OPEN

The influence of AI application on carbon emission intensity of industrial enterprises in China

Yao Lu & ZeFang Liao✉

As a critical aspect of the industry 4.0 era, the application of artificial intelligence (AI) is significant to environmental governance. It serves as a crucial driving force in assisting enterprises in the transition toward low-carbon practices. This paper examines China's A-share industrial enterprises from 2011 to 2022, constructs and trains a word vector model to extract AI-related terms, and the impact of AI applications on the carbon emission intensity of these enterprises is investigated. The findings reveal that enhancing the level of AI application can effectively decrease carbon emission intensity. Specifically, a 1% increase in AI application leads to a reduction of 0.0395% in carbon emission intensity. Further analysis indicates that enterprises can diminish their carbon emission intensity by the optimization of supply chain and green technology innovation. Heterogeneity analysis suggests that utilizing AI is beneficial for reducing the carbon emission intensity of manufacturing, high-tech, and high-pollution enterprises. The results of this study enrich the micro-level research on the relationship between AI and carbon emission intensity, offering valuable insights for enterprises aiming to achieve sustainable development.

Keywords AI application, Reduction of carbon emission, Word vector model

With the rapid advancement of artificial intelligence (AI), the level of AI in China has been steadily escalating. In 2023, the penetration rate of digital research and design tools in China's key industrial enterprises reached 80.1%, while the numerical control rate for critical processes stood at 62.9%. Nevertheless, the challenges posed by energy consumption and carbon emissions in China's industrial sector remain acute during this transformational phase. According to data, industrial enterprises in China accounted for approximately 70% of the total energy consumption and approximately 80% of the country's overall carbon emissions in 2023, underscoring the significant responsibility and challenges faced by these enterprises in pursuing sustainable development. Given this backdrop, the utilization of AI to facilitate carbon emission reduction has garnered widespread attention from the academic community[1–3].

Currently, the majority of scholars have conducted analyses from various perspectives, including the national level[4], provincial level[5], and the lens of industrial agglomeration and its externalities[6]. Their findings reveal that AI can significantly contribute to carbon emission reduction, and this effect is particularly pronounced in regions with advanced AI development[7]. Furthermore, the emission reduction impact of industrial robots exhibits a sustained effect over time[8]. Notably, compared to cities in upstream and midstream regions, AI plays a more prominent role in facilitating carbon emission reduction in downstream cities[9]. However, some scholars caution that amid intelligent development and economic transformation, the deployment of related digital infrastructure can potentially lead to an increase in carbon emission intensity[10]. This impact varies across industries, exhibiting significant differences[11]. For instance, Yu et al.[12] highlights that the carbon emission reduction of AI is not uniformly distributed. While the carbon emission reduction effect within the industry is evident, downstream industries may experience an increase in carbon intensity, thus trapping them in a "low-end lock-in" scenario. Additionally, Wang et al.[13] argue that while the application of industrial robots can indeed reduce carbon emissions to a certain extent, it can also trigger an energy rebound effect, potentially neutralizing the carbon emission reduction benefits of these robots.

In the testing of carbon emission reduction mechanisms through intelligent technologies, scholars have conducted extensive research encompassing aspects such as total factor productivity, energy consumption, and green technological innovation. Cheng et al.[14] utilizing data from listed manufacturing companies spanning from 1998 to 2014, revealed that as enterprises enhance their total factor productivity, increase pollution-specific fixed investments, and optimize factor input structures, the carbon reduction effect of AI becomes increasingly

College of Economics and Management, Shanghai Ocean University, No. 999, Hu Cheng Ring Road, Shanghai 201306, China. ✉email: zfliao@shou.edu.cn

significant. Lv et al.[15] emphasized that intelligent manufacturing primarily reduces industrial emissions by mitigating fossil energy consumption during production and enhancing energy utilization efficiency. Additionally, scholars have delved into the regulatory mechanisms from the perspective of innovation effects, finding that green technological innovation potentiates the carbon emission reduction effect of AI[16].

Regarding the measurement of AI, research primarily focuses on the construction of comprehensive AI indicators. Cao et al.[17], for instance, selected markers of innovative transformation, intangible assets related to digital and intelligent technologies, and fixed assets pertaining to digital and intelligent transformation as the foundation, utilizing the entropy method to establish a comprehensive indicator system for digital and intelligent transformation. Han et al.[18] chose data from the International Federation of Robotics (IFR) as a proxy for AI representation. Furthermore, scholars have leveraged text analysis techniques to construct AI indicators, exploring their impact on corporate green innovation efficiency[19].

Upon reviewing the existing literature, in terms of measuring AI within enterprises, some scholars opt for using the number of industrial robots supplied by the International Federation of Robotics (IFR) as an indicator of AI, or alternatively, the number of imported robots. Some also employ the entropy method for construction. While these indicators can, to some extent, reflect the level of AI application in enterprises, it is crucial to note that industrial robots constitute merely a fraction of AI technology. Using the number of industrial robots as a proxy variable fails to comprehensively capture the extent of AI application in enterprises. Furthermore, given the rapid advancement of AI in China, substituting “import” for “holding” somewhat underestimates the extent of AI utilization in enterprises. Additionally, determining appropriate weighting standards for constructing an AI index poses challenges. As an emerging technology, AI stands out distinctly from others. It aims to simulate, extend, and augment human intelligence, possessing unique technical principles and methodologies. AI is widely applied across various domains, including intelligent manufacturing, natural language processing, and image recognition[20]. In contrast to the broad notion of technological progress, the impact of AI development is unprecedented in the history of technological advancements[21], and its implications and pathways warrant further research.

Based on the above analysis, this paper selects industrial enterprises spanning from 2011 to 2022 as the sample, employing Latent Dirichlet Allocation (LDA) for theme analysis and word vector model to generate an AI vocabulary. Subsequently, the paper utilizes Python to conduct text analysis on the annual reports of listed companies. The potential marginal contributions of this paper are outlined as follows: (1) The cross-disciplinary study of AI and economics represents a frontier area in current academic research. From a text analysis perspective, this paper adopts word vector model to generate AI vocabulary, thereby reducing subjectivity in the measurement process and offering valuable insights for subsequent micro-level research. (2) The majority of existing studies concentrate on national, industry, and other macro-levels, with relatively scant attention given to micro-level research. Building upon the existing literature, this paper further broadens the scope of research by incorporating industrial enterprises, enhancing the generalizability of the research findings. (3) This paper further elucidates the transmission mechanism through which AI influences enterprise carbon emission intensity, from the dual perspectives of "green technology innovation" and "supply chain optimization".

The remaining structure of this paper is as follows: In the second section, we conduct theoretical analysis and formulate research hypotheses. The third section details the data sources and the specification of research model. Subsequently, the fourth section presents findings from empirical results and conduct an in-depth discussion. Finally, we conclude the paper with a summary of our findings, along with implications for policy making and directions for future research.

Theoretical analysis and research hypothesis

The impact of AI application on carbon emission intensity

The Solow growth model underscores the pivotal role of technological advancement in driving long-term economic growth and serving as the cornerstone of sustainable development. AI has emerged as a standout in sustainable development efforts. By enhancing the efficiency of corporate information integration and optimizing information processing capabilities, AI enables stakeholders, including investors and consumers, to access timely and accurate environmental protection information about enterprises. This, in turn, prompts enterprises to make adjustments and prioritize the harmonious development of economic benefits and environmental protection[22]. Furthermore, the development of AI is accompanied by technology absorption and spillover, facilitating the replacement of repetitive and inefficient manual operations. This advancement promotes the automation and intelligence of enterprise production, leading to reduced production costs and optimized production processes[23], thereby enhancing resource utilization. Additionally, enterprises can leverage AI to track and monitor gas emissions, enabling them to regulate carbon emissions across various production stages effectively, finally helps reduce energy consumption and achieves goals of carbon emission reduction[24]. Therefore, this paper posits the following research hypothesis:

Hypothesis 1 The application of AI in industrial enterprises will contribute to the reduction of carbon emission intensity.

