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The impact of AI on enterprise energy management: from the perspective of carbon emissions

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Abstract. Given the significant impact of Artificial Intelligence (AI) technology on corporate energy management and the lack of research in this area, this paper employs text mining techniques to objectively assess the relative level of AI adoption among Chinese listed companies. Using econometric modelling methods, we verify these hypotheses and investigate both the direct and indirect effects of AI on corporate carbon emission intensity. Our research finds that the carbon emission intensity of Chinese enterprises significantly decreased in the early stage, then stabilized, and has notably decreased again in recent years. The average level of AI among listed Chinese enterprises shows an overall upward trend, but the growth rate has slowed down. The level of AI in private enterprises is significantly higher than that in other types of enterprises, while the level of AI in state-owned enterprises is relatively lower. The level of AI in enterprises has a significant negative impact on carbon emission intensity, presenting an "S"-shaped relationship, characterized by initial emission reduction, mid-term rebound, and subsequent emission reduction. AI technology reduces the level of carbon emissions in enterprises by enhancing their green development standards and promoting technological innovation. There are significant differences in the impact of AI levels on carbon emission intensity across different types and regions of enterprises. The empirical conclusions remain robust after addressing endogeneity issues or variable substitution. This study provides important insights for corporate energy transitions and sustainable development, as well as for the formulation of government energy policies.

Keywords: Artificial intelligence, Carbon emissions, Energy management, Mechanisms.

1 Introduction

Climate warming has become a major factor threatening human health and economic development [1, 2]. Reducing carbon emissions has thus become an unavoidable responsibility for enterprises. Corporate energy management, as a strategy for controlling and optimizing energy use, plays a central role in addressing this challenge. Energy management involves effectively planning and monitoring the use of energy within enterprises, ensuring that resources are allocated and utilized in the most reasonable manner. Efficient energy management not only reduces operational costs for enterprises but also significantly decreases their carbon footprint. This is because many corporate activities rely on energy consumption, much of which comes from fossil fuels, directly leading to the emission of greenhouse gases such as carbon dioxide [3].

Statistics show that approximately 80% of global greenhouse gas emissions originate from corporate activities, with a majority being Carbon Dioxide (CO_2) and other gases that significantly impact climate change. In the context of intensifying global climate change, reducing carbon emissions has become a major concern for governments, businesses, and society at large. As one of the world's largest carbon emitters, China's performance in carbon reduction offers valuable lessons for energy management in other countries. Simultaneously, the rapid advancement of technology has led to the widespread application of Artificial Intelligence (AI) across various industries [4]. AI technology can influence a company's energy management level and carbon emission intensity by enhancing green development standards and promoting technological innovation. However, as an emerging technology, the role and impact of AI in energy management, particularly in carbon emission management, have yet to be fully explored and studied.

This paper aims to fill this research gap by systematically investigating the influence of AI capabilities on corporate carbon emission intensity, providing crucial references

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and insights for governmental and corporate energy management. The core questions addressed include: how can we more accurately measure the relative level of AI adoption by corporations? Can AI capabilities influence corporate carbon emission intensity, and if so, is the relationship linear or curvilinear? What is the mechanism by which the level of Artificial Intelligence (AI) affects a company's carbon emission intensity?

To address these issues, this paper first optimizes AI-related keywords, evaluates the current status of AI in sample companies through these keywords, and conducts differential analysis from the perspective of different ownership structures. Secondly, the paper employs a fixed effects model to examine the causal relationship between the level of AI in companies and carbon emission intensity, and verifies the curvilinear relationship between the two. Thirdly, the paper uses a multiple mediation model to test the mechanism by which the level of AI in companies affects carbon emission intensity. Fourthly, the paper conducts heterogeneity analysis from four dimensions at both the corporate and regional levels, deepening the understanding of how the level of AI impacts carbon emission intensity. Lastly, the paper performs robustness checks using variable substitution and instrumental variable methods, verifying the robustness of the conclusions presented.

The main research conclusions of this paper are as follows: (1) Trends in changes in carbon emission intensity. The carbon emission intensity of Chinese enterprises has significantly decreased in the early stage, then tended to stabilize, and has notably decreased again in recent years. (2) Trends in the development of AI levels. The average level of AI among listed Chinese enterprises shows an overall upward trend, but the growth rate has slowed down; the level of AI in private enterprises is significantly higher than that in other types of enterprises, while the level of AI in state-owned enterprises is relatively lower. (3) The relationship between AI and carbon emission intensity. The level of AI in enterprises has a significant negative impact on carbon emission intensity, presenting an "S"-shaped relationship, characterized by initial emission reduction, mid-term rebound, and subsequent emission reduction. (4) The mechanism by which AI affects carbon emission intensity. AI technology reduces the level of carbon emissions in enterprises by enhancing their green development standards and promoting technological innovation. (5) Heterogeneity analysis reveals that non-state-owned enterprises and small and medium-sized enterprises experience a larger decrease in carbon emission intensity after adopting AI technology; enterprises located in central and western regions and those with lower degrees of openness also show a greater reduction in carbon emission intensity after adopting AI technology.

The marginal contributions of this paper are mainly reflected in the following aspects: (1) Theoretical contribution. This paper systematically explores the role of AI in corporate carbon emission reduction, filling a gap in existing research in this field; through empirical analysis, it reveals the nonlinear relationship between AI and carbon emission intensity, deepening the understanding of the role of AI in carbon emission reduction. (2) Methodological contribution. This paper improves the keyword measurement method by integrating and categorizing keywords, enhancing the accuracy and comprehensiveness of measurements; simultaneously, it adopts the bootstrap sampling method for mediating effect testing, providing a more reliable statistical inference method. (3) Practical contribution. Through detailed empirical analysis, this paper provides strong empirical evidence for policymakers and enterprise managers, contributing to the formulation of more effective emission reduction strategies.

The rest of the paper is structured as follows: Section 2 reviews the literature. Section 3 presents the research hypotheses, clarifies the research ideas, sets up the models, and explains the data and variables. Section 4 measures and evaluates the current status of AI in the sample enterprises. Section 5 conducts empirical analysis, including baseline tests, mechanism tests, heterogeneity analysis, and robustness tests. Section 6 summarizes the main conclusions and proposes relevant recommendations.

2 Literature review

This section reviews the literature from three aspects: the measurement of AI levels in enterprises, factors affecting corporate carbon emission intensity, and the impact of AI on corporate carbon emissions.

2.1 Measurement of enterprise AI level

In recent years, although the impact of AI technology on enterprises has become more and more significant, the research on the effective measurement of enterprise AI level is still relatively limited. At present, the quantitative evaluation of enterprise AI level mainly includes the following four paths: first, the maturity model is used to evaluate the AI level of enterprises. This kind of evaluation model is dominated by third-party institutions. At the same time, some scholars have also published relevant studies. They divide the AI development of enterprises into different levels and use multi-dimensional evaluation criteria to evaluate the scores of enterprises at all levels, so as to evaluate the level of enterprise AI. For example, the AI maturity assessment model launched by Gartner divides the enterprise AI level into five levels: planning, experiment, stability, expansion, and transformation [5]. Yablonsky built a model for evaluating the AI level of enterprises by clearly and accurately describing and structuring the information in the fields of multidimensional platforms, artificial intelligence, advanced analysis and big data. However, most of these models have typical subjective color, and the judgment standards of various institutions or scholars are quite different, so it is difficult to effectively evaluate the AI level of enterprises in different periods [6]. The second is to use the designed AI scale to measure the current AI development level of enterprises. Mikalef and Gupta [7] from the perspective of enterprise resource-based theory, took tangible resources, human skills and intangible resources as the key resources for the development of enterprise AI, and developed a scale to assess the level of enterprise AI based on these key resources. This method also has obvious defects. It is difficult to evaluate the AI level of different enterprises in a wide range, and it is also difficult to evaluate the AI level of enterprises in the past. The third is to use third-party data as the evaluation standard of enterprise AI level. For example, Cheng *et al.* [8] constructed the AI level index based on the robot data released by IRF from 2000 to 2014 and took it as the measurement standard of the AI level of enterprises. The advantage of this method is that it can quickly obtain panel data on the AI level of enterprises, which is convenient for empirical research. However, the disadvantage is that the data is mostly old and difficult to reflect the recent AI level of enterprises. Moreover, artificial intelligence technology was not mature until 2010 and using data before 2010 to study the AI level of enterprises lacks persuasiveness. The fourth is to evaluate the AI level of enterprises through text keywords. For example, Yao *et al.* [9] used AI related keywords and the annual reports of Chinese listed companies from 2007 to 2018 to evaluate the AI level of Chinese listed companies. The advantage of this method is that it can not only evaluate the relative level of AI in different enterprises, but also compare the AI level of the same enterprise in different time periods. However, the key vocabulary used by this method is not perfect, and it has not been integrated with the current AI development hotspots, and the annual report data selected is slightly old. In view of the advantages of this method, this paper will optimize this evaluation method to better evaluate the AI level of enterprises.

