the measurement and inspection steps of the sample data.

Variable Selection

Dependent Variable

In accordance with the methods of Zhang et al. [53], the CEE is measured via the Super-EBM model. The reasonable selection of input and output variables can improve the accuracy of DEA, and multiple dimensions, such as the environment, economy, society, and resources, should be comprehensively considered. In general, the consumption of capital, resources, or energy represents input, whereas a product or service represents output. Notably, the more variables there are in the model, the more difficult it is to distinguish the DMU [54]. Therefore, the number of variables should be minimized while retaining the necessary factors of production.

This paper refers to the variables selected in the CEE assessment [55, 56] and considers the applicability of the indicators in the selected model, using the employment population, total fixed asset investment, and total electricity consumption as the input variables. The gross regional product is the desired output, and the total carbon emission is the undesired output.

Independent Variable

The independent variable is AI. Research in the academic field has used industrial robot numbers [57], AI patent application numbers [58], and AI patent grant numbers [59] as proxy variables for AI. The number of industrial robots is limited to measuring AI in the industrial sector, and the analysis of macroeconomic problems is one-sided [60]. AI patents are the core of scientific and technological assets in the process of AI technology innovation in a country, region, or industry and can essentially reveal the ability of AI technology innovation. While patent grants are usually regarded as a more rigorous proxy variable, the patent examination process is affected by many nontechnical factors, and the number of AI applications can comprehensively reflect the innovation activities of enterprises. Therefore, this paper takes the AI application number as a proxy variable for the AI development level and the AI patent grant number as part of the robustness test. In this paper, according to the study of Wu et al. [61], with "artificial intelligence or business intelligence or image understanding or investment decision assist system or intelligent data analysis or intelligent robot or machine learning or semantic search or biometric recognition technology or facial recognition or speech recognition or identity authentication or autonomous driving or natural language processing" as the retrieval type, we search for patent data in the Patenthub patent database and obtain AI patent application data from 2006 to 2021. To reduce the effect of heteroscedasticity, all the data are logarithmic.

Mediating Variables and Threshold Variables

According to the mechanism analysis, the impact of AI on CEE may vary under different levels of industrial structure upgrading and energy efficiency. Therefore, industrial structure upgrading and energy efficiency are both mediating variables and threshold variables. First, industrial structure upgrading typically manifests in two ways: industrial structure advancement and industrial structure rationalization. The former is represented by the ratio of the output value between the tertiary industry and the secondary industry, whereas the Tel coefficient measures the latter. In this paper, industrial structure upgrading consists of industrial structure advancement and industrial structure rationalization based on the entropy power method of synthesis [62]. Second, according to Sun et al. [43], energy efficiency is measured by the ratio of industrial-added value to industrial energy consumption.

Control Variables

To avoid estimation bias due to missing variables, we included a series of control variables in the model. Based on the data availability, we added the following control variables to this study, referring to the studies of Yu et al. [63] and Zhang et al. [64].

First, government research and development (R&D) investment is measured by the ratio of R&D to gross regional product. Second, openness is measured by the total exports and imports ratio to gross regional product. Third, the human capital level is measured by the scientific and technological personnel ratio to the total working population. Fourth, the level of economic development is measured by the per capita GDP index (last year = 100). Finally, the industrial energy consumption level is measured by the ratio of industrial electricity consumption to industrial added value.

Data Sources

This paper selects a sample of nine cities in the PRD for the 2011-2021 period, and the data are derived mainly from the CEADS China Carbon Emission Database, the Patenthub Patent Database, the China Energy Statistical Yearbook, the China Industrial Statistical Yearbook, the China Labor Statistical Yearbook, the China Science and Technology Statistical Yearbook, the China Foreign Trade and Economic Cooperation Statistical Yearbook, and various city statistical yearbooks. Referring to the practice of Ou et al. [65], we interpolate for a small amount of missing data in some years. The main variables are defined as shown in Table 1, and their descriptive statistics are shown in Table 2.

Table 1. Variable definitions.

Variable attribute	Variable name	Variable interpretation
Dependent variable	Carbon Emission Efficiency (CEE)	Percentage calculated from the Super-EBM model.
Independent variable	Artificial Intelligence (AI)	AI patent applications number.
Mediation and threshold variables	Industrial Structure Upgrading (IS)	Industrial structure advancement and industrial structure rationalization are based on the entropy power method of synthesis.
	Energy Efficiency (EE)	The ratio of industrial added value to industrial energy consumption.
Controlled variables	Government R & D investment (GI)	The ratio of R & D to gross regional product.
	Openness (OP)	The ratio of total exports and imports to gross regional product.
	Human Capital (HC)	The ratio of scientific and technological personnel to the total working population.
	Economic Development (ED)	Per capita GDP index measure (last year = 100).
	Industrial Energy Consumption (EC)	The ratio of industrial electricity consumption to industrial added value.