The mediating role of supply chain optimization

AI has established a platform that facilitates information sharing, resource integration, and business collaboration among various stakeholders in the supply chain, thereby mitigating information asymmetry and fostering greater transparency and collaboration. Additionally, it spurs the innovation capabilities and sustainable development potential of the supply chain[25]. A decentralized supply chain encourages enterprises to adopt more flexible production and processing models, such as local production proximate to consumers, which significantly reduces carbon emissions associated with long-distance transportation and prop development of green production and low-carbon supply chains. Furthermore, enterprises enhance their supervision and management capabilities across all aspects of the supply chain through digital transformation and cross-departmental resource sharing[26], providing robust support for supply chain innovation and carbon emission reduction. Given these considerations, the second hypothesis is proposed:

Hypothesis 2 The application of AI in industrial enterprises effectively reduces carbon emission intensity by supply chain optimization.

The mediating role of green technology innovation

AI applications offer enhanced support and assurance for the advancement of green and low-carbon technology[27]. By incorporating new systems and procedures, enterprises leverage intelligent technology to refine production processes, facilitating cleaner production and emission reductions. AI not only accelerates advancements in carbon capture and storage technology, fostering the development of clean energy sources such as solar and wind power[28], but also enhances energy utilization efficiency[29], aiding enterprises in achieving their "green" and "low-carbon" development objectives. In addition, enterprises adopt green and energy-saving production methods to reduce carbon emissions while further reducing production costs, thus gaining a competitive edge in the market[30]. Based on this, the third hypothesis of this paper is proposed:

Hypothesis 3 The application of AI in industrial enterprises effectively reduces carbon emission intensity through green technology innovation.

Data and research design

Data sources

This study defines industrial enterprises primarily as those within the scope of "Classification of National Economic Industries" (GB/T 4754-2017) and the "Regulations on the Division of Three Industries", industrial enterprises here primarily refer to enterprises within China's secondary industry, encompassing mining (excluding mining auxiliary activities), Manufacturing (excluding the repair of metal products, machinery, and equipment), Electricity, Heat, Gas, and Water Production and Supply, as well as Construction. Based on these classification criteria, we matched the corresponding industrial enterprises in CSMAR database. Since 2011, the application of AI in China has exhibited a trend of rapid growth. Given the availability of data samples, this study selects enterprises on the Shanghai and Shenzhen A-share markets from 2011 to 2022 as the sample.

Following measures were implemented to ensure the robustness of our findings: (1) exclude companies with ST, *ST and PT status from the sample; (2) exclude those with significant missing data on essential variables and employing linear interpolation method to fill in missing values; (3) winsorize all continuous variables at the 1% and 99% quantiles to mitigate the impact of extreme values on the experimental outcomes. After these rigorous processes, we obtained 23,419 observations across 3,318 listed companies from 2011 to 2022. The data utilized in this paper primarily originate from the *"China Energy Statistical Yearbook"*, *"China Industrial Statistical Yearbook"*, the CNRDS database, and the CSMAR database. These data were comprehensively processed and analyzed using Stata16.1 and Python.

Variables

Dependent variable

Carbon emission intensity (CEI). Since the Chinese government does not mandate companies to disclose carbon emissions information, there are limitations in obtaining emissions data at the corporate level[31]. While some listed companies do report their carbon emissions in the China Stock Market Accounting Research (CSMAR) Database, the sample size is insufficient to quantitative analysis. Furthermore, some studies have attempted to calculate corporate carbon emissions based on the National Tax Survey Database by converting various energy consumptions; however, this database has not been publicly released yet[32]. Given the current inability to directly obtain carbon emission data from Chinese enterprises, estimating corporate carbon emissions through industry-level data has emerged as a feasible and widely adopted method. This paper adopts the approach of Zhu et al.[33], the measurement of carbon emissions is primarily based on eight types of energy sources disclosed in the China Energy Statistical Yearbook, namely coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. By referencing the IPCC guidelines and the "Guidelines for the Preparation of Provincial Greenhouse Gas Inventories" and other relevant materials, indices such as the lower heating value and carbon content corresponding to each energy source are obtained. Subsequently, the total carbon emissions of the industry are calculated by summing up these values. Carbon emission intensity is primarily measured by the carbon emissions per unit of income of enterprises, expressed in tons per million. The specific approach is outlined as follows:

$$Total\ CO_2\ emissions\ of\ industry = \sum_{S=1}^{8} FC_{its} \times NCV_S \times CC_S \times OF_S \times 44/12$$

$$Carbon\ emission\ intensity = ln\left(\frac{Enterprise\ operating\ costs \times Total\ CO_2\ emissions\ of\ industry}{Industry\ operating\ costs \times Enterprise\ operating\ revenue} \times 10^4\right)$$

where, FC_{its} refers to the consumption of energy *s* in year *t* of industry *i*, NCV_S refers to the average low level heat generation of energy *s*, CC_S refers to the carbon content per unit calorific value of energy *s*, OF_S refers to the oxidation rate of carbon in energy *s*. Precisely as the chemical reaction equation indicates, $C + O_2 = CO_2$, where $44/12$ represents the conversion coefficient from carbon to carbon dioxide.

Independent variable

Artificial Intelligence Applications (AIA). This article utilizes text analysis to assess the level of AI applications within enterprises. The implementation process proceeds as follows: Given that China's AI industry has experienced rapid growth only since 2011, and considering the inherent time lag associated with research reports, this article compiles a comprehensive collection of authoritative reports on AI research spanning the period from 2016 to 2024. This compilation includes notable reports such as the "2019 Artificial Intelligence Development Report" issued by Tsinghua University and the "2020 Artificial Intelligence Index Report" published by the Stanford Human-Centered AI Institute, totaling 56 reports. Subsequently, the collected reports undergo a rigorous stop word removal and corpus cleaning process (Since we analyze Chinese annual reports, the commonly used stop words primarily encompass adverbs like "非常"(very), "仅仅"(just), "如此"(such) and so on; prepositions, including "通过" (through), "关于"(about), "除了"(without), etc.; conjunctions such as "和"(and), "但是"(but), "因为"(because), etc., and some Chinese punctuation marks, like '! # $ % & *'. Due to the excessive number of stop words, they are not all listed here). Utilizing Python, word cloud diagrams are generated to visually represent the data, highlighting the top 100 most frequently occurring words across all reports. Since our word cloud map is based on the Chinese version of the annual report of the enterprise, to enhance comprehensibility, we have created a bilingual word cloud map. As illustrated in Fig. 1, recent reports and research have primarily centered on key terms such as "Artificial Intelligence", "Data", "Development", and "Robot", which offer a glimpse into the profound influence of AI applications on economic growth and societal advancement.

Next, an LDA topic analysis model was conducted on the research report. As evident from Figs. 2 and 3, a topic count of five yielded the lowest perplexity score, the highest consistency score, and a well-separated visualization effect. This underscores the appropriateness of selecting five topics. Subsequently, the top 30 words under each topic were extracted, and ultimately, 22 words were chosen from the two topics of "core and peripheral technologies of AI" and "AI application" as seeds. These two topics not only comprehensively encapsulate the primary application scenarios of AI but also contain AI's fundamental essence.