2.2 Analysis of factors affecting carbon emission intensity of enterprises

There are many factors that affect the carbon emissions of enterprises, mainly reflected in two aspects. The first is the external factors. For example, the government's regulatory policies and the trading price of carbon emission rights. Tang *et al.* [10] found that when there is carbon emission trading, its price will affect the production decisions related to carbon emissions. Li and Miao [11] found that the government's supervision and management, the pressure of economic stakeholders and the pressure of the public are all external factors that affect the carbon performance of enterprises. Second is the internal factors. Liu *et al.* [12] found that output scale is the largest driving factor affecting the current carbon emissions of enterprises, while the impact of industrial structure on carbon emissions is relatively small. This study shows that the production activities of enterprises, especially the consumption of human, financial and material resources, are the main factors affecting the carbon emissions of enterprises. Of course, the industry in which the enterprises are located will also have a certain impact. Xie *et al.* [13] through research, it is found that enterprise size and ownership structure are also factors affecting industrial CO_2 emission intensity. This shows that the scale of enterprises and the level of internal control and governance may also affect the level of carbon emissions of enterprises to a certain extent. Pan *et al.* [14] believes that enterprise technological innovation is also one of the important factors affecting enterprise carbon emissions. AI is fundamentally a kind of technological innovation. From this, we can also preliminarily infer that AI can have a significant impact on enterprise carbon emissions. In the follow-up study of this paper, to prevent the generation of confusion effect, this paper will select the important influencing factors inside the listing as the control variable to ensure the accuracy and reliability of the research conclusion. Since the sample enterprises are all from China, there is no significant difference between the carbon emission policies and carbon emission trading prices they face. Therefore, the impact of external policy regulation and carbon emission trading prices is not considered in the analysis of this paper.

2.3 The impact of AI on energy management

Due to the nascent nature of AI technology, there is relatively less literature specifically examining its impact on corporate energy management or carbon emissions. However, there is more research available on the relationship between AI and corporate green development or renewable energy. The findings from these studies are highly relevant and provide important references for analysing the impact of AI on corporate energy management and carbon emissions. Waheeb [15] discussed the possibility of using AI technology to achieve sustainable energy development. Zhao *et al.* [16] and other scholars believe that AI has great potential in improving energy efficiency and reducing costs, but it is not clear whether it can promote enterprises to accelerate green transformation. Through research, they found that AI can accelerate the transformation of enterprises to renewable energy in the long run, but it may face negative impact in the short-term, because the integration of AI into the renewable energy field faces great challenges. Mittal *et al.* [17] discussed the application of AI in battery charging and battery management system. Ahmad *et al.* [18] systematically discussed the current situation, challenges, and opportunities of the application of AI technology in the sustainable energy industry. Chen *et al.* [19] used data from various cities in China to study and found that, the level of AI can to some extent affect the carbon emissions level of the industry. Zakizadeh *et al.* [20] believes that the application of AI in energy solutions will bring revolutionary changes to the energy industry. Cheng *et al.* [8] found that the AI level of enterprises can affect the environmental performance of enterprises by influencing technological innovation and labor substitution. It can be seen from the existing research that the existing research results mainly analyze the impact of AI technology on enterprise carbon emissions from the perspective of technology, but the research on the specific effect and impact mechanism of this impact is relatively few.

2.4 Conclusion and deficiency

It can be seen from the existing research that the past scholars have made some research achievements in measuring the AI level of enterprises, the factors affecting the carbon emissions of enterprises, and the impact of AI on the carbon emissions and sustainable development of enterprises, but there are still some shortcomings as follows:

First, there are relatively few literatures on the measurement of enterprise AI level, especially those that can compare the enterprise AI level horizontally in a wide range. At the same time, the measurement method that can measure the historical AI level of enterprises is not mature enough and needs to be further optimized. Moreover, the data used is relatively old, which is difficult to reflect the real situation of the current enterprise AI level.

Second, at present, the literature that directly studies the impact of AI on enterprise carbon emissions is relatively rare. Most scholars discuss the impact of AI on green development or sustainable development from the perspective of technology. There are more theoretical studies and less empirical studies, and most of the existing studies are based on industry data, while the research based on micro enterprise data is relatively rare. Can enterprise AI level affect enterprise carbon emission level? If it can have an impact, is the impact linear or curvilinear? At the same time, in addition to the direct impact of AI level on corporate carbon emissions, can it also have an indirect impact on corporate carbon emissions through other factors? Is there a significant difference in the impact effect between enterprises of different nature? These issues are urgent to be discussed and studied.

3 Research design

This section primarily undertakes the following four tasks: First, it conducts theoretical analysis and proposes research hypotheses; second, it outlines the main research approach; third, it sets up the models; and fourth, it provides explanations for the variables and data involved.

3.1 Theoretical analysis and research hypothesis

3.1.1 Direct impact of AI on enterprise carbon emissions

From the research conclusion of the existing literature, AI technology can directly affect the carbon emission level of enterprises by optimizing resource allocation, improving production efficiency, and reducing energy consumption [21]. AI technology plays an important role in production optimization. Through big data analysis and machine learning, AI can optimize production plan and process, reduce energy consumption and material waste. For example, industrial robots and intelligent manufacturing systems can prevent equipment failures, reduce downtime, and improve production efficiency through real-time data analysis and predictive maintenance. In addition, AI technology can also monitor the operation status of the production line in real time, adjust production parameters in time, avoid resource waste, and reduce carbon emissions. AI is widely used in energy management. AI technologies such as smart grid, energy management system and intelligent building can help enterprises optimize energy use and reduce unnecessary energy consumption [22]. For example, smart grid technology can intelligently allocate energy resources according to real-time supply and demand to avoid energy waste. The intelligent building management system can save energy to the greatest extent by automatically adjusting the operation of lighting, air conditioning and other equipment. In addition, AI technology can also reduce energy costs and carbon emissions of enterprises by optimizing energy procurement and use strategies. Of course, we must be aware that the use of AI technology comes with costs, and the impact of AI technology on carbon emission intensity may exhibit diminishing marginal effects. However, with increased investment, once a certain investment bottleneck is broken through, it will significantly promote the reduction of corporate carbon emission intensity.

To sum up, this paper puts forward the following research hypotheses:

> H1: The level of AI in enterprises will have a significant negative impact on carbon emission intensity, showing an S-shaped relationship, characterized by initial emission reduction, followed by diminishing marginal effects during the middle stage, but in the long term, it will still contribute to the reduction of carbon emission intensity.

3.1.2 Indirect impact of AI level on enterprise carbon emissions

AI not only affects enterprise carbon emissions directly, but also indirectly affects enterprise carbon emission intensity through mechanisms such as green development, and technological innovation.

First, green development mechanism

The application of AI in green development has significantly improved the environmental performance and compliance ability of enterprises. Specifically, AI technology helps enterprises more effectively identify and manage carbon emission sources through data analysis and intelligent monitoring. Scholarly research demonstrates that artificial intelligence analytics can be applied across various fields, including risk management and green development [23]. Using AI technology, enterprises can develop intelligent environmental monitoring system to conduct real-time monitoring and analysis of carbon emissions, find abnormalities and take corrective measures in time. For example, The AI driven environmental management platform can automatically collect and analyze environmental data, generate detailed environmental performance reports, and help enterprises optimize emission control strategies. In addition, AI can also improve the compliance of enterprises with environmental regulations, ensure the compliance of enterprises in environmental protection, and improve their scores in green development performance. For example, AI technology can help enterprises track changes in environmental regulations in real time, adjust management measures in time, and ensure compliance. The promoting effect of AI on green development has been proven in Russia, Sweden, the United Kingdom, the United States, and Japan [24].

To sum up, this paper puts forward the following research hypotheses:

H2: The level of AI in enterprises can reduce corporate carbon emission intensity by enhancing the green development standards of enterprises.