Table 2. Descriptive statistics of the variables.

Variable name	Min	Max	Average	Standard error
Carbon emission efficiency	57.05	109.27	80.09	14.09
Artificial intelligence	0	8.05	2.71	2.08
Industrial structure upgrading	48.55	247.58	93.34	40.66
Energy efficiency	19.43	1508.22	240.97	277.72
Government R & D investment	10.83	416.91	177.91	91.32
Openness	2.37	46.52	15.78	10.34
Human capital	4.94	285.70	106.87	63.28
Economic development	97.80	116.6	106.96	4.06
Industrial energy consumption	5.12	25.55	12.41	4.21

Results

Benchmark Regression Results

In this paper, the dual fixed effect model is used for benchmark regression; the control variables are gradually added during the regression process, and the regression results are shown in Table 3. The estimated coefficient in Column (1) is 4.829, which is significant at the 1% level, indicating that AI has significantly improved the CEE in the PRD. The control variables are gradually added to Columns (2) to (6), and the estimated coefficient of AI remains positive and significant at the 1% level, indicating that AI can indeed promote carbon emission reduction. Thus, Hypothesis 1 is verified. Furthermore, the R-squared value is 0.785, indicating a robust data fit and a strong explanatory capacity of the independent variables for the dependent variables.

To analyze the impact of AI on CEE evolution, this study employs a segmented regression method. It calculates the impact coefficients of AI on CEE during three periods: 2006-2010, 2011-2015, and 2016-2021. As shown in Table 4, the results indicate that over time, the influence of AI on the CEE has progressively strengthened, with increasing significance levels and a trend of rising impact coefficients. This finding confirms that with the continuous development of AI, its positive role on the CEE is also intensifying.

Robustness Test

Endogeneity Test

In econometrics, endogeneity issues primarily arise from measurement errors, omitted variables, and reverse causality. Regarding measurement errors, this study employs the Super-EBM model, combining radial and nonradial approaches, which significantly enhances measurement accuracy. For omitted variables, individual and time-fixed effects are utilized, additional control

Table 3. Benchmark regression results.

Variable	(1) CEE	(2) CEE	(3) CEE	(4) CEE	(5) CEE	(6) CEE
AI	4.829***	4.766**	4.392***	4.312***	4.443***	4.454***
	1.152	1.139	1.135	1.144	1.135	1.152
GI		-0.039*	-0.047**	-0.085***	-0.080***	-0.080***
		0.020	0.020	0.030	0.030	0.031
OP			-0.360**	-0.337**	-0.327*	-0.327*
			0.168	0.167	0.168	0.169
HC				0.063*	0.059	0.059
				0.037	0.037	0.037
ED					-0.229	-0.218
					0.319	0.330
EC						0.060
						0.407
Individual fixed	yes	yes	yes	yes	yes	yes
Time fixed	yes	yes	yes	yes	yes	yes
Constant	87.494***	90.585***	103.208***	103.519***	128.732***	126.113***
	3.360	3.680	6.913	6.859	35.824	40.182
R^2	0.763	0.770	0.779	0.785	0.785	0.785

Note: * * *, * *, and * are significant at the 1%, 5%, and 10% levels, respectively, and the values in parentheses represent standard errors, the same as those in the following table.

variables are included, and a multi-period difference-in-differences (DID) test is applied, effectively addressing the issue of omitted variables. The multistage DID model setting idea is as follows. This paper divides the samples into an experimental group and a control group according to the AI development level, then takes the annual average value of AI in all cities as the boundary; those cities above the sample mean are set as the experimental group, while those below the mean are set as the control group. The virtual variable is set and assigned a value of 1 for the experimental group and 0 for the control group. The multiperiod DID interaction term should be the product of two virtual variables; the focus should be on the coefficient of the interaction term.

Table 4. Segmented regression results.

