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Investigating the nonlinear carbon reduction effect of AI: empirical insights from China's provincial level

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In the context of rapid advancement in automation and increasing global warming, understanding the impact of artificial intelligence (AI) on carbon emissions (CES) is a cutting-edge research topic. However, there is limited focus in existing research on the nonlinear carbon reduction effect (CRE) of AI. This paper first theoretically elaborates the dual impact mechanisms of AI on CES and illuminates the nonlinear carbon reduction mechanisms of AI. Then, this study employs panel data encompassing 30 Chinese provinces between 1997 and 2019 to empirically test the net effect of AI on CES and the nonlinear carbon reduction effect of AI through econometric models. The results are as follows: first, although AI can both reduce and increase CES, AI primarily helps decrease CES. This conclusion holds true even after considering robustness, endogeneity, and spatial heterogeneity. Secondly, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. Thirdly, improving the AI development level (AIDL) can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Lastly, even if the AIDL remains constant, improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. To fully harness the potential of AI for green development, concerted efforts should be directed towards enhancing the innovation and application of AI technologies with carbon reduction potential.

KEYWORDS

artificial intelligence, carbon emissions, carbon reduction effect, nonlinear characteristic, China

1 Introduction

Climate change, primarily attributed to carbon emissions (CES) resulting from human activities, has exerted a significant and detrimental impact on human survival and development (Zhang W. et al., 2022; Li et al., 2022; Wang et al., 2023b). The global community has consequently made decarbonization a key priority (Vorozheykina, 2022). Additionally, artificial intelligence (AI) has emerged as one of the most eagerly anticipated technologies. In this context, the impact of AI on CES has become a focal point of scholarly inquiry. Extensive research has highlighted the dual nature of AI's impact on CES, encompassing both reduction and increase (Chen P. et al., 2022; Kaack et al., 2022; Cowls et al., 2023). Hence, the questions arise: Will the development of AI ultimately result in a carbon reduction effect (CRE)? Does the CRE of AI exhibit a nonlinear characteristic? Resolving these inquiries holds substantial theoretical and practical significance. Regrettably, existing studies have not fully addressed the aforementioned questions.

To address these gaps, firstly, this paper will theoretically analyze the carbon reduction mechanisms and carbon increase mechanisms of AI, and will point out that AI will ultimately reduce CES. Secondly, from a theoretical perspective, the paper will illustrate that the improvement of AI development, marketization, human capital, digital infrastructure, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Finally, this paper will empirically test the aforementioned theoretical perspectives using provincial panel data from China spanning from 1997 to 2019 and econometric models.

This paper makes significant contributions in three key points. Firstly, this paper will provide a unified framework for understanding of the impact of AI on CES. Existing research has primarily focused on analyzing the carbon reduction mechanisms and CRE of AI. While some studies also consider the carbon increase mechanisms and carbon increase effect of AI, there is limited research that systematically analyzes both the carbon reduction and increase mechanisms within a unified framework. Moreover, there is relatively little discussion in existing research regarding the crucial question of whether the CRE or the carbon increase effect of AI is greater. This paper, at the theoretical level, systematically analyzes both the carbon reduction and increase mechanisms of AI and empirically confirms the viewpoint that the CRE of AI is greater than the carbon increase effect. Secondly, this paper will contribute to a deeper understanding of the CRE of AI. Although existing research indicates that AI can reduce CES, there is limited analysis of the nonlinear characteristic of the CRE of AI. This paper, both theoretically and empirically, confirms that the improvement of AI development, marketization, human capital, digital infrastructure, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thirdly, our research employs more refined methodologies to gauge the AI development level (AIDL). Measuring the AIDL represents a contemporary research Frontier. Current research primarily relies on industrial robot data and AI patent data to assess AIDL. However, industrial robot data predominantly reflects the extent of intelligent manufacturing rather than offering a holistic evaluation of AIDL. Although AI patent data can offer a holistic evaluation of AIDL, previous studies have employed a limited set of keywords in their searches for AI patents. In contrast, our paper measures AIDL using a broader array of AI-related keywords.

The rest of our study is outlined as follows: Section 2 provides a systematic literature review. Section 3 introduces the theoretical framework and research hypotheses. Section 4 introduces the empirical models and details the sources of data. Section 5 provides the empirical results and discussion. Section 6 provides the conclusions, implications, and limitations.

2 Literature review

The literature pertinent to our research can be categorized into three key domains: the measurement of carbon emission level (CEL) and the influencing factors of CES, the measurement of AIDL, and the impact of AI on CES.

2.1 The measurement of CEL and the influencing factors of CES

Currently, there are four proxy variables employed to characterize CEL. The initial proxy variable is the total CES (Wang et al., 2023b; Ding et al., 2023; Tang and Yang, 2023). Some scholars have developed carbon emission databases containing total CES data (Shan et al., 2020). Furthermore, a positive correlation exists between satellite light data and total CES, prompting some scholars to derive total CES based on satellite light data (Meng et al., 2023). The second proxy variable pertains to carbon density, quantified as the ratio of total CES to GDP (Chen P. et al., 2022; Li et al., 2022; Tang and Yang, 2023), the ratio of total CES to the value added by the secondary industry (Yi et al., 2022), or the ratio of industry energy-related CES to industry sales value (Liu et al., 2022). The third proxy variable relates to *per capita* CES, determined by dividing total CES by the year-end population (Wang et al., 2023b; Tang and Yang, 2023). The fourth proxy variable is carbon emission performance, a measure that considers both economic development and total CES. Typically, it is assessed using a Data Envelopment Analysis (DEA) model featuring multiple input and output indicators (Zhang W. et al., 2022).