Second, technological innovation mechanism

AI promotes the rapid development of enterprise technological innovation and indirectly reduces carbon emissions by promoting R&D and innovation activities. AI technology can optimize the R&D process and improve the efficiency of R&D investment. For example, through machine learning and data analysis, AI can help enterprises identify the most potential R&D projects, optimize the allocation of R&D resources, reduce unnecessary R&D investment, and improve the success rate of technological innovation. Some scholarly research indicates that AI can play a significant role in complex data processing, root cause analysis, feature estimation, process optimization, product improvement, fault diagnosis, and testing, all of which can save R&D time and enhance the success rate of R&D efforts [25].In addition, AI can also promote the development of new technologies and products, especially the application of energy-saving and environmental protection technologies. For example, AI driven optimization algorithm can improve the energy efficiency of production process, develop more energy-saving products and processes, and reduce carbon emissions. Through the application of AI technology, enterprises can develop energy-efficient technologies and products in a shorter time and improve their competitiveness and environmental performance in the market. The promotion of technological innovation by AI has been demonstrated by some scholars [26].

To sum up, this paper puts forward the following research hypotheses:

H3: The level of AI can reduce corporate carbon emission intensity by promoting technological innovation within enterprises.

Based on the above theoretical analysis, this paper puts forward three research hypotheses, and the subsequent paper will test the validity of these hypotheses through empirical research.

3.2 Research ideas

To further explore the impact of AI on the intensity of enterprise carbon emissions, this paper will first theoretically explore the possible direct and indirect impact of AI level on enterprise carbon emissions intensity. Second, this paper will use AI keywords to evaluate the AI level of enterprises and analyze the differences from the perspective of different enterprise properties. Third, this paper will use the fixed effect model and bootstrap sampling method to empirically study the direct impact of enterprise AI level on enterprise carbon emissions, including straight-line impact and curve impact, verify the relevant assumptions in the theoretical analysis, and conduct heterogeneity analysis. Finally, robustness checks are conducted using variable substitution and instrumental variable methods to examine the robustness of the empirical results.

To sum up, the research framework of this paper is shown in Figure 1.

3.3 Model setting

3.3.1 Benchmark model

To verify the impact of enterprise AI level on enterprise carbon emission this paper draws lessons from Yang *et al.* [27] and other articles build a benchmark model. The model setting is shown in equations (1)–(3):

$$carbon_{it} = c + \beta_1 AI_{it} + \beta_2 control_{it} + \mu_{1it} + \delta_{1it} + \varepsilon_{1it} \quad (1)$$

$$carbon_{it} = c + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 control_{it} + \mu_{2it} + \delta_{2it} + \varepsilon_{2it} \quad (2)$$

$$carbon_{it} = c + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 AI_{it}^3 + \beta_4 control_{it} + \mu_{3it} + \delta_{3it} + \varepsilon_{3it}. \quad (3)$$

Of which, i and t represent the enterprise and time, respectively, c represents the intercept term of the equation, $carbon_{it}$ represents the carbon emission intensity of enterprise i in year t; AI_{it} represents the artificial intelligence level of enterprise i in year t, AI_{it}^2 represents the square term of the enterprise's artificial intelligence level, AI_{it}^3 represents the cubic term of artificial intelligence level; $control_{it}$ represents the control variable, representing the value of the control variable for enterprise i in year t; μ_{it} represents the fixed effect of enterprise i that does not change over time, δ_{it} represents a fixed time effect, e_{it} represents the random interference term.

3.3.2 Multiple mediation model

This paper constructs a multiple mediation model as shown in equations (4)–(6).

$$gw_{it} = c + a_1 AI_{it} + a_2 control_{it} + \mu_{1it} + \delta_{1it} + \varepsilon_{1it} \quad (4)$$

$$th_{it} = c + b_1 AI_{it} + b_2 control_{it} + \mu_{2it} + \delta_{2it} + \varepsilon_{2it} \quad (5)$$

$$carbon_{it} = c + w_1 AI_{it} + w_2 th_{it} + w_3 gw_{it} + w_4 control_{it} + \mu_{3it} + \delta_{3it} + \varepsilon_{3it}. \quad (6)$$

Of which, i and t represent the enterprise and time, respectively, c represents the intercept terms of the equation, $carbon_{it}$ represents the carbon emission intensity of enterprise i in year t; AI_{it} represents the artificial intelligence level of enterprise i in year t; $carbon_{it}$ represents the control variable, representing the value of the control variable for enterprise i in year t; gw_{it} represents the level of green development of enterprise i in year t, used to measure the level of green development of the enterprise; th_{it} represents the number of patent applications made by enterprise i in year t, used to measure the level of technological innovation of the enterprise; μ_{it} represents the fixed effect of enterprise i that does not change over time, δ_{it} represents a fixed time effect, e_{it} represents the random interference term.

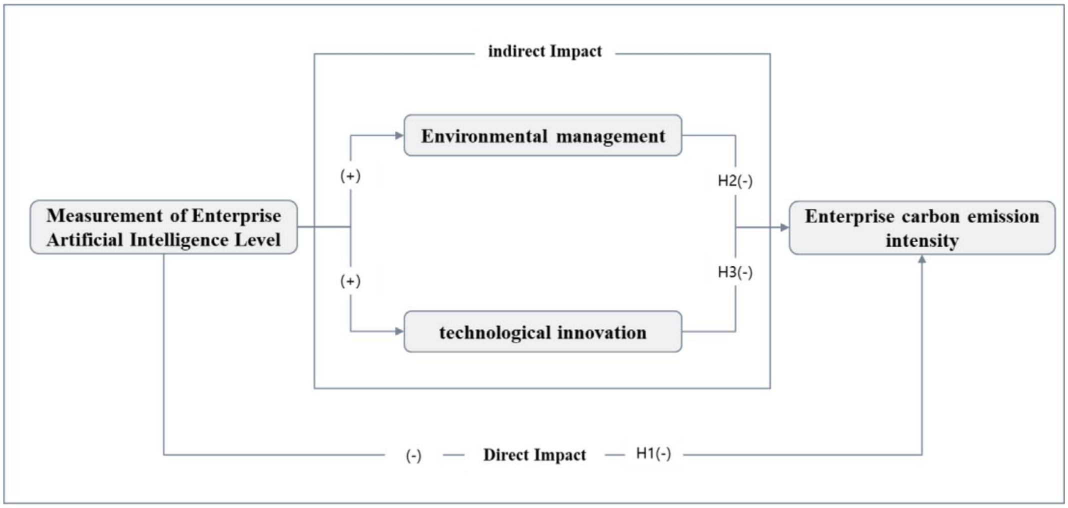

Fig. 1. Research framework of this paper.

Table 1. Explanation of variables.

Variable category	Variable name	Variable code	Metrics
DV	Carbon emission intensity	$carbon1$	Annual carbon emissions divided by total costs
		$carbon2$	Annual carbon emissions divided by total assets
CV	AI level	AI	Company's AI level this year
	Enterprise size	$income$	Business income of the enterprise in the current year
	Company revenue	roa	Return on Assets
	Shareholder structure	$top1$	Shareholding ratio of the largest shareholder
	Enterprise operation efficiency	$operate$	Turnover rate of total assets of the enterprise in the current year
	Investment in fixed assets	fix	Growth rate of fixed assets of the enterprise in the current year
	Industry classification	sic	Industry of the enterprise in the current year
	risk appetite	$debt$	Debt-to-equity ratio
MV	Green development	gr	Corporate Green Development Level
	Technical innovation	th	Annual Patent Applications by the Company

Note: DV is the abbreviation for Dependent Variable, IV is the abbreviation for Independent Variable, CV is the abbreviation for Control Variable, and MV is the abbreviation for Mediating Variable.

3.4 Variable and data description

3.4.1 Variable description

The explained variables, explanatory variables and control variables of the model are shown in Table 1.

3.4.2 Data description

For the total carbon emissions of enterprises, this paper will learn from the practice of Wang *et al.* [28], collect the direct greenhouse gas emissions and indirect greenhouse gas emissions of enterprises (the greenhouse gas generated by purchased power and heat consumed) from the social responsibility report, annual report and sustainable development report issued by enterprises every year, and sum them as the total annual carbon emissions of enterprises. For enterprises that have not directly disclosed their annual carbon emissions but have disclosed different types of energy consumption, the direct greenhouse gas emissions and indirect greenhouse gas emissions of enterprises are calculated respectively according to the accounting methods and reporting guidelines for greenhouse gas emissions of enterprises of different industries issued by the national development and Reform Commission, and the total emissions of enterprises are the sum of the two.