Given the GloVe word vector model's thorough consideration of global information, its suitability for extensive training on large-scale corpora, and the ease of parameter adjustment, therefore this paper utilizes the GloVe model to identify relevant terms associated with AI in the annual reports of listed companies, leveraging the generated seed words. Subsequently, we calculate the cosine similarity of these related terms and conduct word frequency analysis. Keywords with a frequency below ten are excluded, ultimately compiling an AI vocabulary containing 94 terms (See the appendix at the end of the paper) to assess the level of AI integration within industrial enterprises. The detailed construction process is illustrated in Fig. 4.

Mechanism variables

Supply chain optimization (Chain). This paper employs supply chain concentration as a metric. Specifically, this paper adopts the practice of Huang[34] and Gu[35], calculating the average purchase and sales ratio of the top five suppliers and customers to assess the degree of optimization within the enterprise's supply chain. The index reflects the concentration of upstream and downstream partners in the supply chain, and to a certain extent reflects the strength of enterprises' digital external integration capabilities[36].

Green technological innovation (TGP). In terms of assessing green technological innovation, this study employs the number of green patents as a proxy, drawing inspiration from the research conducted by Lan[37] and Cui[38]. Specifically, green technology innovation in this study is gauged by taking the logarithm of the total count of green patents (comprising green invention patents and green utility patents), incremented by one. The green patent dataset encompasses company information, the year of application and authorization, the number of green invention patent applications, and the number of green utility model patent applications.

Fig. 1. Word cloud map of AI research.

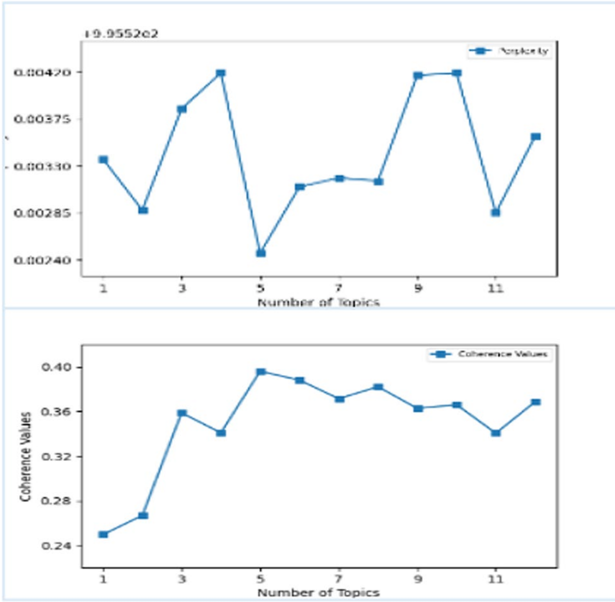

Fig. 2. Perplexities and the coherence values.

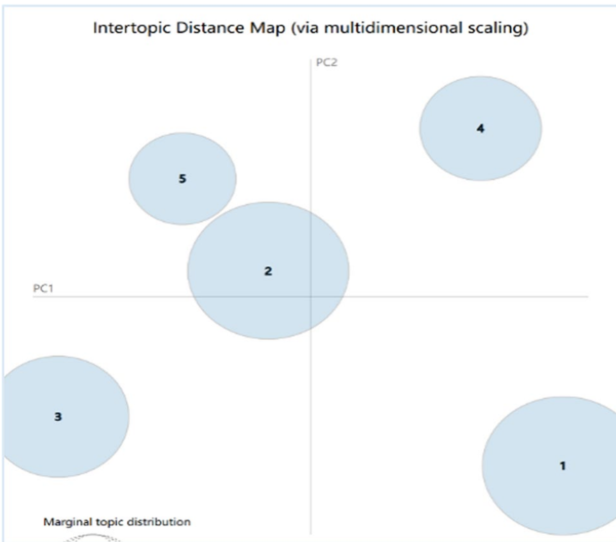

Fig. 3. Graph of visualization.

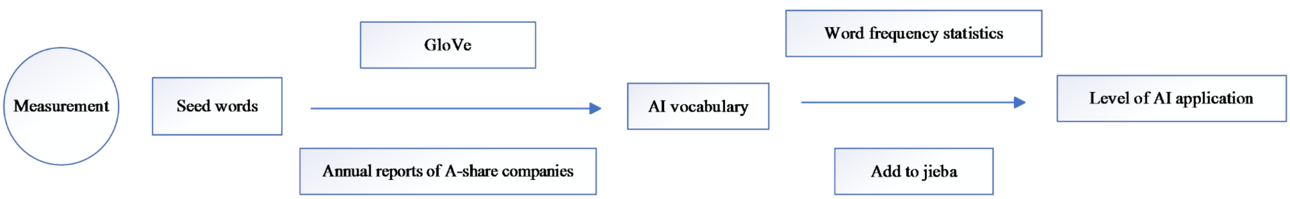

Fig. 4. Flow chart of measurement of AI.

Control variables

Drawing on existing research to minimize potential errors, this paper selects control variables from two distinct levels: corporate finance and corporate governance, thereby enhancing the credibility of our research findings.

The first level focuses on financial indicators, including: (1) Enterprise size (Size), measured by logarithm of total assets; (2) Fixed Assets Ratio (Fixed), representing the percentage of fixed assets relative to total assets; (3) Profitability (OPR), measured as the percentage of operating profit to operating income; (4) Asset Turnover (ATO), calculated as the percentage of operating income to the ending balance of assets; (5) Financial Leverage (LEV), Assessed by the ratio of total liabilities to total assets.

The second level delves into indicators pertaining to corporate governance, specifically including: (1) Company Age (Ages), calculated as the logarithm of the difference between the observation year and the year of establishment plus 1; (2) Board Size (LBoard), represented by the logarithm of the number of directors plus 1; and (3) Equity Concentration (TOP1), reflecting the shareholding ratio of the largest shareholder.

These indicators encompass diverse aspects, including the company's operational history, asset composition, profitability, operational efficiency, governance framework, and equity distribution, providing a comprehensive understanding of the company's operational status and governance environment. Additionally, these indicators are intricately linked to the company's business decisions, resource allocation, technological advancements, and environmental protection initiatives, exerting a direct or indirect influence on carbon.

Upon conducting a correlation analysis on these variables, the results showed that the maximum correlation coefficient was 0.5215, less than 0.7, indicating that there was no significant multicollinearity problem[39]. This validates the appropriateness of selecting these variables as control variables. Table 1 descriptive statistics, highlighting that the CEI ranges from a minimum of -5.6941 to a maximum of 1.7799, with a standard deviation of 1.9676, underscoring substantial variations in carbon emission intensity across different industrial enterprises. Similarly, the AIA variable exhibits a standard deviation of 1.3375 and a notable disparity between its maximum and minimum values, reflecting the diverse levels of AI application across various enterprises.

Specification of model

To explore the intricate relationship between artificial intelligence and carbon emission intensity, this paper establishes and examines the following model:

$$CEI_{i,t} = \beta_0 + \beta_1 AIA_{i,t} + \beta_i \sum Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

where, $CEI_{i,t}$ is an explanatory variable, denoting the carbon emission intensity of enterprise *i* in year *t*. $AIA_{i,t}$ is the explanatory variable, which represents the application of artificial intelligence of enterprise *i* in year *t*. $Controls_{i,t}$ denotes the above control variables, μ_i and γ_t denote individual fixed effects and year fixed effects respectively, $\varepsilon_{i,t}$ refers to the random error term.

Results

Baseline regression result

Table 2 presents the baseline regression results. The regression outcomes elaborated in columns (1) and (2) indicate that, after controlling for time and individual effects, a 1% increase in AI application corresponds to a 0.0413% reduction in carbon emission intensity, achieving a significance level of 1%. Upon incorporating control variables in columns (3), (4), and (5), the model's goodness-of-fit is further improved. Notably, to ensure the currency of the study, column (4) presents the regression results without linear interpolation, revealing a significant negative correlation between AIA and CEI at the 1% level. Meanwhile, the baseline regression results displayed in column (5) align closely with those reported in column (2) of Table 2, maintaining a significance level of 1%. Specifically, a 1% increase in AI application translates to a 0.0395% decrease in the carbon emission intensity of enterprises.