Variable	CEE 2006-2010	CEE 2011-2015	CEE 2015-2021
AI	3.771	2.110*	3.456***
	(2.372)	(1.231)	(0.986)
Controlled variable	Control	Control	Control
R^2	0. 101	0.737	0.857

The model is shown in Equation (8):

$$CEE_{i,t} = \alpha + \varphi_1 AI_{i,t} + \varphi_2 Treat + \varphi_3 AI_{i,t} \times Treat + \sum \sigma Control_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \tag{8}$$

Given that there is no reverse causality between AI and the CEE, prudently, and the impact of AI on CEE also requires some time to manifest, this paper introduces a lagged one-period AI variable as an instrumental variable to mitigate endogeneity. The regression results are presented in Columns (1) and (2) of Table 5. Overall, the results indicate that after addressing endogeneity issues, the impact of AI on C remains robust.

Other Robustness Tests

1) Independent variable replacement test

The independent variable is the AI development level, which is measured by the number of AI patent applications. Here, the number of patent grants is used as a proxy, which can reduce the deviation caused by different measurement methods. In the rapidly developing PRD, the application of AI is notable not only in technological innovation but also in policy promotion and industrial transformation. Due to the

Table 5. Results of the robustness test.

Variable	(1) Multistage DID	(2) Time lag effect test	(3) Independent variable replacement test	(4) Split-sample test
AI/Treat*AI	2.015***	2.555**	2.623***	5.173**
	(0.561)	(1.100)	(0.986)	(1.179)
Controlled variable	control	control	control	control
Individual fixed	yes	yes	yes	yes
Time fixed	yes	yes	yes	yes
R^2	0.782	0.844	0.771	0.746

mature AI ecosystem in the region, patent grants are a more substantial reflection of the implementation and transformation capabilities of AI. Therefore, using patent grants as an alternative variable, the regression results, shown in Column (3) of Table 5, are significantly positive and significant at the 1% level, further confirming the robustness of the research findings.

2) Split-sample test

Considering that the selection of the sample time window may impact the research results, the 2006-2015 data were selected again for the dual fixed effects model regression. The results are shown in Column (4) of Table 5; the sign and significance of the independent variable coefficients have not changed substantially, indicating that this study's conclusions remain relatively robust.

Mechanism Test

Table 6 reports the test results of industrial structure upgrading and energy efficiency; Columns (1) and (2) present the test results of the mediating effect of industrial structure upgrading, while Columns (3) and (4) present the test results of the mediating effect of energy efficiency. There are two points that should be highlighted. First, the influence of AI on industrial structure upgrading at the 1% level is significant. When AI and industrial structure upgrading act together on CEE, both have significant positive effects at the 1% level, indicating that the mediating mechanism through which AI improves CEE via industrial structure upgrading is established. Second, although AI is not found to significantly affect energy efficiency, both AI and energy efficiency are significantly positive at the 1% level when they act together on CEE; thus, the mediating effect needs to be further discerned. According to the mediation effect test method proposed by Wen et al. [66], the test result is confirmed via the bootstrap method. The test results are shown in Table 7; the confidence interval ranges from 0.584 to 2.018 and excludes 0, proving the mediating effect's existence. Thus, Hypothesis 2a and Hypothesis 2b are verified.

Threshold Effect Test

Referring to the method of Hansen [67], this paper first conducts a panel threshold existence test.

Table 6. Results of the mediating effect test.

Variable	(1) Industrial structure upgrading		(2) Energy efficiency	
	IS	CEE	EE	CEE
AI	7.204***	3.018***	20.818	3.901***
	(1.993)	(1.687)	(17.423)	(1.067)
IS		0.199***		
		(0.051)		
EE				0.026***
				(0.006)
Controlled variable	Control	Control	Control	Control
Individual fixed	yes	yes	yes	yes
Time fixed	yes	yes	yes	yes
R^2	0.923	0.767	0.874	0.819

Table 7. Results of the bootstrap test.

Effect type	Coefficient	Standard error	P value	Confidence intervals
Direct impact	1.770	0.526	0.001	0.7382572–2.801695
Indirect impact	1.301	0.366	0.000	0.5835908–2.018044

The results show that industrial structure upgrading and energy efficiency significantly pass the single threshold test, whereas the results of the double threshold and triple threshold tests are not significant. Accordingly, this paper sets a single threshold regression model with industrial structure upgrade and energy efficiency as the threshold variables. The regression results of the panel threshold model are shown in Table 8. First, when the index of industrial structure upgrading is less than or equal to 113.017, that is, when industrial structure upgrading is at a lower level, the impact on CEE is 1.204; however, when the index of industrial structure upgrading is greater than 113.017, that is, when industrial structure upgrading is at a higher level, the impact on CEE is 4.416. Second, when the energy efficiency is less than or equal to 644.180, that is, when the energy efficiency is low, the impact on CEE is 2.184; however, when the energy efficiency is greater than 644.180, that is, when the energy efficiency is high, the impact on CEE is 5.025. This suggests that the promotional effect of AI on low-carbon transformation is more pronounced under higher levels of industrial structure upgrading and energy efficiency. Once these thresholds are exceeded, the facilitating role of AI on CEE significantly intensifies. Thus, Hypothesis 3 is verified.