The measurement standard of carbon emission intensity is calculated in the following two ways: First, the natural logarithm of the ratio of the firm's annual total carbon

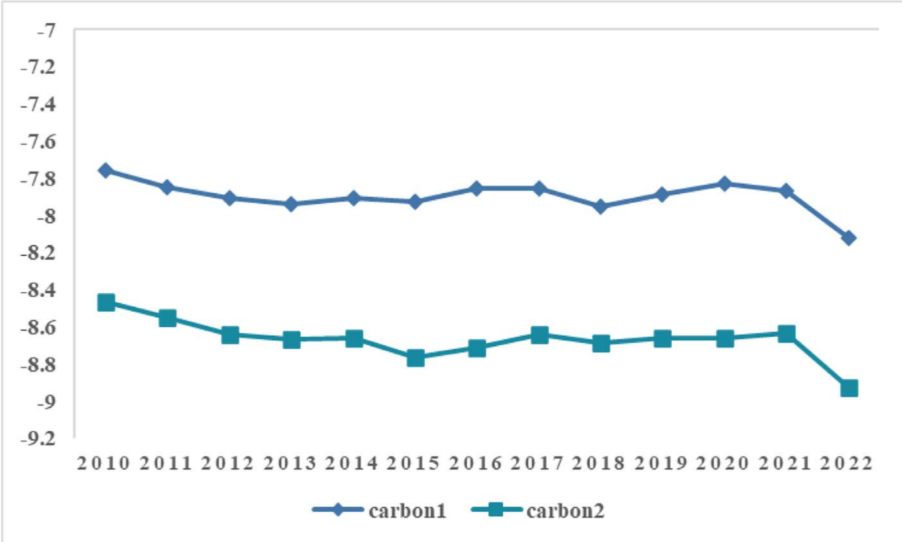

Fig. 2. Trend chart of carbon emission intensity. Note: carbon1 represents the carbon emission intensity calculated by the first method; carbon2 indicates the carbon emission intensity calculated by the second method.

emissions to its total costs (carbon1). Second, the natural logarithm of the ratio of the firm's annual total carbon emissions to its year-end total assets (carbon2). The former is the core explained variable of this paper, and the latter is the alternative variable of robustness test. The reasons for choosing these two methods as the measurement standard of enterprise carbon emission intensity are as follows:

First, from the content of the literature review, the most important factor affecting the carbon emissions of enterprises is the output scale of enterprises, that is, the larger the output scale of enterprises, the more carbon emissions of enterprises. The output of enterprises, from plant equipment, raw materials to finished products, will be reflected in the assets and costs of enterprises. Dividing the total amount of carbon emissions by the total assets or costs of enterprises can objectively and comprehensively reflect the intensity of carbon emissions of enterprises.

Second, total assets are the sum of all resources of an enterprise, including fixed assets, current assets, etc. Using total assets as the denominator can reflect the carbon emissions per unit of assets under different sizes of enterprises. Since the total asset is an absolute value, using it as the denominator can make a direct comparison of carbon emission intensity among enterprises of different sizes. The lower the intensity of carbon emissions, the higher the efficiency of carbon emissions when enterprises use assets for production, that is, the less carbon emissions per unit asset.

Third, the total cost includes production cost, management cost, sales cost, etc., which is the price that enterprises must pay to obtain output. Using the total cost as the denominator can reflect the carbon emissions per unit cost under different operating efficiencies. Because the total cost is strictly linked to the total output of the enterprise, using it as the denominator can make a direct comparison of the carbon emission intensity of enterprises with different output sizes. The lower the intensity of carbon emissions, the higher the efficiency of carbon emissions, that is, the less carbon emissions per unit cost.

The annual average value of carbon emission intensity calculated by the two methods is shown in Figure 2.

From Figure 2, it can be observed that the annual average trends of carbon intensity calculated using both methods are relatively close. Additionally, the overall trend in carbon intensity for Chinese listed companies shows a downward pattern.

For the independent variable AI, this study calculates the frequency of AI-related keywords appearing in the annual reports, takes the natural logarithm of this frequency, and uses it as an indicator of the company's AI level.

Regarding control variables, based on previous scholarly research, key factors influencing corporate carbon emissions include the scale of production, industry characteristics, shareholder structure, operational efficiency, fixed asset investment, industry classification, and risk preferences. Following the approach of other scholars [29], this study first includes production scale as a control variable, measured by corporate revenue (income) and return on assets (roa). Second, shareholder structure is included as a control variable, measured by the shareholding ratio of the largest shareholder (top1). Third, operational efficiency is included as a control variable, measured by the asset turnover ratio (operate); companies with higher operational efficiency tend to produce more output, which can lead to increased carbon emissions. Fourth, investment in fixed assets is included as a control variable, measured by the growth rate of fixed assets (fix); an increase in fixed assets is likely to result in higher carbon emissions. Fifth, industry classification (sic) is included as a control variable, acknowledging that different industries have significantly varying energy structures, energy usage efficiencies, and technology levels; controlling for industry classification effectively accounts for these differences. The industry classification standard refers to the

Table 2. Statistical results of variable description.

Variable	Obs	Mean	Std. D.	Min	Max
DV					
*carbon*1	30,925	−7.903	0.425	−17.463	−0.022
*carbon*2	30,925	−8.677	0.752	−19.775	−1.588
IV					
AI	30,925	46.886	105.236	0.000	2533.000
CV					
income	30,912	21.514	1.504	8.428	28.830
roa	30,925	0.041	0.244	−29.609	22.005
*top*1	30,925	35.210	15.113	0.290	100.000
operate	30,911	0.607	0.418	0.000	8.601
fix	30,915	20.363	1.723	7.197	27.320
sic	30,925	3.730	2.248	1.000	19.000
debt	30,925	0.423	0.274	0.007	28.548
MV					
gw	30,925	1.168	0.279	0.300	1.705
th	30,925	0.981	1.805	0.000	9.899

Note: DV is the abbreviation for Dependent Variable, IV is the abbreviation for Independent Variable, CV is the abbreviation for Control Variable, and MV is the abbreviation for Mediating Variable.

industry classification guidelines published by the China Securities Regulatory Commission in 2012. Sixth, the risk preference of the company is included as a control variable, measured by the debt-to-assets ratio (debt); companies with higher risk preferences are more likely to pursue profits at any cost, without regard for environmental protection.

The measure of the mediating variable green development (gr) is the level of green development of the enterprise. Scholars often choose ESG scores as a standard for measuring green development; however, this practice is not sufficiently scientific, as ESG includes three components – environmental, social responsibility, and governance – which do not truly reflect the green development status of the enterprise. Therefore, this paper draws on the practices of other scholars [30], using the frequency of green keywords appearing in annual reports, with logarithms taken, as the evaluation standard for the level of green development of enterprises.

The measure of the mediating variable technological innovation (th) is the number of patents held by the enterprise. Common standards for measuring technological innovation include R&D investment, the number of patent applications per year, and the number of patents granted per year. Since the number of patents is result-oriented and better represents the true technological capabilities of the enterprise, the number of patents is often used as an evaluation standard for technological innovation. Due to the longer authorization period for patents and the presence of many uncontrollable factors, resulting in significant data volatility, this paper chooses the total number of patents granted in the same year as the measure of technological innovation.

The data for this article comes from the Guotai Junan database and Wind database, as well as relevant information released by enterprises, such as annual reports, social responsibility reports, and sustainable development reports.

Since the period of this study is 13 years (2010–2022), and the time is relatively short, this paper omits the stationarity test of variables.

The descriptive statistics of explained variables, explanatory variables, control variables, and intermediary variables are shown in Table 2.

In the subsequent model estimation, to eliminate the influence of extreme values, this article will perform a 1% tail reduction on continuous variable. For variables with larger or smaller values, this article will improve the stationarity of the variables by taking the logarithm of the variables. This paper also conducted a multicollinearity test for all variables, and the results showed that the VIF values for all variables were less than 10, indicating that there is no multicollinearity issue among the variables. Additionally, this paper performed a correlation analysis for each variable, and the analysis results are shown in Table 3. From the table, the correlations between all variables are less than 0.5, further confirming that there is no multicollinearity among the variables. Table 3 also shows a significant negative correlation between AI and carbon emission intensity, which is consistent with the conclusion of Hypothesis 1.