Existing research indicates that numerous factors can influence CES. For example, economic development, *per capita* income, population size, technological advancement, green technology innovation, openness, urbanization, industrial concentration, industrial upgrading, energy regulations, energy demand, energy consumption, energy intensity, energy prices, energy structure, energy efficiency, energy innovations, human capital, carbon taxation, financial development, transportation infrastructure, environmental regulation, marketization, green total factor productivity (GTFP), working hours, digital economy, and AI can influence CES (Chen Y. et al., 2022; Zhang X. et al., 2022; Li et al., 2022; Yi et al., 2022; Wang et al., 2023b; Ding et al., 2023; Meng et al., 2023; Tang and Yang, 2023; Yanzhe and Ullah, 2023).

2.2 The measurement of AIDL

Given the rapid development, extensive application, and the challenge of defining precise boundary and composition for AI, an ongoing debate persists regarding the measurement of AIDL (Damioli et al., 2021; Bianchini et al., 2023). Consequently, a consensus on the measurement of AIDL remains elusive. Presently, there are five proxy variables utilized to gauge AIDL. The first proxy variable is the frequency of AI-related terms appearing in the reports of publicly listed companies (Zhang W. et al., 2022) or in the annual government work reports (Tang and Yang, 2023). The second proxy variable is the industrial robot data sourced from the International Federation of Robotics (IFR). This encompasses metrics such as the increment of industrial robots (Li and Tian, 2023), the increment of industrial robots per worker (Chen Y. et al., 2022), the stock of industrial robots (Zhang X. et al., 2022; Liu et al., 2022; Wang et al., 2023b; Li and Tian, 2023), the stock of industrial robots per unit of GDP (Li et al., 2022), the stock of industrial robots per worker (Chen P. et al., 2022; Chen et al., 2022 Y.; Li et al., 2022; Lv et al., 2022; Vorozheykina, 2022; Yang and Shen, 2023), and the adjusted penetration of industrial robots (Acemoglu and Restrepo, 2020; Chen Y. et al., 2022). The third proxy variable relates to the number of AI patents (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). The fourth proxy variable involves AI-related research paper counts (Li et al., 2022). The fifth proxy variable employs an AI Index (Ding et al., 2023; Maslej et al., 2023), typically exemplified by Stanford University's AI Index (Maslej et al., 2023).

2.3 The impact of AI on CES

Extensive research has highlighted the dual nature of AI's impact on CES, encompassing both reduction and increase (Chen P. et al., 2022; Kaack et al., 2022; Cowls et al., 2023). On the one hand, AI has the potential to reduce CES through various pathways. AI can reduce CES by fostering green technology innovation, improving energy efficiency, and driving industrial upgrading (Elnour et al., 2022b; Himeur et al., 2022; 2023; Ding et al., 2023). The deployment of industrial robots can diminish CES by promoting green technology innovation, optimizing the industry structure, enhancing digital infrastructure, improving GTFP, lowering energy intensity, driving technological innovation, promoting research and development investment, encouraging manual labour substitution, saving work time, and promoting green employment (Chen P. et al., 2022; Chen et al., 2022 Y.; Elnour et al., 2022a; Li et al., 2022; Meng et al., 2022; Wang et al., 2023b; 2024; Li and Tian, 2023).

On the other hand, AI can also contribute to a surge in CES through various channels. First, the operation of computationally intensive industrial robots will consume substantial energy and will generate CES (Wang et al., 2023b). Training and deploying large AI models, such as ChatGPT, can generate substantial CES (An et al., 2023). Second, in addition to being responsible for the CES generated during the operational phase, AI devices should also share responsibility for the embodied emissions resulting from other stages of its life cycle, including the raw material extraction phase, manufacturing phase, transportation phase, and hardware disposal phase (Kaack et al., 2022; Wu et al., 2022; Cowls et al., 2023). Third, the digital infrastructures supporting AI development have significantly contributed to increased CES by increasing energy consumption (Tang and Yang, 2023). Last, AI's capacity to enhance production and consumption efficiency can result in a rebound effect, leading to increased production and consumption level and consequently, elevated CES (Kaack et al., 2022).