The underlying reason for this phenomenon may stem from the dual role of AI in internal regulation and external supervision. On the internal regulation front, enterprises leverage AI technology to meticulously manage production processes, optimize resource allocation, and maintain real-time monitoring of energy

Variables	Observations	Mean	SD	Min	Max
CEI	23,419	−2.7971	1.9676	−5.6941	1.7799
AIA	23,419	1.7901	1.3375	0.0000	5.2149
Size	23,419	22.1286	1.2147	20.0473	25.9290
Fixed	23,419	0.2324	0.1438	0.0168	0.6749
OPR	23,419	0.0863	0.1576	−0.6778	0.5066
ATO	23,419	0.6103	0.3456	0.1083	2.1180
LEV	23,419	0.3911	0.1932	0.0521	0.8588
Ages	23,419	2.8988	0.3330	1.0986	4.1744
LBoard	23,419	2.2311	0.1713	1.7918	2.7081
TOP1	23,419	0.3417	0.1445	0.0905	0.7367

Table 1. Summary statistics.

Variables	(1) CEI	(2) CEI	(3) CEI	(4) CEI	(5) CEI
AIA	− 0.6824***	− 0.0413***	− 0.5275***	− 0.0394***	− 0.0395***
	(− 94.0164)	(− 3.6586)	(− 71.9758)	(− 3.5578)	(− 3.5739)
Size			0.2592***	0.0553*	0.0555*
			(25.8517)	(1.7460)	(1.7548)
Fixed			4.8579***	0.4360***	0.4373***
			(62.1805)	(3.3221)	(3.3371)
OPR			− 0.1103	− 0.4071***	− 0.4081***
			(− 1.5722)	(− 8.1358)	(− 8.1629)
ATO			0.3591***	0.1365***	0.1369***
			(11.7005)	(2.6590)	(2.6771)
LEV			− 0.0497	− 0.3111***	− 0.3136***
			(− 0.7360)	(− 3.6563)	(− 3.6916)
Ages			0.0867***	− 0.2694*	− 0.2689*
			(2.7409)	(− 1.8540)	(− 1.8528)
LBoard			0.5705***	− 0.0845	− 0.0843
			(9.2302)	(− 1.3955)	(− 1.3946)
TOP1			0.3028***	0.0897	0.0909
			(4.1406)	(0.5370)	(0.5441)
Constant	− 1.5755***	− 2.2386***	− 10.5349***	− 2.6248***	− 2.6315***
	(− 83.0470)	(− 94.0978)	(− 46.5317)	(− 3.5855)	(− 3.6001)
Observations	23,419	23,419	23,419	23,372	23,419
Firm FE	No	Yes	No	Yes	Yes
Year FE	No	Yes	No	Yes	Yes
R-squared	0.2152	0.1938	0.4058	0.2087	0.2092

Table 2. Results of the baseline regression. t-values or z-values in parentheses, ***, **, and * represent significant at the 1%, 5%, and 10% levels, respectively, and are the same as in the table below if not otherwise noted.

consumption and carbon emissions, thereby ensuring the effective implementation of various environmental protection measures[40]. Concurrently, in terms of external supervision, the application of AI facilitates greater transparency in corporate environmental protection information, facilitating stakeholder oversight and encouraging enterprises to prioritize environmental protection and carbon emission reduction efforts[41].

Robustness test

This article primarily adopts the approach of substituting core variables and lagged variables to conduct stability tests.

Alternative variable

Considering the "Management's Discussion and Analysis" (MD&A) section of the parent company's annual report, which comprehensively includes a summary of future development, current operational status, and technological applications[42], this study utilizes an established AI vocabulary to conduct a word frequency analysis on the MD&A section, aiming to assess the level of AI integration. The regression outcomes presented in the first column of Table 3 reveals a statistically significant negative correlation between MDA_AIA and CEI at the 1% level. This underscores the robustness of the baseline regression results, even after altering the measurement approach for the explanatory variable.

Drawing inspiration from established methods for quantifying corporate carbon emissions intensity, this article follows the carbon dioxide calculation standards set by the Xiamen Energy Conservation Center[43]. As evident in column (2) of Table 3, upon substituting the measurement technique for carbon emission intensity, a statistically significant negative correlation emerges between AI application and carbon emission intensity at the 5% level, with a correlation coefficient of 0.0145. This finding aligns closely with the baseline regression results, confirming the conclusion that the implementation of AI in enterprises can effectively reduce carbon emission intensity.

Lag independent variable

When enterprises embark on intelligent upgrades, the investment cycle and system debugging emerge as pivotal factors that cannot be neglected. Typically, the deployment and effectiveness of AI infrastructure involve a protracted cycle, spanning from the decision-making stage through actual implementation to the eventual demonstration of emission reduction outcomes. Concurrently, enterprises must allocate substantial time and resources to debugging and optimizing AI equipment and systems, aiming to strike a balance between production

Variables	Alternative key variables		Lag independent variable	
	(1)	(2)	(3)	(4)
	Alternative independent variable	Alternative dependent variable	Lag one period	Lag two period
MDA_AIA	− 0.0278***			
	(− 2.8887)			
AIA		− 0.0145**		
		(− 2.4711)		
L.AIA			− 0.0319***	
			(− 2.7845)	
L2.AIA				− 0.0203*
				(− 1.9430)
Constant	− 2.5773***	− 1.2275***	− 2.8762***	− 2.7063***
	(− 3.5258)	(− 3.0321)	(− 3.4732)	(− 2.8817)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	23,419	23,419	19,509	16,571
R-squared	0.2081	0.1872	0.1877	0.1444

Table 3. Robustness test.

efficiency and environmental sustainability. Consequently, a notable lag exists between the implementation of AI applications in enterprises and the reduction of carbon emission intensity. In recognition of this, the present study applies lag processing to the explanatory variables, with the pertinent regression results presented in columns (3) and (4) of Table 3. Notably, the findings indicate that even after introducing a one-period and two-period lag in the independent variables, the results retain statistical significance at the 1% and 10% levels, thereby reinforcing the conclusion that AI application can effectively mitigate the carbon emission intensity of enterprises.

Endogeneity test
Considering the endogeneity issues caused by reverse causality, omitted variables, and sample selection bias, this paper adopts instrumental variable method, multidimensional fixed effects, and propensity score matching (PSM) to alleviate possible endogeneity problems and ensure the accuracy of our estimation.

Instrumental variable
To mitigate endogenous issues in our research, this paper draws on the approach of Long[44] and Lin[45], selecting the number of mobile phone users at the end of the year at the city level as the instrumental variable (IV1). Additionally, following the approach proposed by Zheng[46], we adopt the length of optical cable lines in cities as the instrumental variable (IV2).

Specifically, the number of mobile phone users and the length of optical cables reflect the level of regional informatization and the status of telecommunications infrastructure construction[47], correlating with the development of internet and digital technologies. The advancement of digital technologies, such as the internet, serves as a specific platform for the application of AI in businesses, while the level of infrastructure development also influences the application of AI[48]. On the other hand, it's noteworthy that an increase in mobile phone users and cable length does not result in significant carbon dioxide emissions, nor does it directly impact the carbon emission intensity of enterprises. Consequently, the chosen instrumental variables satisfy exogenous conditions.