4 Measurement and difference analysis of AI level

This section primarily measures the AI levels of the sample enterprises and simultaneously demonstrates the differences among State-Owned Enterprises (SOEs), private enterprises, privately-owned enterprises, and other types of enterprises from the perspective of different enterprise natures.

Table 3. Correlation analysis of variables.

	*carbon*1	*AI*	*income*	*roa*	*top*1	*operate*	*fix*	*sic*	*debt*
carbon	1								
AI	−0.04	1							
income	−0.08	−0.01	1						
roa	0.22	−0.01	0.03	1					
*top*1	0.13	−0.08	0.20	0.07	1				
operate	0.00	−0.04	0.36	0.11	0.08	1			
fix	−0.13	−0.08	0.77	−0.05	0.17	0.09	1		
sic	−0.02	−0.09	0.04	−0.03	0.06	−0.19	−0.11	1	
debt	−0.20	−0.03	0.43	−0.23	0.04	0.08	0.34	0.23	1

4.1 Enterprise AI level measurement

In terms of measuring the level of AI in enterprises, this paper refers to the practices of other scholars [30, 31], we used http//www.cninfo.com as a data source to obtain the annual reports of Chinese listed companies. Through in-depth analysis of these annual reports, we have counted the frequency of keywords related to AI, which is used as a basis to evaluate the relative level of the application of AI in various enterprises. The reasons for choosing the annual report of enterprises as the basis for analysis are as follows: first, the annual report of enterprises is an important document that listed companies must disclose to the public every year, including the company's financial status, operating results, major events, strategic development, and other aspects of information. This information has been reviewed by audit and regulatory agencies and has high authority and credibility. Therefore, through the analysis of enterprise annual reports, we can understand the application and development level of enterprise AI more comprehensively. Second, the information in the annual report of the enterprise reflects the real operation situation and strategic direction of the enterprise. The frequency of AI keywords in the annual report can indirectly reflect the importance of AI technology, investment, and the actual application of AI technology in enterprise operation. Third, because the format and content of annual reports of enterprises have relatively uniform standards, it is convenient to compare the annual reports of different enterprises horizontally. By comparing the frequency of AI keywords in the annual reports of different enterprises, we can evaluate the relative level of AI applications of different enterprises. Fourth, by analyzing the frequency of AI keywords in the annual reports of enterprises for consecutive years, we can observe the long-term trend of the application level of AI in enterprises.

In the process of selecting the key fields of text analysis, this paper is deeply inspired by the research framework of Yao *et al.* [9] and has carried out in-depth expansion and improvement based on it. For its 68 keywords, we have carefully reprocessed them to identify and analyze the AI related content involved in the text more accurately. The following are the key strategies adopted in this paper:

First, we implemented the integration of keywords. For example, the terms "neural network", "convolutional neural network" and "deep neural network" are unified into the broader category of "neural network". At the same time, we also integrate the terms "intelligent chip", "intelligent computing", "intelligent environmental protection" and "intelligent search" into the broader field of "intelligence". Such integration not only reduces the risk of repeated statistics, but also solves the problem that the original keywords are difficult to fully cover the diversity of AI applications.

Secondly, we classify the integrated keywords systematically. These keywords are divided into three categories: first, keywords closely related to AI core technologies and algorithms, which directly reflect the core capabilities and innovation direction of AI technology; Second, the keywords related to AI infrastructure and development tools, such as "cloud computing", "data governance" and "data security", cover the key support technologies required for the implementation of AI technology; The third is the specific application scenario of AI, which shows the practical application and influence of AI technology in different fields and industries.

Finally, based on classification, we added some keywords in combination with the hot spots and trends of current enterprise AI practice. These new keywords include "big model", "digital man", "digital twin", "precision medicine" and "precision marketing", which reflect the latest development and application trend of AI technology. After such optimization and expansion, we finally built a new list containing 116 keywords (as shown in Table 4), aiming to cover and analyze AI related content in the text more comprehensively.

Taking Chinese listed enterprises as the research object, taking 2010–2022 as the research period, using the keywords in Table 4, through text analysis, the average AI level of Chinese listed enterprises from 2010 to 2022 is calculated as shown in Figure 3.

As can be seen from Figure 3, although there are some fluctuations in the average AI level of Chinese listed enterprises, the overall upward trend is obvious, and the growth rate has slowed down in recent years.

4.2 Variance analysis

To further explore the differences of AI level of enterprises with different natures, this paper analyzes the differences of AI level of enterprises with different natures from the

Table 4. Key words of AI level.

Category	Keyword
Artificial intelligence core technology and algorithm	Neural networks, deep learning, natural language processing, computer vision, long-term and short-term memory, distributed computing, knowledge representation, support vector machines, pattern recognition, knowledge maps, biometrics, image recognition, feature recognition, voiceprint recognition, machine reading comprehension, text analysis, brain like computing, cognitive computing, fusion architecture, machine translation, cloud, cloud native, perception technology, real-time tracking technology, human-computer interaction, emotional computing, hybrid reality, video surveillance, face recognition, image processing, data science, quantum computing, algorithms, reinforcement learning, target detection
AI infrastructure and development tools	Cloud computing, cloud ecology, cloud services, cloud platform, public cloud, private cloud, medium platform, data integration, data network, data governance, Internet of things, IOT platform, sensors, remote control, data management, data standards, digital control, data center, digital technology, digital network, digitization, cloud it, blockchain, industrial cloud, distributed computing, multi-party security computing, differential privacy technology, brain computing, cognitive computing, green computing, converged architecture, flow computing, graph computing, memory computing, network security, autonomous navigation, data lake, computing power
AI application scenarios	Unmanned, intelligent, intelligent AI. Visualization, numerical control, manufacturing execution system, virtualization, data mining, virtual manufacturing, automation, big data, speech synthesis, speech recognition, future factory, data analysis, fault prediction, digital intelligence, adaptive control, digital marketing, investment decision support system, image understanding, authentication, predictive analysis, social media analysis, digital human, robot, semantic web, digital footprint, creative computing, digital twin, big model, precision medicine, precision marketing, carbon footprint computing, telemedicine, Digital Humanities, digital terminal, multimodal interaction

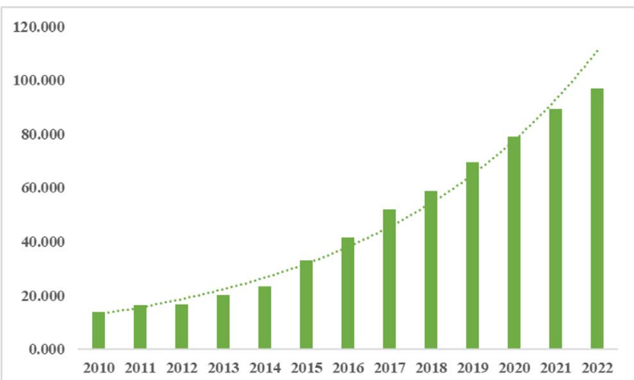

Fig. 3. Average score of AI level over the years.

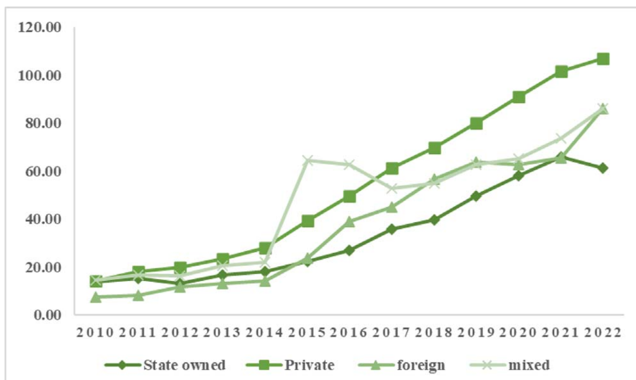

Fig. 4. Average scores of AI levels of enterprises of different natures over the years. Note: "state owned" means a state-owned enterprise; "Private" means private enterprise; "Foreign" foreign enterprise; "Mixed" means a mixed ownership enterprise.

perspective of different enterprise natures. The average AI level of enterprises of different nature is shown in Table 4.

As can be seen from Figure 4, the trend of AI level of enterprises of different natures is relatively consistent. Among them, the average AI level of Chinese private enterprises is significantly higher than that of other types of enterprises, while the AI level of Chinese state-owned enterprises is significantly lower than that of other types of enterprises and has a downward trend in recent years. The AI level of foreign-funded and mixed ownership enterprises is at the middle level but fluctuates greatly. The possible reason is that the number of foreign-funded and mixed ownership listed enterprises is relatively small, so the data fluctuates greatly.