The dual nature of AI's impact on CES sparks ongoing debate regarding the net effect of AI on CES. Presently, there exist three main perspectives regarding this point. The first perspective contends that the net effect of AI on CES is negative. This perspective has been substantiated by research conducted at various levels, including the city (Chen P. et al., 2022; Zhang W. et al., 2022; Wang et al., 2023b), provincial (Wang et al., 2023a; Ding et al., 2023), manufacturing industry (Liu et al., 2022; Li and Tian, 2023), and national (Chen Y. et al., 2022; Li et al., 2022) levels. Furthermore, the CRE of AI demonstrates spatial heterogeneity (Chen P. et al., 2022; Chen et al., 2022 Y.; Zhang W. et al., 2022; Li et al., 2022; Meng et al., 2022; Wang et al., 2023b; 2024; Ding et al., 2023), time heterogeneity (Liu et al., 2022), industry heterogeneity (Li et al., 2022; Liu et al., 2022; Li and Tian, 2023; Wang et al., 2024), and spatial spillover (Zhang W. et al., 2022; Ding et al., 2023) characteristics. Some scholars have also pointed out that the intensity of the CRE of AI is closely related to the scale of high-skilled labor, digital endowment, and the intensity of environmental regulation (Wang et al., 2024). The second viewpoint holds that the net effect of AI on CES is positive. This perspective has been substantiated by certain studies (Bianchini et al., 2023; Tang and Yang, 2023). For example, some scholars have suggested that the carbon increment effect of AI is weaker in regions with large green technology endowments (Bianchini et al., 2023). The third perspective considers the net effect of AI on CES to be uncertain. Some scholars have proposed that estimating the overall immediate impact of AI on CES is exceedingly challenging due to the absence of data on the deployment rate of AI, the diversity of application areas, and the lack of precise procedures to attribute emissions effect to AI usage (Kaack et al., 2022). Some scholars have proposed that the development of AI does not necessarily lead to an immediate carbon emission effect, and AI can only reduce carbon emissions in the industrial sector when the level of intelligence reaches a certain threshold (Wang et al., 2024). Some scholars have also proposed that the impact of industrial robots on CES exhibits an inverted U-shaped relationship (Liu et al., 2024).

In summary, existing research has not systematically analyzed the impact mechanisms and effects of AI on CES. There is a shortfall in revealing the nonlinear CRE of AI and precisely measuring the AIDL. The main purpose of this paper is to address these gaps by utilizing provincial panel data from China.

3 Theoretical analysis and hypotheses development

3.1 The net effect of AI on CES

AI can both reduce and increase CES. On the one hand, AI can reduce CES. Firstly, AI can play a pivotal role in guiding scientists, governments, and individuals to mitigate CES (Yi et al., 2022; Al-Nefaie and Aldhyani, 2023; Hu and Man, 2023; Nassef et al., 2023; Zadmirzaei et al., 2023; Zhao et al., 2023). Secondly, AI assumes a crucial role in promoting the innovation, dissemination, and adoption of green technologies (Chen P. et al., 2022; Li et al., 2022), thereby reducing CES. Thirdly, AI, which plays a crucial role in accelerating the shift of energy supply structure and energy consumption structure from a high CES scenario to a low CES scenario, is effective in mitigating CES (Chen Y. et al., 2022; Yi et al., 2022). Fourthly, AI contributes to CES reduction by facilitating the industrial structure with high CES transfer to the industrial structure with low CES (Chen P. et al., 2022; Ding et al., 2023). Fifthly, AI can enhance energy efficiency and GTFP (Paryanto et al., 2015), thereby mitigating energy consumption and CES. Sixthly, AI contributes to CES reduction by reducing trade-related costs and enhancing openness, because enhanced openness can attract foreign enterprises with advanced green technologies and management practices. Lastly, AI plays a vital role in carbon reduction by enhancing the efficiency of carbon capture (Priya et al., 2023).

On the other hand, AI can also increase CES. Firstly, AI system, including AI models and AI devices, is carbon-intensive due to its heavy energy reliance, continuous upgrading, and widespread utilization (Strubell et al., 2019; Kaack et al., 2022; Bianchini et al., 2023; Bieser et al., 2023; Cowls et al., 2023; Jean-Quartier et al., 2023). Secondly, AI has the potential to impede the transition to a more sustainable energy structure, consequently contributing to increased CES. For instance, oil companies can utilize AI to extract and sell oil and gas more efficiently, which could hinder the energy structure transformation. Thirdly, AI may lead to a rebound effect in production and consumption, consequently resulting in increased CES (Huang et al., 2022; Kaack et al., 2022). Lastly, AI can potentially contribute to increased CES by enhancing openness and expanding the scale of trade. Drawing upon the above, this paper proposes the following hypothesis:

Hypothesis 1: Although AI can exert both positive and negative impact on CES, but the CRE of AI is greater, and the net effect is a reduction in CES.

3.2 The nonlinear CRE of AI

The nonlinear CRE of AI primarily stems from two aspects. On the one hand, change in the AIDL can affect the marginal CRE of AI, thereby leading to a nonlinear CRE of AI. Data, computational infrastructure, and algorithms constitute the pivotal elements of the AI system. Unlike other inputs, data often yields increasing marginal return, thereby leading to an increasing marginal CRE of AI and a nonlinear CRE of AI. For example, as the scale of data grows, AI models trained on data can become more precise in predicting CES and can offer more possibilities to promote carbon reduction. Some scholars have observed an increasing positive marginal effect of intelligent manufacturing on industrial GTFP (Yang and Shen, 2023). Therefore, this paper proposes the following hypothesis:

Hypothesis 2: The enhancement of AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

On the other hand, variations in other factors that facilitate the innovation and implementation of AI technologies can also impact the marginal CRE of AI, thereby leading to a nonlinear CRE of AI. Firstly, change in the level of marketization can impact the marginal CRE of AI and lead to a nonlinear CRE of AI. Increased marketization can enhance the ability to optimize resource allocation and provide more opportunities in the market to unlock the business potential of technologies (Yi et al., 2022). Consequently, a higher degree of marketization encourages the innovation and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Secondly, change in the level of human capital can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. AI comprises a complex technological ecosystem. Undoubtedly, the innovation and application of AI technologies pose substantial challenges. Thus, a higher level of human capital enables a more effective identification, innovation, absorption, and application of AI technologies, drawing upon prior relevant knowledge, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Thirdly, change in the level of digital infrastructures can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. Data is pivotal in both the development and application of AI technologies. A higher level of digital infrastructures can enhance the generation, collection, storage, transmission, and analysis of valuable data. Consequently, improved digital infrastructures foster the advancement and utilization of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Fourthly, change in the level of economic development can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. Greater economic development will amplify the capacity and demand for AI products and services. This, in turn, promotes the innovation and application of AI technologies, further magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Fifthly, change in the level of openness can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. A higher level of openness translates to more opportunities for acquiring new knowledge. Consequently, greater openness facilitates the identification, innovation, absorption, and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Lastly, change in the level of government intervention can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. AI is recognized as a strategic technology, prompting many countries to implement policies aimed at fostering its innovation and application. Therefore, a higher level of government intervention accelerates the pace of innovation and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Drawing upon the above, this paper proposes the following hypothesis:

Hypothesis 3: The improvement of marketization, human capital, digital infrastructures, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

4 Models and data

4.1 Models

This paper will employ the following model to test whether the net effect of AI on CES is negative (Li et al., 2022):

$$\begin{aligned}CEL_{it} = {} & \alpha_0 + \alpha_1 AIDL_{it} + \alpha_2 lnpgdp_{it} + \alpha_3 gover_{it} + \alpha_4 lnfdi_{it} \\ & + \alpha_5 lnindus_{it} + \alpha_6 lndroad_{it} + \alpha_7 urban_{it} + \alpha_8 lngreen_{it} \\ & + \alpha_9 estruc_{it} + \alpha_{10} higher_{it} + \alpha_{11} gtfp_{it} + \alpha_{12} lnenergy_{it} \\ & + \omega_i + \omega_t + \omega_{it} \end{aligned} \tag{1}$$

where, i represents the province, and t denotes the year. CEL_{it} represents the carbon emission level. $AIDL_{it}$ denotes the AI development level. $lnpgdp_{it}$, $gover_{it}$, $lnfdi_{it}$, $lnindus_{it}$, $lndroad_{it}$, $urban_{it}$, $lngreen_{it}$, $estruc_{it}$, $higher_{it}$, $gtfp_{it}$, and $lnenergy_{it}$ are the control variables, and these variables represent economic development level, government intervention level, openness level,

TABLE 1 The variable symbols and measurement methods.

Variables	Symbols	Measurement methods
CEL	*lncb*	Natural logarithm of total CES (tons) (Tang and Yang, 2023)
	lndcb	Natural logarithm of the ratio of total CES to real GDP (tons/100 million CNY) (Tang and Yang, 2023)
	lnpcb	Natural logarithm of the ratio of total CES to the year-end population (tons/10,000 people) (Tang and Yang, 2023)
AIDL	*lnAI*	Natural logarithm of the quantity of AI patents (count) (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023)
	lnstock	The operational stock of industrial robots (Chen et al., 2022b; Li et al., 2022; Yang and Shen, 2023)
	lninstall	The increment of industrial robots (Chen et al., 2022b; Li et al., 2022; Yang and Shen, 2023)
Economic development level	*lnpgdp*	Natural logarithm of real *per capita* GDP (CNY *per capita*) (Tang and Yang, 2023)
Government intervention level	*gover*	The proportion of government expenditure in GDP (%) (Zhang et al., 2022a)
Openness level	*lnfdi*	Natural logarithm of FDI (100,000 CNY) (Wang et al., 2023b)
Industrial scale	*lnindus*	Natural logarithm of the quantity of employees in the secondary industry (10,000 employees) (Liu et al., 2022)
Transportation development level	*lndroad*	Natural logarithm of the density of roads and railways (miles per square kilometre) (Chen et al., 2023)
Urbanization level	*urban*	Proportion of construction land area to the total area (%) (Li et al., 2022)
Green technological innovation level	*lngreen*	Natural logarithm of the quantity of granted green patents (count) (Zhang et al., 2022a; Yi et al., 2022)
Energy structure	*estruc*	The ratio of coal consumption to total energy consumption (%) (Yi et al., 2022)
Industrial structure upgrading	*higher*	The ratio of value-added in the tertiary industry to that in the secondary industry (%) (Meng et al., 2023)
Green total factor productivity	*gtfp*	Measured using a global super-efficiency SBM model (Li et al., 2022)
Energy consumption level	*lnenergy*	Natural logarithm of total energy consumption (tons of standard coal) (Wang et al., 2023b)
Marketization level	*lnmarket*	Natural logarithm of the marketization index (Yi et al., 2022)
Human capital level	*hcapital*	Average number of college students per 10,000 population
Digital infrastructure level	*digital*	Mobile phone exchange capacity per 10,000 people

industrial scale, transportation development level, urbanization level, green technological innovation level, energy structure, industrial structure upgrading, green total factor productivity, and energy consumption level, respectively. The literature basis for selecting these control variables and the measurement methods for the CEL, the AIDL, and the control variables are presented in Table 1. α_0 is the intercept term. ω_i, ω_t and ω_{it} are the province fixed effect, the time fixed effect, and the random error term, respectively. The coefficient of AI is negative, indicating that the net effect of AI on CES is negative.

As depicted in Table 1. To demonstrate the robustness of the empirical results, this article will adopt three methods to measure the CEL in the empirical analysis.