Columns (1) and (2) of Table 4 present the results of the regression analyses for first-and second-stage. It is evident that the Kleibergen-Paap rk LM statistic is statistically significant at the 1% level, thereby rejecting the null hypothesis of of the under-identification of instrumental variables. The Cragg-Donald Wald F statistic, with a value of 22.565, surpasses the critical value of 19.93 at the 10% level, suggesting the absence of a weak instrumental variable issue. Furthermore, the p-value of the Hansen J statistic, which is 0.9064, further indicates that there is no issue of over-identification of instrumental variables. Examining the regression results in Table 4, we observe that in Column (1), the two instrumental variables exhibit a significant positive correlation with the variable AIA at the 1% level. In Column (2), the regression coefficient of AIA remains significantly negative at the 5% level, which is consistent with the baseline regression results, confirming the validity of our study's conclusions even after accounting for potential endogenous issues.

Multidimensional fixed effects
Although this paper endeavors to control for variables associated with carbon emission intensity, some variables will inevitably be omitted from the model. Consequently, drawing upon the research of Pu[49], we have incorporated additional industry fixed effects, city fixed effects, and city-year interaction effects into our research model to mitigate potential endogeneity issues stemming from omitted variables. The regression results presented in columns (3) to (5) of Table 4 demonstrate that AI application continues to significantly decrease the

Variables	Instrumental variable		Multidimensional fixed effects			PSM
	(1)	(2)	(3)	(4)	(5)	(6)
	AIA	CEI	CEI	CEI	CEI	CEI
AIA		− 0.2596**	− 0.0146**	− 0.0143**	− 0.0118*	− 0.0348**
		(− 2.2959)	(− 2.3361)	(− 2.3053)	(− 1.7210)	(− 2.5306)
IV1	0.0033***					
	(3.8621)					
IV2	0.0402***					
	(2.5773)					
Constant	− 3.3590***	− 3.3515***	− 1.0653**	− 0.9383*	− 0.1824	− 3.0036***
	(− 9.7518)	(− 7.4084)	(− 2.1203)	(− 1.7911)	(− 0.3154)	(− 3.1544)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	
City FE				Yes	Yes	
City × Year					Yes	
LM statistic	32.282					
	[0.0000]					
Wald F statistic	22.565					
	{19.93}					
Hansen J statistic	0.014					
	[0.9064]					
Observations	23,147	23,147	23,419	23,419	23,419	11,955
R-squared	0.4021	0.1366	0.5938	0.5974	0.6817	0.2040

Table 4. Endogeneity test. *P*-value in [] and critical values at the 10 percent level of the Stock-Yogo weak identification test in {}.

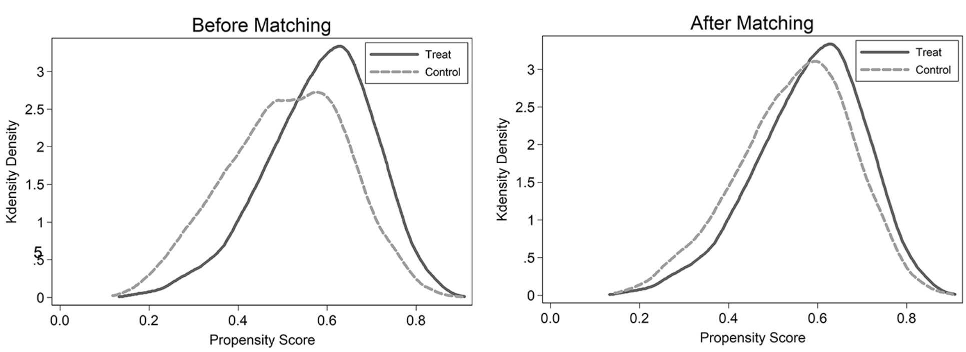

Fig. 5. Comparison of kernel density before and after matching.

Propensity score matching
To address the endogeneity issues arising from sample self-selection, this paper employs the Propensity Score Matching (PSM) method for sample matching, aiming to ensure the robustness of our research findings. Specifically, refer to the grouping method employed by Cao[50] in the study, we categorize the samples into two groups based on the median level of AI application: those exceeding the average and those falling below it. Subsequently, a 1:1 nearest-neighbor matching strategy is implemented. The effectiveness of PSM is validated through the comparison of kernel density curves before and after matching, as depicted in Fig. 5. Notably, the curves exhibit a closer alignment after matching, indicating a high-quality matching process. Finally, a regression analysis is conducted on the PSM-processed samples, and the results are presented in Table 4. The correlation coefficient between AIA and CEI is statistically significant at the 5% level, thus confirming the validity of Hypothesis 1.

Mechanism analysis
To investigate the mediating role of supply chain optimization and technological advancements, this paper establishes a corresponding model for rigorous examination.

$$Med_{i,t} = \beta_0 + \beta_1 AIA_{i,t} + \beta_i Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

$$CEI_{i,t} = \beta_0 + \beta_1 AIA_{i,t} + \lambda_1 Med_{i,t} + \beta_i \sum Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

Mechanistic analysis of supply chain optimization
The regression result presented in column (2) of Table 5 reveals a significant negative correlation between AIA and Chain at the 10% level, suggesting that the implementation of AI significantly reduces supply chain concentration. Leveraging its robust data processing and analytical capabilities, AI enables enterprises to comprehensively evaluate multiple suppliers, fostering diversification and decentralization in supplier selection. This approach mitigates over-reliance on any single supplier, thereby enhancing the flexibility and resilience of the supply chain while mitigating the risks associated with high concentration. Upon incorporating Chain into the regression analysis, the results in column (3) of Table 5 indicate that while the coefficient associated with the level of AI application has attenuated compared to the baseline regression, it maintains a significant negative correlation with carbon emission intensity at the 1% level. This finding suggests the existence of a mediating effect. A decentralized supply chain encourages enterprises to adopt more agile production and processing methodologies, promoting green production practices and low-carbon development, ultimately leading to a reduction in carbon emission intensity. Consequently, AI application in optimizing supply chains effectively reduces the carbon emission intensity of enterprises, thus validating Hypothesis 3.

Mechanistic analysis of green technology innovation
As indicated in column (4) of Table 5, the correlation coefficient between AI and TGP stands at 0.0320, suggesting a statistically significant positive correlation at the 1% significance level. This underscores that the introduction of AI has enabled enterprises to access more information and resource support, thereby accelerating the pace of resource sharing and knowledge dissemination, and ultimately promoting the innovation of green technology. In column (5) of Table 5, upon including both TGP and AIA in the regression analysis, it is observed that AIA maintains a significant negative correlation with CEI at the 1% significance level. This indicates that the application of AI opens up more avenues for green technological innovation in enterprises, facilitates the cross-diffusion of green and low-carbon technologies, and promoted the utilization of clean energy, ultimately leading to a reduction in carbon emission intensity. Consequently, hypothesis 4 is confirmed.

To comprehensively validate the mediating effect, this paper utilizes the bootstrap method to conduct 1000 sampling tests within a 95% confidence interval. As presented in Table 5, the results reveal that the 95% confidence interval excludes zero, thereby confirming the validity of the two mediating effect paths chosen in this study. Specifically, the application of AI in enterprises can effectively mitigate carbon emission intensity through supply chain optimization and green technology innovation.

Heterogeneity analysis

The heterogeneity analysis is conducted from three perspectives: industry characteristics, technology intensity, and pollution intensity.