5 Empirical test

In this section, the paper first conducts benchmark tests, followed by mechanism tests to verify the impact relationship and influence pathways between AI and carbon emission intensity. Based on this, heterogeneity analyses are performed. Finally, robustness checks are conducted using variable substitution and instrumental variable methods.

5.1 Benchmark analysis

To investigate the relationship between AI development level and corporate carbon emission intensity, this study estimates the benchmark model based on Equations (1)–(3). In terms of estimation methods, this study first conducted a Hausman test. The test revealed a p-value below the 1% significance level, indicating a significant difference between the fixed effects model and the random effects model. This suggests that the fixed effects model better captures individual heterogeneity, whereas the random effects model does not handle this heterogeneity well. Therefore, this study chose the fixed effects model for estimation. The estimation results are presented in Table 5.

From Table 5, it can be observed that:

Column (1): Without control variables, the coefficient of AI is −0.0009 and is statistically significant at the 1% level. This indicates that a higher AI development level is associated with a significant reduction in corporate carbon emission intensity.

Column (2): When control variables are included, the coefficient of AI remains −0.0004 and is statistically significant at the 1% level. This suggests that even after accounting for other factors, AI still has a significant negative impact on corporate carbon emission intensity.

Column (3): Adding the quadratic term for AI (AI2), the coefficient of AI2 is 0.0000 and is statistically significant at the 1% level. This implies a nonlinear relationship where the negative impact of AI on carbon emission intensity diminishes as AI levels increase.

Column (4): Adding both the quadratic and cubic terms for AI (AI2 and AI3), the coefficients for AI2 and AI3 are 0.0000 and −0.0000, respectively, and both are statistically significant at the 1% level. This suggests an inverse U-shaped relationship between AI and carbon emission intensity, supporting Hypothesis 1.

Column (5): Using cluster-robust standard errors to account for potential within-firm correlation, the coefficients for AI, AI2, and AI3 remain significant and consistent with previous columns. This provides more robust evidence, further supporting the negative impact of AI development level on carbon emission intensity and the inverse U-shaped relationship between AI and carbon emission intensity.

5.2 Mechanism test

To further explore the indirect impact mechanism of AI level on carbon emission intensity, this paper uses equations (4)–(6) and selects bootstrap sampling method to study the mediating effect of AI level on carbon emission intensity. The reasons for choosing bootstrap sampling method for mediating effect test are as follows: first, bootstrap sampling method is a nonparametric statistical method, which does not need to assume the distribution form of data, so it has stronger applicability. When exploring the impact of enterprise AI level on carbon emission intensity, it may be difficult to determine its specific distribution form due to the complexity or uncertainty of the data. At this time, the use of nonparametric statistical methods such as bootstrap sampling method can avoid this problem and obtain more accurate results. The second is bootstrap sampling method, which extracts many self-help samples from the original samples to simulate the overall distribution, to make statistical inference. This method can generate many self-help samples and calculate the sampling distribution of statistics based on these samples. Through this method, we can more accurately estimate the confidence interval and significance level of the mediating effect, to judge whether the AI level of enterprises has an indirect impact on the intensity of carbon emissions. Third, a significant advantage of bootstrap method is that it can be used in any sample size. The bootstrap sampling method can effectively test the mediating effect regardless of the amount of data on the AI level and carbon emission intensity of enterprises. The inspection results are shown in Table 6.

Since bootstrap sampling is based on a limited number of samples with put back sampling, it will lead to fluctuations in the effect estimates obtained from the sampling. Such fluctuations may lead to differences between the bootstrap evaluation results and the real effect values, especially in the case of complex data distribution or small samples. Therefore, the results need to be corrected, and the corrected results are shown in Table 7.

From Table 7, it can be seen that after correction, the coefficients for the total impact of AI on carbon emission intensity (carbon1) (b1), the indirect impact through green development level (gr) (b2), the indirect impact through technological innovation (th) (b3), the direct effect (b4), and the total indirect effect (b5) all remain statistically significant and negative, indicating a consistent reduction in carbon emission intensity. Specifically, the corrected coefficient for the total indirect effect (b5) is −7.1E-05, suggesting that AI significantly reduces carbon emission intensity by enhancing the level of green development and promoting technological innovation. Moreover, the direct effect of AI on carbon emission intensity (b4) remains negative after bias correction, although its confidence interval now includes a value closer to zero, implying a more refined understanding of the direct effect of AI. Overall, these findings underscore the role of AI in fostering corporate green development and technological innovation, which is critical for reducing corporate carbon emissions. Hypotheses 3 and 4 are validated.

5.3 Heterogeneity analysis

5.3.1 Firm heterogeneity analysis

At the corporate level, this study categorizes the sample enterprises into the following two categories: (1) According to ownership nature, the sample enterprises are divided into state-owned enterprises (marked as OT) and non-state-owned enterprises (marked as PVT). (2) Based on the size of the enterprise, using the number of employees, the sample enterprises are categorized into large enterprises (marked as LF) and small and medium-sized enterprises (marked as SM). The criterion for dividing enterprise sizes

Table 5. Benchmark analysis.

	(1)	(2)	(3)	(4)	(5)
	*carbon*1	*carbon*1	*carbon*1	*carbon*1	*carbon*1
AI	−0.0009***	−0.0004***	−0.0009***	−0.0011***	−0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI^2			0.0000***	0.0000***	0.0000***
			(0.000)	(0.000)	(0.000)
AI^3				−0.0000***	−0.0000***
				(0.000)	(0.000)
CV	*NO*	*YES*	*YES*	*YES*	*YES*
FE	*YES*	*YES*	*YES*	*YES*	*YES*
N	30920	30900	30900	30900	30900
R^2	0.2576	0.3339	0.3356	0.3358	0.3358

Note: *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. CV stands for "Control Variables". Column (1) presents the regression results without control variables; Column (2) presents the results with added control variables; Column (3) presents the results with the addition of the quadratic term for AI; Column (4) presents the results with the addition of both the quadratic and cubic terms for AI; Column (5) presents the results with the addition of both the quadratic and cubic terms for AI, and cluster-robust standard errors are used to obtain more robust standard errors. From the regression results, the AI development level has a significant negative impact on carbon emission intensity.

Table 6. Indirect impact mechanism test 1.

	Coefficient	Bootstrap SE	$P > z$	95%CI	
				LL	UL
*b*1	−0.0004	2.04E-05	0.000	−0.0004	−0.0003
*b*2	−4.9E-05	4.28E-06	0.000	−5.7E-05	−4.03E-05
*b*3	−2.3E-05	4.26E-06	0.000	−3.1E-05	−1.42E-05
*b*4	−4.4E-05	2.01E-05	0.030	−8.3E-05	−4.24E-06
*b*5	−7.1E-05	7.02E-06	0.000	−8.5E-05	−5.74E-05

Note: b1 represents the total impact of AI on carbon1 (carbon emission intensity), including both direct and indirect effects; b2 represents the indirect effect of AI on carbon1 through gr (green development level); b3 represents the indirect effect of AI on carbon1 through th (technological innovation); b4 represents the direct effect of AI on carbon1; b5 represents the total indirect effect. The results indicate that AI enhances corporate green development levels and promotes technological innovation, thereby reducing the carbon emission intensity of enterprises.

Table 7. Results after correction.

	Coefficient	Bias	Bootstrap SE	95%CI	
				LL	UL
*b*1	−0.0004	0.0003	2.04E-05	−0.0004	−0.0003
*b*2	−4.9E-05	4.86E-05	4.28E-06	−5.60E-05	−3.90E-05
*b*3	−2.3E-05	1.43E-05	4.26E-06	−2.55E-05	−2.55E-05
*b*4	−4.4E-05	−6.76E-06	2.01E-05	−7.80E-05	3.61E-06
*b*5	−7.1E-05	6.29E-05	7.03E-06	−8.50E-05	−5.74E-05

Note: b1 represents the total impact of AI on carbon1 (carbon emission intensity), including both direct and indirect effects; b2 represents the indirect effect of AI on carbon1 through gr (green development level); b3 represents the indirect effect of AI on carbon1 through th (technological innovation); b4 represents the direct effect of AI on carbon1; b5 represents the total indirect effect. The results indicate that AI enhances corporate green development levels and promotes technological innovation, thereby reducing the carbon emission intensity of enterprises.