As shown in Table 1. To demonstrate the robustness of the empirical results, this paper will also adopt three methods to measure the AIDL in the empirical analysis. First, this study will use the number of AI patents to characterize the AIDL. Several studies have chosen the quantity of AI patents (lnAI) to characterize the AIDL (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). However, identifying AI patents is not a straightforward task, as there is no unified criterion for their identification, unlike green patents. To address this challenge, most studies begin by selecting keywords related to AI and then extract the quantity of AI patents from the patent database using a keyword-matching approach (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). In this paper, we will also extract the quantity of AI patents from the patent database based on a keyword-matching approach. Table 2 shows the keywords related to AI, drawing from existing studies and the AI category (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). In comparison with previous research, this paper adopts a more extensive list of AI-related keywords and further categorizes them into hardware, software, and application layers.

TABLE 2 AI-related keywords for extracting the number of AI patents.

AI	AI-related keywords
Hardware layer	intelligent processing unit, intelligent processor, inference chip, intelligent chip, AI chip, neural network chip, brain-like chip, accelerator, acceleration processor, acceleration chip, hard acceleration, acceleration core, acceleration unit, smart sensor, application-specific integrated circuit, field programmable gate array, graphics processor, image signal processor, neural processing unit, tensor processor, tensor processing unit, data processor, data processing unit, integrated processing unit, collaborative processing unit, mass processor, deep learning processor, edge computing
Software layer	natural language, computer vision, machine vision, augmented reality, AR, image recognition, speech recognition, voiceprint recognition, object tracking, speech processing, sentiment analysis, speaker recognition, scene understanding, machine translation, speech synthesis, information extraction, biometrics, face recognition, iris recognition, video recognition, pattern recognition, predictive analytics, semantic, speech-to-speech, text-to-speech, character recognition, text recognition, machine learning, supervised learning, support vector machines, biological heuristic methods, genetic algorithms, swarm intelligence, classification and regression trees, decision trees, learning algorithms, deep learning, instance learning, multitasking learning, reinforcement learning, rule learning, transfer learning, fuzzy logic, expert system, logic programming, neural network, CNN, latent representation, probabilistic graphical model, probabilistic reasoning, descriptive logic, generative adversarial network, multilayer perception, MLP, hidden Markov model, HMM, clustering, random forest, stochastic method, probabilistic method, feature selection, Bayesian network, gradient lift, gradient descent, GBDT, data mining, learning model, self-learning, objective function, logistic regression, latent Dirichlet distribution, cognitive computing, artificial intelligence, AI, artificial reality, automatic classification, Bayesian model, big data, computational neuroscience, data science, evolutionary computing, gesture recognition, holographic display, knowledge representation, machine intelligence, machine-to-machine, mixed reality, neuro-linguistic programming, object detection, predictive model, probabilistic model, statistical learning, voice recognition, virtual reality, VR, unsupervised learning, path planning, knowledge graph, swarm intelligence, intelligent cloud, intelligent speech, quantum computing, cloud computing, image recognition, federated learning
Application layer	smart industry, smart factory, smart manufacturing, smart energy, smart water affairs, smart detection, smart inspection, smart monitoring, smart city, smart transportation, smart network, smart traffic management, smart bus, intelligent parking, unmanned driving, autonomous driving, intelligent medical, clinical decision support system, intelligent medical case, intelligent finance, intelligent marketing, smart logistics, smart education, smart agriculture, smart farming, smart greenhouses, smart irrigation, smart weather, smart house, smart life, smart security, human-computer interaction, smart robot, smart search, intelligent recommendation, virtual assistant, intelligent assistant, chat machine, self-driving car, humanoid robot, internet of things, robot, smart glasses, unmanned aerial vehicle, unmanned aerial system

Second, we will use both the cumulative inventory of operational industrial robots and the growth in the quantity of industrial robots to measure the AIDL. Following the methodology of related studies (Chen Y. et al., 2022; Li et al., 2022; Yang and Shen, 2023), we can obtain the cumulative inventory of operational industrial robots (*lnstock*) and the growth in the quantity of industrial robots (*lninstall*) at the provincial level, which can be measured as follows:

$$robot_{pt} = \sum_j \left(\frac{labour_{pjt}}{labour_{jt}} \times robot_{jt} \right) \tag{2}$$

where, p represents the province. t denotes the year. j is the type of industry. $robot_{pt}$ denotes the cumulative inventory of operational industrial robots or the growth in the quantity of industrial robots. $labour_{pjt}$ and $labour_{jt}$ represent the labour force quantity. $robot_{jt}$ is the operational stock of industrial robots or the increment of industrial robots.

This paper will employ the following model to test whether the improvement of AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI (Li et al., 2022):

$$\begin{aligned} CEL_{it} = {} & \lambda_0 + \lambda_1 AIDL_{it} + \lambda_2 AIDL_{it}^2 + \lambda_3 lnpgdp_{it} + \lambda_4 gover_{it} \\ & + \lambda_5 lnfdi_{it} + \lambda_6 lnindus_{it} + \lambda_7 lndroad_{it} + \lambda_8 urban_{it} \\ & + \lambda_9 lngreen_{it} + \lambda_{10} estruc_{it} + \lambda_{11} higher_{it} + \lambda_{12} gtfp_{it} \\ & + \lambda_{13} lnenergy_{it} + \xi_i + \xi_t + \xi_{it} \end{aligned} \tag{3}$$

where, $AIDL_{it}^2$ is the quadratic term of AIDL. The meanings of other variables are similar to that in Formula (1).