Heterogeneity based on industry characteristic
Referring to the study by Xu et al.[51], the sample categorizes enterprises into manufacturing and non-manufacturing enterprises based on industry types. Columns (1) and (2) of Table 6 present the regression results. The findings indicate that, compared to non-manufacturing enterprises, AI application in manufacturing enterprises exhibits a significant negative correlation with carbon emission intensity at the 1% level, suggesting that the use of AI in manufacturing enterprises is more conducive to reducing carbon emission intensity. This correlation may

	(1)	(2)	(3)	(4)	(5)
Variables	**CEI**	**Chain**	**CEI**	**TGP**	**CEI**
AIA	− 0.0395***	− 0.0026*	− 0.0391***	0.0320***	− 0.0387***
	(− 3.5739)	(− 1.7894)	(− 3.5171)	(4.2329)	(− 3.5065)
Chain			0.1764*		
			(1.6684)		
TGP					− 0.0260***
					(− 3.1698)
Constant	− 2.6315***	0.8896***	− 2.7884***	− 1.2790**	− 2.6648***
	(− 3.6001)	(8.4337)	(− 3.6986)	(− 2.4744)	(− 3.6390)
Control	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,419	23,419	23,419	23,419	23,419
R-squared	0.2092	0.1122	0.2100	0.0385	0.2099
Bootstrap		[− 0.00151, − 0.00009]		[− 0.00150, − 0.00035]	

Table 5. Mechanism anal sis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Industry characteristic		Technology intensity		Pollution intensity	
	Manufacturing	Non-manufacturing	High-tech	Low-tech	High-polluting	Low-polluting
AIA	− 0.0296***	− 0.0054	− 0.0259**	− 0.0156	− 0.0207**	0.0005
	(− 2.8695)	(− 0.2307)	(− 2.3157)	(− 1.2334)	(− 2.0125)	(0.0636)
Constant	− 2.4430***	2.8011	− 3.3814***	− 3.1067**	− 1.5848*	− 3.5612***
	(− 3.5558)	(1.6129)	(− 4.5990)	(− 2.2574)	(− 1.6954)	(− 6.2243)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,728	1691	17,330	6089	7243	16,176
R-squared	0.2351	0.2452	0.2670	0.2519	0.1765	0.3768

Table 6. Heterogeneity analysis.

stem from the fact that listed manufacturing enterprises typically have significant carbon emissions, and AI can comprehensively and systematically transform the manufacturing industry by monitoring and providing real-time feedback on pollutant emissions during the production process. Conversely, non-manufacturing enterprises emit fewer pollutants, thus AI does not play a significant role in these enterprises.

Heterogeneity based on technology intensity
Following the approach of Wang et al.[52], we categorized these enterprises into three major sectors and 19 sub-sectors (The three categories are manufacturing (C), information transmission, software and information technology services (I), and scientific research and technology services (M); The 19 categories include C25, C26 and C27, C28, C29, C31, C32, C34, C35, C36, C37, C38, C39, C40, C41, I63, I64, I65 and M73). The pertinent findings are outlined in columns (3) and (4) of Table 6. Notably, compared to enterprises operating in the low-tech sector, the AI application in high-tech industries exhibits a statistically significant negative correlation with carbon emission intensity at the 5% level. This underscores the fact that AI is more effective in mitigating carbon emission intensity among high-tech enterprises. Typically, high-tech industries boast superior automation and intelligence, facilitating the seamless integration of AI systems for energy conservation and carbon emission reduction. Additionally, these industries often possess robust technological foundations and innovative capabilities, enabling them to rapidly adopt and deploy AI, thereby achieving energy efficiency and emission reduction objectives ultimately.

Heterogeneity based on pollution intensity
Referring to Liu et al.[53], we categorize enterprises into high-pollution and low-pollution enterprises based on their pollution intensity (Code for high-pollution enterprises: B06, B07, B08, B09, C17, C19, C22, C25, C26, C28, C29, C30, C31, C32, D44). The regression results are presented in columns (5) and (6) of Table 6. The findings indicate that, in comparison to low-pollution industries, the adoption of AI in high-pollution industries is more beneficial for reducing carbon emission intensity. This may be attributed to the fact that high-pollution industries are typically energy-intensive, characterized by complex production processes and high energy consumption, resulting in a significant proportion of carbon emissions. AI can optimize production processes, enhance energy usage efficiency, and ultimately decrease carbon emission intensity through intelligent scheduling, predictive maintenance, and energy management systems.

Conclusions, policy implications, and discussion
Conclusion
This article, based on data from China's A-share industrial enterprises spanning from 2011 to 2022, employs machine learning to assess the level of AI application and investigates the impact of AI application on corporate carbon emission intensity. The research findings indicate that:

1. Enterprises can effectively reduce carbon emission intensity by enhancing their level of AI application. For every 1% increase in the level of AI within an enterprise, the carbon emission intensity decreases by 0.0395%. This finding remains valid after various robustness checks, such as addressing endogeneity issues, substituting core explanatory variables, and lagging core variables. AI facilitates the process of production automation and intelligence within enterprises, enhancing energy utilization efficiency and driving the transformation and upgrading of enterprises. By monitoring and regulating carbon emissions across different production stages, it achieves a reduction in carbon emission intensity.
2. Mechanism analysis indicates that enterprises can effectively reduce carbon emission intensity through two pathways: supply chain optimization and green technology innovation. AI stimulates the innovation capability and sustainable development potential of the supply chain, prompting enterprises to adopt more flexible production and processing models, thereby achieving a sustainable development model that reduces costs and carbon emissions. Furthermore, the application of AI promotes green technology innovation, assisting enterprises in achieving "green" and "low-carbon" development goals, effectively reducing carbon emission intensit .

3. Heterogeneity is explored from three aspects: industry characteristic, technological intensity, and pollution intensity. The results indicate that for manufacturing enterprises, high-tech enterprises, and high-pollution enterprises, the use of AI can better assist them in achieving the goal of reducing carbon emission intensity. This finding provides a basis for formulating differentiated AI promotion policies for enterprises across different industries and types.

Policy implications

Based on the aforementioned conclusions, we propose the following recommendations:

1. Accelerating the process of enterprises' intelligent transformation. The government should encourage enterprises to utilize emerging technologies, integrate AI into their development planning, and provide policy support that combines low-carbon development with intelligent transformation. On the other hand, the government should strive to enhance enterprises' understanding of sustainable development and eliminate the short-sighted thinking that excessively prioritizes their immediate interests. For enterprises, it is essential to recognize that AI serves as a catalyst for sustainable development. Enterprises should expedite the integration of AI into their daily operations, incorporating emerging technologies into a series of production activities such as intelligent management, intelligent supervision, and intelligent production, continuously unleashing the impact of AI on enterprise transformation and upgrading.
2. Enterprises should fully leverage the role of supply chain optimization and green technology innovation in carbon emission reduction. Governments should encourage and support enterprises to establish green technology innovation laboratories, strengthen cooperation in green technology innovation in core areas of carbon emission reduction among manufacturing enterprises, universities, research institutes, and other relevant institutions, and actively explore new models of deep collaboration between industry, academia, and research. Simultaneously, enterprises should promote the application of AI in all aspects of production and operation, advance low-carbon procurement policies, optimize logistics networks, adopt clean transportation methods, and implement monitoring and management of carbon emissions in the supply chain.
3. Tailored differentiated policies for promoting AI should be formulated for enterprises. The government should devise differentiated development policies based on the characteristics of different industries and types of enterprises. By means of fiscal subsidies, tax incentives, special funds, low-interest loans, etc., enterprises are encouraged to apply AI for carbon emission reduction. Enterprises should also actively apply AI and formulate corresponding carbon emission reduction strategies based on their own industry characteristics.