Table 8. Heterogeneity tests at the corporate level.

	OT	*PVT*	*LF*	*SM*
	(1)	(2)	(3)	(4)
	*carbon*1	*carbon*1	*carbon*1	*carbon*1
AI	−0.0001***	−0.0007***	−0.0002***	−0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)
CV	*YES*	*YES*	*YES*	*YES*
FE	*YES*	*YES*	*YES*	*YES*
N	15206	15314	10875	19909
R^2	0.3090	0.3945	0.2735	0.3793

Note: *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. CV stands for "Control Variables." The analysis results indicate significant differences among the groups.

Table 9. Heterogeneity tests at the regional level.

	EC	*CWC*	*High-CLI*	*Low-CLI*
	(1)	(2)	(3)	(4)
	*carbon*1	*carbon*1	*carbon*1	*carbon*1
AI	−0.0003***	−0.0008***	−0.0003***	−0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)
CV	*YES*	*YES*	*YES*	*YES*
FE	*YES*	*YES*	*YES*	*YES*
N	21486	9401	15201	15574
R^2	0.3683	0.2781	0.3423	0.3631

Note: *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. CV stands for "Control Variables." The analysis results indicate significant differences among the groups.

is the 50th percentile of the number of employees; enterprises above the 50th percentile are classified as large, and those below are classified as small and medium-sized. The estimation results are shown in Table 8.

From Table 8, the role of AI in reducing carbon emission intensity varies depending on the nature and scale of the enterprise. Non-state-owned enterprises and small and medium-sized enterprises show a greater decrease in carbon emission intensity after adopting AI technology. This may be because non-state-owned enterprises and small and medium-sized enterprises are more flexible in management and operations, allowing them to more quickly adapt to and utilize new technologies, thereby achieving better emission reduction effects.

5.3.2 Regional heterogeneity analysis

At the regional level, this study categorizes the sample enterprises into the following two categories: (1) According to the degree of economic development, the sample enterprises are divided into eastern enterprises (marked as EC) and central and western enterprises (marked as CWC). (2) Based on the degree of openness to foreign investment, using the ratio of foreign-invested and Hong Kong, Macao, and Taiwan enterprises to domestic enterprises as the measurement standard, the enterprises are categorized into those with high openness (marked as High-CLI) and those with low openness (marked as Low-CLI). The criterion for dividing the degree of openness is the 50th percentile of the measurement standard; enterprises above the 50th percentile is classified as having high openness, and those below are classified as having low openness. The estimation results are shown in Table 9.

From Table 9, the role of AI in reducing carbon emission intensity varies depending on the region's level of economic development and degree of openness to foreign investment. Enterprises in central and western regions and those with lower levels of openness show a greater decrease in carbon emission intensity after adopting AI technology. This may be because these regions and enterprises have more room for improvement and can better leverage new technologies to achieve emission reduction targets.

5.4 Robustness test

5.4.1 Variable substitution method

To further test the stability of the model, this paper employs variable substitution to examine the stability of the empirical conclusions. The measurement standard

Table 10. Variable substitution method.

	(1)	(2)	(3)	(4)	(5)
	*carbon*1	*carbon*1	*carbon*1	*carbon*1	*carbon*1
AI	−0.0008***	−0.0005***	−0.0011***	−0.0015***	−0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI^2			0.0000***	0.0000***	0.0000***
			(0.000)	(0.000)	(0.000)
AI^3				−0.0000***	−0.0000***
				(0.000)	(0.000)
CV	*NO*	*YES*	*YES*	*YES*	*YES*
FE	*YES*	*YES*	*YES*	*YES*	*YES*
N	30920	30900	30900	30900	30900
R^2	0.6069	0.7540	0.7550	0.7552	0.7552

Note: *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. CV stands for “Control Variables.” Column (1) presents the regression results without control variables; Column (2) presents the regression results with added control variables; Column (3) presents the regression results with the addition of the squared term of AI; Column (4) presents the regression results with the addition of both the squared and cubic terms of AI; Column (5) presents the regression results with the addition of both the squared and cubic terms of AI, along with cluster processing to obtain more robust standard errors. The regression results show that the level of AI in enterprises has a significant negative impact on carbon emission intensity.

Table 11. Instrumental variable method.

	(1)	(2)	(3)	(4)
	*carbon*1	*carbon*1	*carbon*1	*carbon*1
AI	−0.0012***	−0.0002***	−0.0045***	−0.0004***
	(0.000)	(0.000)	(0.001)	(0.000)
constant	−7.6178***	−8.4958***		
	(0.037)	(0.028)		
CV	*YES*	*YES*	*YES*	*YES*
FE	*NO*	*NO*	*YES*	*YES*
N	30561	23896	30554	23525
R^2	0.0429	0.1257	−0.2540	0.0654

Note: *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively. CV stands for “Control Variables.” Columns (1)–(2) present the regression results when the proportion of employees in the computer industry and the lagged two-period AI level are used as instrumental variables, with the estimation method being OLS. Columns (3)–(4) present the regression results when the proportion of employees in the computer industry and the lagged two-period AI level are used as instrumental variables, with the estimation method being the fixed effects model. From the results, after addressing the endogeneity issue, the negative impact of the AI level of enterprises on carbon emission intensity remains valid.

for carbon emission intensity is changed from carbon1 to carbon2, and the recalculated results are shown in Table 10.

From Table 10, although the magnitude of the regression coefficients has changed, the coefficient significance and signs remain consistent with those of the benchmark regression, indicating good robustness of this study. That is, the level of AI in enterprises has a significant negative impact on carbon emission intensity, and the relationship between the two is S-shaped.

5.4.2 Instrumental variable method

In the previous sections, we examined the causal relationship between the level of AI and corporate carbon emission intensity, but we could not resolve the endogeneity issue arising from reciprocal causality. Therefore, this paper selects the instrumental variable method to further test the robustness of the research conclusions.

For the selection of instrumental variables, this paper refers to the practices of other scholars [32], choosing the lagged two-period AI level and the number of employees in the city's information transmission, computer services, and software industry as instrumental variables. In terms of relevance, a higher number of employees in the computer industry indicate a higher level of informatization in the city, which is conducive to enhancing the AI level of enterprises, thus significantly influencing the AI level of enterprises. The AI level of enterprises typically exhibits persistence and lag effects, so the lagged two-period AI level of enterprises is strongly correlated with the current level of digitalization of enterprises. In terms of exogeneity, the number of employees in the computer industry in the city has no direct association with corporate carbon emission intensity, meeting the exogeneity condition; the lagged two-period AI level of enterprises cannot affect the current carbon emission intensity of enterprises. Although the lagged two-period AI level may have some correlation with the error term of corporate carbon emission intensity, controlling for a series of control variables can largely weaken or eliminate potential impacts, thus the lagged two-period AI level also meets the exogeneity condition.

The regression results using the instrumental variable method are shown in Table 11. Columns (1)–(2) present the regression results when the proportion of employees in the computer industry and the lagged two-period AI level are used as instrumental variables, with the estimation method being OLS. Columns (3)–(4) present the regression results when the proportion of employees in the computer industry and the lagged two-period AI level are used as instrumental variables, with the estimation method being the fixed effects model. In columns (1)–(4) of Table 11, the coefficients of AI are all significant, indicating that even after addressing the endogeneity issue through the instrumental variable method, the negative impact of the AI level of enterprises on carbon emission intensity remains valid.

6 Conclusion

This paper finds the following conclusions through research:

1. Trends in changes in carbon emission intensity. The carbon emission intensity of Chinese enterprises has significantly decreased in the early stage, then tended to stabilize, and has notably decreased again in recent years.
2. Trends in the development of AI levels. The average level of AI among listed Chinese enterprises shows an overall upward trend, but the growth rate has slowed down; the level of AI in private enterprises is significantly higher than that in other types of enterprises, while the level of AI in state-owned enterprises is relatively lower and has shown a downward trend in recent years; the level of AI in foreign-funded and mixed-ownership enterprises is at an intermediate level but with greater volatility.
3. The relationship between AI and carbon emission intensity. The level of AI in enterprises has a significant negative impact on carbon emission intensity, presenting an "S"-shaped relationship, characterized by initial emission reduction, mid-term rebound, and subsequent emission reduction.
4. The mechanism by which AI affects carbon emission intensity. AI technology reduces the level of carbon emissions in enterprises by enhancing their green development standards and promoting technological innovation.
5. Heterogeneity analysis reveals that non-state-owned enterprises and small and medium-sized enterprises experience a larger decrease in carbon emission intensity after adopting AI technology; enterprises located in central and western regions and those with lower degrees of openness also show a greater reduction in carbon emission intensity after adopting AI technology.