Heterogeneity Test

The PRD contains areas with different resource endowments and development stages, divided into core and peripheral cities. The core cities include Guangzhou, Shenzhen, and Zhuhai. These cities have a large economic aggregate, developed industries, and a high degree of openness to the outside world. The peripheral cities include Foshan, Dongguan, Huizhou, Zhongshan, Jiangmen, and Zhaoqing. While these cities' economic development levels are relatively low, they have also developed rapidly in recent years. Thus, verifying the existence of heterogeneity between different regions is conducive to the formulation of corresponding policies according to local conditions. This paper divides the PRD into core and peripheral cities for sample regression, and the results are shown in Table 9. The coefficient of AI on CEE is positive, and all the coefficients are significant at the 5% level, once again indicating that AI plays a significant role in promoting CEE improvement. Moreover, a comparison of the coefficients of the impact of AI on CEE between the core cities and the peripheral cities reveals that the coefficient in the core cities is greater. This suggests that in core cities with faster economic development, greater marketization, and greater openness to the outside world, the influence of AI on enhancing CEE is more prominent. Thus, Hypothesis 3 is verified.

Table 8. Results of the threshold effect test.

Variable	(1) IS	(2) EE
Threshold value h1	113.017	644.180
IS·I	1.204**	2.184**
(Th≤h1)	(0.384)	(0.901)
IS·I	4.416***	5.025***
(Th>h1)	(0.379)	(0.822)
Controlled variable	control	control
R^2	0.198	0.127

Discussion

Results Analysis

Recent research has revealed two views on the impact of AI on CEE. The first is that AI is one of the key technologies used to promote green and low-carbon development and can thus improve CEE (Ye et al., 2024) [40]; however, the second is that the excessive popularity of AI may have a rebound effect (Sun et al., 2024) [43]. In this paper, the PRD in China is taken as the subject, and it is shown that AI can improve CEE in this region, which supports the first argument. This study can provide a theoretical basis for improving the CEE in the PRD.

Recent research shows that AI can improve CEE through industrial structure upgrading and energy efficiency [68, 69]. The study presented in this paper

Table 9. Results of the heterogeneity test.

Variable	(1) Core cities	(2) Peripheral cities
AI	8.902**	3.089***
	(3.685)	(1.135)
Individual fixed	yes	yes
Time fixed	yes	yes
R^2	0.786	0.822

also supports this conclusion. An additional contribution is identifying the nonlinear relationship that extant research has ignored. With the inclusion of industrial structure upgrading and energy efficiency improvement, there is an obvious nonlinear feature of the influence of AI on CEE in the PRD. To enable AI to play a more active role in carbon reduction, there must be a certain level of industrial structure upgrading and energy efficiency, representing an enormous challenge for underdeveloped regions.

Through heterogeneity analysis, one of the contributions of this paper shows that significant differences were found in the effectiveness of AI in promoting CEE in different regions of the PRD. With more advanced technological infrastructure, more abundant human resources, and a higher level of economic development, core cities can engage in the more effective use of AI technology, thus playing a stronger role in promoting CEE. In peripheral cities with relatively backward economic development, marketization, and openness, although the influence of AI is not as strong as that in core cities, AI can become a useful tool for long-term development. By using big data, cloud computing, and other AI technologies to capture user needs accurately, peripheral cities can deeply integrate AI with the low-carbon economy and continuously enhance their core competitiveness. This also necessitates that policymakers take appropriate supportive measures, considering the actual situation in peripheral cities, when promoting AI technology.

Policy Implications

First, we need to play a full role in the dividend effect of AI in improving CEE. The essence of a low-carbon economy is a technological innovation economy, and AI enabling many industries is an inevitable requirement of low-carbon transformation. On the one hand, it is necessary to strengthen the research and development of AI technologies, especially in the field of green and low-carbon, and promote the deep integration of AI and green and low-carbon industries, such as renewable energy and efficient storage technologies, to form synergistic effects. On the other hand, strict energy efficiency standards and norms should be established to ensure that new technologies improve efficiency without leading to an increase in overall energy consumption. Digital centers and other new infrastructure energy consumption assessment systems should be improved to develop AI technology with a green and low-carbon development orientation.