Discussion

This study based on data from China's A-share industrial enterprises, concludes that AI plays a catalytic role in reducing carbon emission intensity. However, when extending this to other developing countries, it is necessary to comprehensively consider structural constraints and local adaptation. On one hand, the energy structure of the economy, technical talent reserves, and the level of digitalization of infrastructure constitute fundamental constraints, necessitating priority to overcome the bottleneck of technology implementation. On the other hand, the application of AI requires adjusting technical parameters and policy tools in accordance with local production scenarios to avoid "failure of technology transplantation." Based on China's experience, it is recommended that developing countries can advance in stages: by attracting technology transfers from multinational corporations, establishing AI emission reduction demonstration zones in key sectors such as energy and manufacturing, simultaneously strengthening the cultivation of local AI talent and collaborative innovation in industry-academia-research, and gradually developing customized solutions tailored to resource endowments, ultimately achieving a synergistic advancement of environmental protection and technological development.

Based on this study, future research can be conducted in the following directions. Specifically, firstly, it is necessary to further explore whether AI has a spatial spillover effect on carbon emission reduction. Secondly, some influencing mechanisms have not yet been explored, and AI may indirectly affect carbon emission intensity through other pathways. What's more, there is room for optimization and iteration in the GloVe word vector model trained in this paper, thereby further enhancing the accuracy of word association. Last but not least, exploring the bidirectional spillover effects generated when developing countries introduce external AI and their impact on local AI innovation is also an intriguing topic. Future research can be conducted in these directions to further refine the related studies between AI and carbon emission intensity.

Data availability

Some or all data, models, or codes generated or used during the study are available from the corresponding author by request.

Appendix I. AI vocabulary (Chinese version)

人工智能	计算机视觉	图像识别	知识图谱	智能教育	增强现实
智能政务	特征提取	商业智能	支持向量机	模式识别	物联网
人机对话	人机交互	数据挖掘	智慧银行	智能客服	虚拟现实
自动驾驶	无人驾驶	智慧金融	大数据营销	智能芯片	边缘计算

云计算	深度神经网络	深度学习	特征识别	智能零售	智能医疗
智能运输	智能家居	大数据风控	自动化	可穿戴产品	增强智能
大数据运营	神经网络	语音合成	人机协同	智能农业	智能音箱
强化学习	大数据分析	大数据管理	智能计算	语音交互	机器学习
生物识别	语音识别	智能监管	智能语音	声纹识别	人脸识别
智能体	大数据处理	分布式计算	智能传感器	智能搜索	智能环保
服务机器人	工业机器人	仓储机器人	物流机器人	智能风控	智能工厂
可视化	脑科学	传感网	模型训练	智能驾驶	智能座舱
大数据	智慧网络	智慧建筑	智慧医疗	自然语言处理	智能家电
大模型	仿真	智能系统	自主学习	卷积神经网络	人形机器人
计算中心	智能制造	智能商务	智慧农场	智能港口	智慧家居
智能推荐	智能矿山	智能金融	智能交通		

Appendix II. AI vocabulary (English version)

Artificial intelligence	**Computer vision**	**Image recognition**	**Knowledge graph**	**Smart education**	**Augmented reality**
Smart Government	Feature Extraction	Business Intelligence	Support Vector Machine	Pattern Recognition	Internet of Things
Human–Computer Dialogue	Human–Computer Interaction	Data Mining	Smart Banking	Intelligent Customer Service	Virtual Reality
Autonomous Driving	Unmanned Driving	Smart Finance	Big Data Marketing	Intelligent Chip	Edge Computing
Cloud Computing	Deep Neural Network	Deep Learning	Feature Recognition	Smart Retail	Smart Healthcare
Smart Transportation	Smart Home	Big Data Risk Control	Automation	Wearable Products	Enhanced Intelligence
Big Data Operations	Neural Network	Speech Synthesis	Human–Machine Collaboration	Smart Agriculture	Smart Speaker
Reinforcement Learning	Big Data Analysis	Big Data Management	Intelligent Computing	Voice Interaction	Machine Learning
Biometric Recognition	Voice Recognition	Intelligent Supervision	Intelligent Voice	Voiceprint Recognition	Facial Recognition
Intelligent Agent	Big Data Processing	Distributed Computing	Intelligent Sensor	Intelligent Search	Intelligent Environmental Protection
Service Robot	Industrial Robot	Warehouse Robot	Logistics Robot	Intelligent Risk Control	Smart Factory
Visualization	Brain Science	Sensor Network	Model Training	Intelligent Driving	Intelligent Cockpit
Big Data	Smart Network	Smart Building	Smart Healthcare	Natural Language Processing	Smart Home Appliances
Large Model	Simulation	Intelligent System	Self-Learning	Convolutional Neural Network	Humanoid Robot
Computing Center	Smart Manufacturing	Smart Business	Smart Farm	Intelligent Port	Smart Home
Intelligent Recommendation	Smart Mine	Intelligent Finance	Intelligent Transportation		

Received: 22 November 2024; Accepted: 2 April 2025
Published online: 12 April 2025

References

1. Zhao, C., Li, Y., Liu, Z. & Ma, X. Artificial intelligence and carbon emissions inequality: Evidence from industrial robot application. *J. Clean. Prod.* **438**, 140817 (2024).
2. Liu, B., Yang, X. & Zhang, J. Nonlinear effect of industrial robot applications on carbon emissions: Evidence from China. *Environ. Impact. Asses.* **104**, 107297 (2024).
3. Song, J., Chen, Y. & Luan, F. Air pollution, water pollution, and robots: Is technology the panacea. *J. Environ. Manage.* **330**, 117170 (2023).