The above conclusion tells us that to promote Chinese enterprises to further reduce carbon emissions, enterprises and the government should work together to promote the application of AI technology in enterprise energy transformation and energy conservation and emission reduction. Specifically, we can start from the following two aspects:

First, enterprises should actively enhance their application levels of AI technology to improve their green development standards and innovation capabilities. Specific measures include increasing R&D investment, introducing AI talents, promoting the application of AI in environmental management, and reducing carbon emissions through intelligent production and green supply chain management. At the same time, environmental performance should be included in the assessment system, and AI technology should be used to monitor and feedback carbon emissions in real time, to ensure the realization of emission reduction targets.

Second, the government should formulate incentive policies and standards to promote the wide application of AI technology in enterprises. Specifically, it includes providing financial support and tax incentives, setting up a special fund for AI and environmental protection, formulating AI application standards and carbon emission standards, and promoting industrial cooperation and exchanges. By establishing a monitoring and evaluation system, the government can monitor the carbon emissions of enterprises in real time to ensure the effect of policy implementation, to promote the win-win of economic and environmental benefits.

Third, the government should prioritize supporting the carbon reduction efforts of specific types of enterprises. Specifically, non-state-owned enterprises and small and medium-sized enterprises should receive greater support in terms of fiscal assistance and tax incentives to help them overcome funding and technological challenges. Additionally, special support funds should be established for enterprises located in central and western regions and those with lower degrees of openness, to aid these enterprises in AI technology research and development and application, thereby better promoting their emission reduction efforts.

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Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

References

1 Zhao J., Zhou N. (2021) Impact of human health on economic growth under the constraint of environment pollution, *Technol. Forecast. Soc. Change* **169**, 120828.
2 Yuan X., Li H., Zhao J. (2020) Impact of environmental pollution on health – evidence from cities in China, *Soc. Work Public Health* **35**, 413–430.
3 Majeed Y., Khan M.U., Waseem M., Zahid U., Mahmood F., Majeed F.F., Sultan M., Raza A. (2023) Renewable energy as an alternative source for energy management in agriculture, *Energy Rep.* **10**, 344–359.
4 Loureiro S.M.C., Guerreiro J., Tussyadiah I.P. (2021) Artificial intelligence in business: state of the art and future research agenda, *J. Bus. Res.* **129**, 911–926.
5 Shaq (2024) *AI Ready (2): Combat assessment – enterprise AI maturity evaluation model* [Blog post], Retrieved from https://zhuanlan.zhihu.com/p/681183964 (in Chinese).
6 Yablonsky S.A. (2021) AI-driven platform enterprise maturity: from human led to machine governed, *Kybernetes* **50**, 2753–2789.
7 Micallef P., Gupta M. (2021) Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance, *Inf. Manag.* **58**, 103434.
8 Cheng K., Jin Z., Wu G. (2024) Unveiling the role of artificial intelligence in influencing enterprise environmental performance: evidence from China, *J. Clean. Prod.* **440**, 140934.
9 Yao J.Q., Zhang K.P., Guo L.P., Feng X. (2024) How does artificial intelligence improve corporate production efficiency? – from the perspective of labor skill structure adjustment, *Manag. World* **40**, 2, 101–116, 133, 117-122 (in Chinese).
10 Tang H., Xiao H., Wei Z. (2019) Research on the influencing factors and mechanism of production in carbon emission-dependent enterprises, *Chin. J. Manag.* **16**, 12, 1841–1846 (in Chinese).
11 Li Y., Miao B. (2022) Review of research on the influencing factors of corporate carbon performance, *Acc. Fin. Mon.* **10**, 63–69 (in Chinese).
12 Liu Q.C., Kong L.Q., An Z.Y. (2014) Analysis of energy-related carbon emission factors in China's manufacturing industry, *China Popul. Resour. Environ.* **24**, 2, 14–18 (in Chinese).
13 Xie L., Wang T., Zhang T. (2019) Factors affecting the intensity of industrial carbon emissions: empirical evidence from Chinese heterogeneous subindustries, *Emerg. Mark. Financ. Tr.* **55**, 1357–1374.
14 Pan T., Zhang J., Wang Y., Shang Y. (2024) The impact of environmental regulations on carbon emissions of Chinese enterprises and their resource heterogeneity, *Sustainability* **16**, 3, 1058.
15 Waheeb R.A. (2023) Sustainable ENERGY by using AI, *SSRN Electron. J.*
16 Zhao Q., Wang L., Stan S.E., Mirza N. (2024) Can artificial intelligence help accelerate the transition to renewable energy? *Energy Econ.* **134**, 107584.
17 Mittal A., Dumka L., Singh Kharka K.P., Soni M., Goyal H. R. (2024) Smart energy: artificial intelligence (AI) in charging and battery management systems, in: *2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 11–12 March, IEEE, pp. 68–73.
18 Ahmad T., Zhang D., Huang C., Zhang H., Dai N., Song Y., Chen H. (2021) Artificial intelligence in sustainable energy industry: status quo, challenges and opportunities, *J. Clean. Prod.* **289**, 125834.
19 Chen P., Gao J., Ji Z., Liang H., Peng Y. (2022) Do artificial intelligence applications affect carbon emission performance? – Evidence from panel data analysis of Chinese cities, *Energies* **15**, 15, 5730.
20 Zakizadeh M., Zand M. (2024) AI-driven energy intelligence: revolutionizing the energy sector through smart energy solutions, in: *2024 10th International Conference on Web Research (ICWR)*, Tehran, Iran, Islamic Republic, 24–25 April, IEEE, pp. 355–363.
21 Zhong J., Zhong Y., Han M., Yang T., Zhang Q. (2023) The impact of AI on carbon emissions: evidence from 66 countries, *Appl. Econ.* **56**, 2975–2989.
22 Fernando Y., Hor W.L. (2017) Impacts of energy management practices on energy efficiency and carbon emissions reduction: a survey of Malaysian manufacturing firms, *Res. Conserv. Recycl.* **126**, 62–73.
23 Kushnarevych A. (2024) Researching the topic of AI data analysis in loyalty programs, in: *Proceedings of the 23rd European Conference on Research Methodology for Business and Management Studies*, Porto, Portugal, 4–5 July. https://doi.org/10.34190/ecrm.23.1.2401.
24 Chutcheva Y., Kuprianova L.M., Seregina A.A., Kukushkin S.N. (2022) Environmental management of companies in the oil and gas markets based on AI for sustainable development: An international review, *Front. Environ. Sci.* **10**, 952102.
25 Podder I., Fischl T., Bub U. (2023) Artificial intelligence applications for MEMS-based sensors and manufacturing process optimization, *Telecom* **4**, 1, 165–197.
26 Liu T., Yu Z. (2022) The relationship between open technological innovation, intellectual property rights capabilities, network strategy, and AI technology under the Internet of Things, *Oper. Manag. Res.* **15**, 793–808.
27 Yang G., Yang G., Yang W. (2023) Research on the influence of depth and breadth of equity reform on the performance of state owned enterprises based on dynamic panel data model, *Fluct. Noise Lett.* https://doi.org/10.1142/S0219477524400145.
28 Wang H., Liu J.Z., Zhang L.H. (2022) Carbon emissions and asset pricing: evidence from Chinese listed companies, *J. Econ.* **9**, 2, 28–75.
29 Luo Y., Tian N., Wang D., Han W. (2023) Does digital transformation enhance firm's ESG performance? Evidence

from an emerging market, *Emerg. Mark. Fin. Tr.* **60**, 825–854.

30 Loughran T., Mcdonald B. (v) When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *J. Fin.* **66**, 35–65.

31 Abbaskhani H., Pakmaram A., Rezaei N., Sales J.B. (2024) Enhancing going concern prediction models: integrating text mining with data mining approaches, *Iran. J. Acc. Auditing Finance* **8**, 3, 27–42.

32 Zhong T.-Y., Cheng Y.-M., Li J.-N. (2023) Digital transformation and labor investment efficiency: alleviating the under-investment or inhibiting the over-investment? *Western Forum* **2**, 29–42 (in Chinese).