Second, the government should give full play to the indirect driving role of industrial structure upgrading and energy efficiency in transforming the low-carbon economy. On the one hand, the government should steadily promote the upgrading and rationalization of the industrial structure, accelerate the elimination of backward production capacity with high pollution and high energy consumption, and increase the proportion of intelligent manufacturing and middle- and high-end service industries in GDP. The integration and optimization of the industrial chain should promote the synergistic effect between upstream and downstream industries so that overall carbon emissions are reduced. On the other hand, the government should encourage the establishment and improvement of energy management systems to monitor and evaluate energy consumption and improve energy use efficiency. Energy efficiency improvement projects, such as industrial energy conservation renovations, green building evaluations, and the construction of low-carbon transportation systems, should be implemented in key areas such as industry, construction, and transportation.

Third, interregional cooperation should be strengthened, and synergies between regions should be promoted to implement differentiated low-carbon transition policies. Core cities in the Pearl River Delta region, such as Shenzhen and Zhuhai, as well as peripheral cities, such as Jiangmen and Zhaoqing, must consider their respective development stages, resource endowments, industrial structures, and market demands when implementing low-carbon transformation policies. Core cities, typically equipped with advanced technology, complete industrial chains, and abundant capital resources, can adopt more aggressive strategies. They can leverage AI to promote the development of high-value-added, low-energy-consuming industries and establish AI research and development platforms to provide technical support and achievement transformation for peripheral cities. Peripheral cities, which face potential limitations in technology, capital, and talent, should focus on practicality and feasibility. By utilizing the technological spillover effects from core cities, peripheral cities can strengthen the introduction and absorption of energy-saving and emission-reduction technologies, gradually enhancing their own low-carbon development capabilities. This can provide markets and resources for core cities, creating a virtuous cycle within the region. Through such differentiated strategies, the PRD will effectively achieve regional low-carbon transformation and promote balanced development.

Limitations and Future Prospects

These findings hold significant implications for other regions exploring the impact of AI on CEE. This study not only provides a theoretical foundation and reference framework for research in other areas but also offers policymakers possible pathways for low-carbon transformation. This will contribute to advancing green and low-carbon transitions in China and globally.

Similar to most studies, this study has several limitations and provides directions for future research. First, because microdata has not yet been disclosed, how AI affects the CEE of enterprises is an issue that deserves further exploration in future field research that aims to collect such data. Second, while this study reflects the heterogeneity present among regions, there is also heterogeneity among different industries; thus, the future can be deeply analyzed from different perspectives to provide a more detailed basis for policymaking. Finally, this study covers only the PRD in China. Due to data availability, the 2006-2021 dataset spans from the early development to the rapid expansion of AI but does not reflect the latest advancements in AI (such as generative AI) post-2021. The PRD experienced unique policy support and economic transformation during 2006-2021, especially the support of AI and green low-carbon policies, which has led to its rapid and effective AI development. As a result, gaps in these conditions in other regions may lead to inconsistent replication. In the future, the analysis can be extended to subsequent years when studying other AI innovation zones to verify the applicability of the conclusions in regions with different levels of economic development.

Conclusions

Both AI development and CEE improvement are necessary for high-quality development. This paper, which is based on a mechanism analysis and 2006-2021 panel data from the PRD, uses dual fixed-effect regression, mediating effects, threshold effects, and heterogeneity analysis to discuss the influence of AI on the CEE direction, the influence mechanism, and the possible heterogeneity relationship.

The findings show that, first, AI can significantly improve CEE. After a series of endogenous tests and robustness tests, this promotion effect is shown to remain significant. Second, industrial structure upgrading and energy efficiency are both significant at the 1% level, highlighting their mediating role between AI and CEE; this indicates that AI mainly promotes CEE by promoting industrial structure upgrading and energy efficiency improvement. In addition, the impact of AI on CEE is nonlinear; that is, with industrial structure upgrading and energy efficiency improvement, the effect of AI plays a more significant role in CEE. Finally, the impact of AI between the core cities and the peripheral cities in the PRD highlights heterogeneity in CEE, in which the promotion effect on the core cities is more significant than that in peripheral cities.

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Conflict of Interest

The authors declare no conflict of interest.

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