4. Li, Y., Zhang, Y., Pan, A., Han, M. & Veglianti, E. Carbon emission reduction effects of industrial robot applications: Heterogeneity characteristics and influencing mechanisms. *Technol. Soc.* **70**, 102034 (2022).
5. Nie, Y., Zhou, Y., Wang, H., Zeng, L. & Bao, W. How does the robot adoption promote carbon reduction?: Spatial correlation and heterogeneity analysis. *Environ. Sci. Pollut. R.* **30**, 113609–113621 (2023).
6. Liu, Y., Zhang, X. & Shen, Y. Technology-driven carbon reduction: analyzing the impact of digital technology on China's carbon emission and its mechanism. *Technol. Forecast. Soc.* **200**, 123124 (2024).
7. Zhou, W., Zhuang, Y. & Chen, Y. How does artificial intelligence affect pollutant emissions by improving energy efficiency and developing green technology. *Energy Econ.* **131**, 107355 (2024).
8. Dong, M., Wang, G. & Han, X. Impacts of artificial intelligence on carbon emissions in China: In terms of artificial intelligence type and regional differences. *Sustain. Cities. Soc.* **113**, 105682 (2024).
9. Huang, Q., Chen, Q., Qin, X. & Zhang, X. Study on the influence of industrial intelligence on carbon emission efficiency–empirical analysis of China's Yangtze River Economic Belt. *Environ. Sci. Pollut. R.* **30**, 82248–82263 (2023).
10. Wang, L., Chen, Y., Ramsey, T. S. & Hewings, G. J. Will researching digital technology really empower green development?. *Tech. Soc.* **66**, 101638 (2021).
11. Che, S., Wen, L. & Wang, J. Global insights on the impact of digital infrastructure on carbon emissions: A multidimensional analysis. *J. Environ. Manage.* **368**, 122144 (2024).
12. Yu, Y., & Du, Y. Effects of global value chain along with digitalization on green growth. *Int. J. Environ. Sci. Technol*., 1–18 (2024).
13. Wang, J., Wang, W., Liu, Y. & Wu, H. Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. *Technol. Soc.* **72**, 102208 (2023).
14. Cheng, K., Jin, Z. & Wu, G. Unveiling the role of artificial intelligence in influencing enterprise environmental performance: Evidence from China. *J. Clean. Prod.* **440**, 140934 (2024).
15. Lv, H., Shi, B., Li, N. & Kang, R. Intelligent manufacturing and carbon emissions reduction: Evidence from the use of industrial robots in China. *Int. J. Environ. Res. Public. Health* **9**, 15538 (2022).
16. Chen, Y. & Jin, S. Artificial intelligence and carbon emissions in manufacturing firms: The moderating role of green innovation. *Processes.* **11**, 2705 (2023).
17. Cao, B., Li, L., Zhang, K. & Ma, W. The influence of digital intelligence transformation on carbon emission reduction in manufacturing firms. *J. Environ. Manage.* **367**, 121987 (2024).
18. Han, W. Z. & Zhang, Y. M. Carbon reduction effect of industrial robots: Breaking the impasse for carbon emissions and development. *Innov. Green. Dev.* **3**, 100158 (2024).
19. Wang, Z., Zhang, T., Ren, X. & Shi, Y. AI adoption rate and corporate green innovation efficiency: Evidence from Chinese energy companies. *Energy. Econ.* **132**, 107499 (2024).
20. Xu, Y. et al. Artificial intelligence: A powerful paradigm for scientific research. *The Innov.* **2**, 100179 (2021).
21. Bianchini, S., Müller, M. & Pelletier, P. Artificial intelligence in science: An emerging general method of invention. *Res. Policy* **51**, 104604 (2022).
22. Raihan, A. A review of the potential opportunities and challenges of the digital economy for sustainability. *Innov. Green. Dev.* **3**, 100174 (2024).
23. Gerbert, P. et al. Industry 4.: The future of productivity and growth in manufacturing industries. *Boston Consulting Group* **9**, 54–89 (2015).
24. Shi, C., Feng, X. & Jin, Z. Sustainable development of China's smart energy industry based on artificial intelligence and low-carbon economy. *Energy. Sci. Eng.* **10**, 243–252 (2022).
25. Khin, S. & Ho, T. C. Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *Int. J. Innov. Sci.* **11**, 177–195 (2019).
26. Lai, K. H., Feng, Y. & Zhu, Q. Digital transformation for green supply chain innovation in manufacturing operations. *Transport. Res. E-log.* **175**, 103145 (2023).
27. Li, X. & Yue, S. Blessing or curse? The role of digital technology innovation in carbon emission efficiency. *J. Environ. Manage* **365**, 121579 (2024).
28. Habiba, U. M. M. E., Xinbang, C. & Anwar, A. Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions?. *Renew. Energy* **193**, 1082–1093 (2022).
29. Huang, J., Xiang, S., Wang, Y. & Chen, X. Energy-saving R&D and carbon intensity in China. *Energy Econ.* **98**, 105240 (2021).
30. Zhao, Z. et al. Green innovation and carbon emission performance: The role of digital economy. *Energy Policy* **195**, 114344 (2024).
31. Shang, Y., Raza, S. A., Huo, Z., Shahzad, U. & Zhao, X. Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. *Int. Rev. Econ. Finance* **86**, 1–13 (2023).
32. Yu, P., Hao, R., Cai, Z., Sun, Y. & Zhang, X. Does emission trading system achieve the win-win of carbon emission reduction and financial performance improvement? — Evidence from Chinese A-share listed firms in industrial sector. *J. Clean. Prod.* **333**, 130121 (2022).
33. Zhu, H., Bao, W. & Yu, G. How can intelligent manufacturing lead enterprise low-carbon transformation? Based on China's intelligent manufacturing demonstration projects. *Energy* **313**, 134032 (2024).
34. Huang, J., Han, F. & Li, Y. Government as major customer: The effects of government procurement on corporate environmental, social, and governance performance. *Finance Res. Lett.* **54**, 103781 (2023).
35. Gu, J., Shi, X., Wang, P. & Xu, X. Examining the impact of upstream and downstream relationship stability and concentration on firms' financial performance. *J. Bus. Res.* **141**, 229–242 (2022).
36. Geng, Y., Xiang, X., Zhang, G. & Li, X. Digital transformation along the supply chain: Spillover effects from vertical partnerships. *J. Bus. Res.* **183**, 114842 (2024).
37. Lan, Y., Yuan, Z., Tang, R., Hsu, S. C. & Wei, H. H. Green innovation and the ESG disconnect: Evidence from green patenting in the construction industry in China. *J. Manage. Eng.* **41**, 04024066 (2025).
38. Cui, X., Wang, C., Sensoy, A., Liao, J. & Xie, X. Economic policy uncertainty and green innovation: Evidence from China. *Econ. Model.* **118**, 106104 (2023).
39. Dormann, C. G., Elith, J., Bacher, S. & Lautenback, S. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography* **36**, 27–46 (2013).
40. Guo, Y., Zhang, W., Qin, Q., Chen, K. & Wei, Y. Intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources. *Soft. Comput.* **27**, 4061–4076 (2023).
41. Issa, J., Abdulrahman, L. M., Abdullah, R. M., Sami, T. M. G. & Wasfi, B. AI-powered sustainability management in enterprise systems based on cloud and web technology: Integrating IoT data for environmental impact reduction. *J. Inf. Technol.* **3**, 156–176 (2024).
42. Fedorova, E., Drogovoz, P., Nevredinov, A., Kazinina, P. & Qitan, C. Impact of MD&A sentiment on corporate investment in developing economies: Chinese evidence. *Asian. Rev. Account.* **30**, 513–539 (2022).
43. Du, J., Li, Z., Shi, G. & Wang, B. Can, "environmental protection fee to tax" reduce carbon emissions? Evidence from China. *Financ. Res. Lett.* **62**, 105184 (2024).
44. Long, Y., Liu, L. & Yang, B. The effects of enterprise digital transformation on low-carbon urban development: Empirical evidence from China. *Technol. Forecast. Soc. Change* **201**, 123259 (2024).
45. Lin, Y., Qian, W., Zhang, X. & Yang, Y. The impact of auditing centralization on carbon productivity: Evidence from China's vertical management auditing reform. *Pol. J. Environ. Stud.* **33**, 1230–1485 (2024).

46. Zheng, S., Duan, Y. & Ward, M. R. The effect of broadband internet on divorce in China. *Technol. Forecast. Soc. Change* **139**, 99–114 (2019).
47. Lu, J., Xiao, Q. & Wang, T. Does the digital economy generate a gender dividend for female employment?. *Evid. China. Telecommun. Policy* **47**, 102545 (2023).
48. Yang, X., Lei, G. & Wang, X. Can the development of digital construction reduce enterprise carbon emission intensity? New evidence from Chinese construction enterprises. *Front. Ecol. Evol.* **11**, 1250593 (2023).
49. Pu, Z., Qian, Y., & Liu, R. Is digital technology innovation a panacea for carbon reduction? *Technol. Econ. Dev. Econ.*, 1–29 (2024).
50. Cao, L., Wang, Y., Yu, J., Zhang, Y. & Yin, X. The impact of digital economy on low-carbon transition: What is the role of human capital ?. *Finance Res. Lett.* **69**, 106246 (2024).
51. Xu, Y., Li, S., Zhou, X., Shahzad, U. & Zhao, X. How environmental regulations affect the development of green finance: Recent evidence from polluting firms in China. *Renew. Energy* **189**, 917–926 (2022).
52. Wang, J., Liu, Y., Wang, W. & Wu, H. How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. *J. Clean. Prod.* **406**, 136954 (2023).
53. Liu, S., Li, D. & Chen, X. Environmental regulatory pressures and the short-term debt for long-term investment of heavy-polluting enterprises: quasi-natural experiment from China. *Environ. Sci. Pollut.* **30**, 62625–62640 (2023).

Author contributions
As the first author of this article, Yao Lu wrote the main manuscript text, analysed the data and trained the word vectoer model. As the corresponding author, ZeFang Liao reviewed and revised the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to Z.L.

Reprints and permissions information is available at www.nature.com/reprints.