This paper will employ the following models to test whether the improvement of marketization, human capital, digital infrastructures, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI (Li et al., 2022), respectively:

$$\begin{aligned} CEL_{it} = {} & \gamma_0 + \gamma_1 AIDL_{it} + \gamma_2 lnpgdp_{it} + \gamma_3 gover_{it} + \gamma_4 lnfdi_{it} \\ & + \gamma_5 lnindus_{it} + \gamma_6 lndroad_{it} + \gamma_7 urban_{it} + \gamma_8 lngreen_{it} \\ & + \gamma_9 estruc_{it} + \gamma_{10} higher_{it} + \gamma_{11} gtfp_{it} + \gamma_{12} lnenergy_{it} \\ & + \gamma_{13} lnmarket_{it} + \gamma_{14} lnmarket_{it} \times AIDL_{it} + \tau_i + \tau_t + \tau_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} CEL_{it} = {} & \beta_0 + \beta_1 AIDL_{it} + \beta_2 lnpgdp_{it} + \beta_3 gover_{it} + \beta_4 lnfdi_{it} \\ & + \beta_5 lnindus_{it} + \beta_6 lndroad_{it} + \beta_7 urban_{it} + \beta_8 lngreen_{it} \\ & + \beta_9 estruc_{it} + \beta_{10} higher_{it} + \beta_{11} gtfp_{it} + \beta_{12} lnenergy_{it} \\ & + \beta_{13} hcapital_{it} + \beta_{14} hcapital_{it} \times AIDL_{it} + \delta_i + \delta_t + \delta_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} CEL_{it} = {} & \zeta_0 + \zeta_1 AIDL_{it} + \zeta_2 lnpgdp_{it} + \zeta_3 gover_{it} + \zeta_4 lnfdi_{it} \\ & + \zeta_5 lnindus_{it} + \zeta_6 lndroad_{it} + \zeta_7 urban_{it} + \zeta_8 lngreen_{it} \\ & + \zeta_9 estruc_{it} + \zeta_{10} higher_{it} + \zeta_{11} gtfp_{it} + \zeta_{12} lnenergy_{it} \\ & + \zeta_{13} digital_{it} + \zeta_{14} digital_{it} \times AIDL_{it} + \varepsilon_i + \varepsilon_t + \varepsilon_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} CEL_{it} = {} & \eta_0 + \eta_1 AIDL_{it} + \eta_2 lnpgdp_{it} + \eta_3 gover_{it} + \eta_4 lnfdi_{it} \\ & + \eta_5 lnindus_{it} + \eta_6 lndroad_{it} + \eta_7 urban_{it} + \eta_8 lngreen_{it} \\ & + \eta_9 estruc_{it} + \eta_{10} higher_{it} + \eta_{11} gtfp_{it} + \eta_{12} lnenergy_{it} \\ & + \eta_{13} lnpgdp_{it} \times AIDL_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} CEL_{it} = {} & \theta_0 + \theta_1 AIDL_{it} + \theta_2 lnpgdp_{it} + \theta_3 gover_{it} + \theta_4 lnfdi_{it} \\ & + \theta_5 lnindus_{it} + \theta_6 lndroad_{it} + \theta_7 urban_{it} + \theta_8 lngreen_{it} \\ & + \theta_9 estruc_{it} + \theta_{10} higher_{it} + \theta_{11} gtfp_{it} + \theta_{12} lnenergy_{it} \\ & + \theta_{13} lnfdi_{it} \times AIDL_{it} + \vartheta_i + \vartheta_t + \vartheta_{it} \end{aligned} \tag{8}$$

TABLE 3 The results of descriptive statistics and the data sources of variables.

Variables	Observations	Mean	Standard deviation	Min	Max	Data source
lncb	690	18.9381	1.0096	13.6048	21.2539	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
lndcb	690	10.3258	0.7453	7.3874	12.3145	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnpcb	690	10.7881	0.7981	7.1371	13.0943	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnAI	690	4.0295	2.5475	0.0000	10.3975	PatentHub (https://www.patenthub.cn/search/advanced.html)
lnstock	420	7.3783	1.7594	2.6567	11.8745	International Federation of Robotics (https://ifr.org/)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						China Research Data Service Platform (https://www.cnrds.com/Home/Login)
lninstall	420	6.1720	1.6419	1.7267	10.2445	International Federation of Robotics (https://ifr.org/)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						China Research Data Service Platform (https://www.cnrds.com/Home/Login)
lnpgdp	690	9.6777	0.7764	7.7003	11.5619	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnindus	690	7.7405	1.1881	4.1225	10.2340	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lndroad	690	8.5143	0.9232	5.3192	9.9881	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
gover	690	0.2012	0.1048	0.0530	0.7583	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
urban	690	0.0157	0.0280	0.0001	0.1952	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lngreen	690	5.8767	1.9457	0.0000	10.4248	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
estruc	690	0.9629	0.3790	0.0248	2.4609	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
hihger	690	1.1230	0.5707	0.4346	5.2340	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
gtfp	690	0.3732	0.3023	0.1124	4.6188	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnfdi	690	11.1415	2.5600	0.4828	17.7481	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
lnenergy	690	18.1827	0.8339	15.1765	19.8411	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)

(Continued on following page)

TABLE 3 (*Continued*) The results of descriptive statistics and the data sources of variables.

Variables	Observations	Mean	Standard deviation	Min	Max	Data source
hcapital	690	0.0139	0.0080	0.0011	0.0389	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
digital	570	1.0946	0.7146	0.0803	3.7877	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnmarket	690	1.8155	0.3685	0.3097	2.4418	China Provincial Marketization Index Database (https://cmi.ssap.com.cn/)

$$\begin{aligned} CEL_{it} = {} & \mu_0 + \mu_1 AIDL_{it} + \mu_2 lnpgdp_{it} + \mu_3 gover_{it} + \mu_4 lnfdi_{it} \\ & + \mu_5 lnindus_{it} + \mu_6 lndroad_{it} + \mu_7 urban_{it} + \mu_8 lngreen_{it} \\ & + \mu_9 estruc_{it} + \mu_{10} higher_{it} + \mu_{11} gtfp_{it} + \mu_{12} lnenergy_{it} \\ & + \mu_{13} gover_{it} \times AIDL_{it} + v_i + v_t + v_{it} \end{aligned} \tag{9}$$

where, $lnmarket_{it}$, $hcapital_{it}$, and $digital_{it}$ denote marketization level, human capital level, and digital infrastructure level. The literature basis for selecting above three variables and the measurement methods for above three variables are presented in Table 1. The meanings of other variables are similar to those in Formula (1). The coefficient of AI and the interaction term are both significant and share the same sign, indicating that the moderating variable can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

4.2 Data sources

A balanced panel dataset comprising 30 Chinese provinces for the period spanning 1997–2019 has been used in this study. Tibet, Hong Kong, Macao, and Taiwan are excluded from the analysis because of data unavailability. Missing data has been imputed using the interpolation method. For all currency-measured variables, the influence of inflation has been removed by using the GDP index of each province, with the base period price level set at 1998. The natural logarithm has been applied to some variables to ensure data stability and address heteroscedasticity issues. Table 3 shows the results of descriptive statistics and the data sources of variables.

5 Results and discussion

5.1 The spatial and temporal characteristics of the development of AI in China

Figure 1 demonstrates the chronological evolution of the number of AI patents in China from 1997 to 2019. In Figure 1, we characterize the temporal evolution of AI patent counts in China during the study period using two indicators: the total number of AI patents per year and the average number of AI patents per province per year. Two significant observations can be made from Figure 1. First, both indicators show a growth trend, indicating that the number of AI patents in China has been increasing consistently. Second, the values of both indicators have shown an accelerated growth trend since 2012, especially after 2014, with a significantly faster growth rate. This is attributed to the breakthrough advancements made in AI technologies such as deep learning, image recognition, natural language processing, and intelligent chips during this period. For instance, in 2012, Google's deep learning algorithm achieved a breakthrough performance in the ImageNet image recognition competition. This demonstrates that the AI patent data used in this study can effectively capture the evolution of AI technology development. It further reinforces the scientific validity of the AI patent data employed in this research.

Table 4 presents the spatial distribution of the number of AI patents across China's provinces in certain years. From Table 4, it can be observed that the provinces with a high level of economic development and technological innovation capability, such as Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Henan, Hubei, Hunan, Shaanxi, Sichuan, and Chongqing, possess a larger number of AI patents. This indicates that AI technological innovation is closely related to the level of economic development and technological innovation capability.

5.2 Results of the AI's CRE test

5.2.1 Results of baseline regression

Table 5 shows the results based on Formula 1. Three findings can be obtained. First, it can be found from the model 5A-5C that when adopting different dependent variables, the AI coefficients are highly significant and exhibit negative values. The results imply that although AI can exert both positive and negative impacts on CES, the CRE of AI is more substantial. In other words, the net effect of AI on CES is negative, and the Hypothesis 1 can be supported. This finding aligns with the conclusion in existing research (Ding et al., 2023). Second, when replacing the core explanatory variable, related coefficients in model 5D-5I also exhibit negative values although some coefficients are insignificant. The results can provide support for Hypothesis 1 again. Third, the CRE of AI in model 5A-5C is greater than that in model 5D-5I. The results indicate that measuring the AIDL based on Formula 2 would underestimate the CRE of AI. Instead, employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate

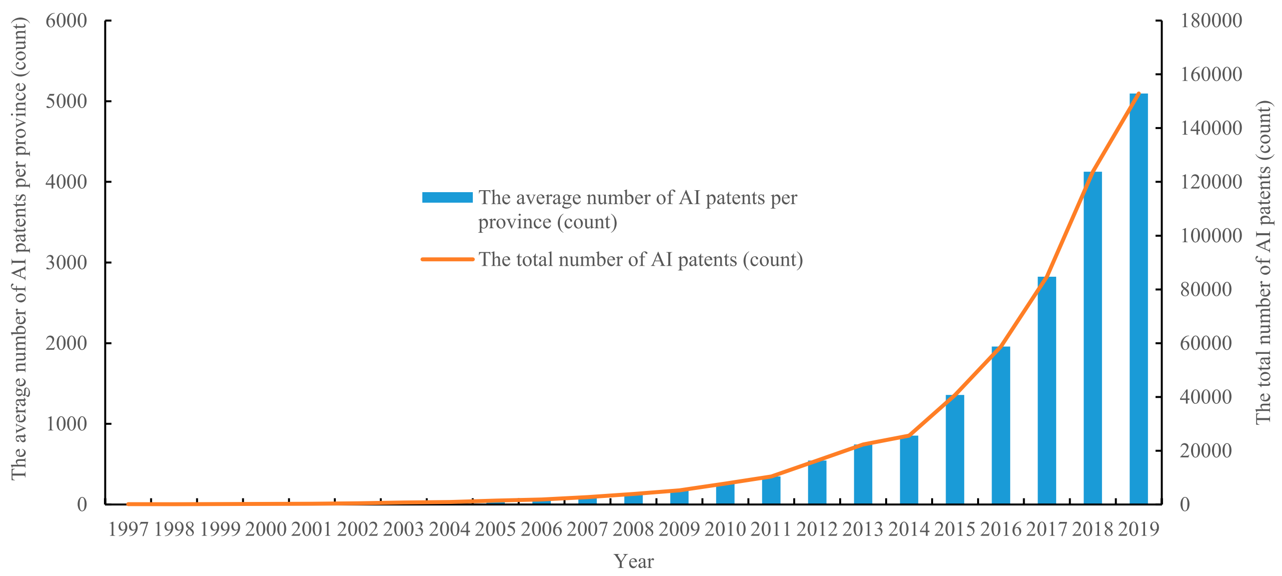

FIGURE 1
The chronological evolution of the number of AI patents in China from 1997 to 2019.

measurement of the AI's CRE. Therefore, in the following sections, we will continue our analysis by using AI patent data.

5.2.2 Results of endogenous processing

Endogeneity issue may be present in this study for several reasons. Firstly, there could be a reverse causality relationship between AI and CES. For instance, AI can reduce CES, and regions with higher CES may have a stronger incentive to adopt AI for carbon reduction. Secondly, errors may arise due to missing variables. Although the current model incorporates some control variables, certain factors influencing CES may not have been included. Lastly, measurement errors may exist in the model because some variables used in this study may not have been precisely measured due to data availability. Consequently, this paper aims to address the endogeneity problem using the instrumental variable (IV) method.

The IV chosen must exhibit a strong association with AI while being unrelated to the error term. In this research, we utilize a lagged phase of AI as the IV for endogeneity testing (Liu et al., 2022; Wang et al., 2023b). Table 6 presents the results of the endogeneity treatment. Model 6A details the first-stage empirical outcomes of the 2SLS method, and the second-stage empirical results provided in model 6B. Firstly, the null hypothesis regarding the IV's identifiability can be rejected because the Anderson canon. corr. LM statistic is significant. The null hypothesis of weak IV can also be rejected since the Cragg-Donald Wald F statistic is significant. Because the model 6A passes the Anderson-Rubin Wald test, the null hypothesis that the sum of endogenous regression coefficients equals zero can be rejected. The above tests indicate that the IV we selected is appropriate. Secondly, in model 6B, the AI coefficient is significantly negative, reaffirming AI's capacity to decrease CES. This outcome aligns with the results in Table 5. Thirdly, the results in model 6C and 6D are similar to the results in model 6B. The results imply that when adopting different dependent variables, the results of the endogeneity treatment are robust.

5.2.3 Results of spatial heterogeneity analysis

Variations in AIDL and CEL exist among different regions in China due to disparities in resource endowments, developmental phases, and national policies (Ding et al., 2023). To investigate whether there is spatial heterogeneity in the CRE of AI, this research classifies the 30 provinces into eastern, central, and western regions. Table 7 shows related results. Two findings can be obtained. Firstly, it is evident that when adopting different dependent variables, most of the coefficients of AI are highly significant and exhibit negative values although some of the coefficients of AI in the western region are insignificant. The results imply that the net effect of AI on CES is negative in three regions, reaffirming the validity of Hypothesis 1. This finding aligns with the conclusion of existing research (Ding et al., 2023). Secondly, the absolute value of the AI coefficient in model 7A is less than that in model 7B and 7C, the absolute value of the AI coefficient in model 7D is greater than that in model 7E and 7F, and the absolute value of the AI coefficient in model 7G is greater than that in model 7H, and 7I. The results indicate that, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. The eastern region has been the most active in technological innovation in China, with a significant advantage in the innovation and application of AI technologies. Therefore, AI can effectively reduce carbon intensity and *per capita* CES in the eastern region. The eastern region has also experienced the fastest economic and population growth in China, leading to continuous growth in CES. Thus, AI has limited impact on reducing the total CES in the eastern region.

5.2.4 Results of time heterogeneity analysis

Figure 1 indicates that China has experienced rapid growth in AI patent counts since 2012. Given this, we hypothesize that there may be temporal heterogeneity in the impact of AI on CES in China. Therefore, we will use 2012 as a temporal dividing point to investigate the temporal heterogeneity of AI's influence on CES.

TABLE 4 The spatial distribution of the number of AI patents in China's provinces in some years.

Year provinces	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2006	1997
Beijing	21,756	15,462	11,662	8,372	5,946	4,510	3,564	2,893	2054	1,608	410	27
Tianjin	3,321	2,922	2,306	2018	1,257	737	600	479	285	223	61	2
Hebei	1811	1,659	1,054	906	490	306	260	187	86	94	13	2
Shanxi	738	538	342	245	171	133	118	84	46	26	7	1
Inner Mongolia	334	247	236	122	151	40	25	22	15	19	3	0
Liaoning	3,090	2,401	1862	1,422	1,241	768	659	425	392	283	105	5
Jilin	1,253	904	664	468	291	230	191	143	113	66	15	0
Heilongjiang	1803	1,479	1,396	1,017	855	546	540	371	258	217	57	8
Shanghai	9,980	7,021	5,612	3,763	2,579	1889	1,662	1,472	1,047	866	302	5
Jiangsu	18,029	15,027	9,949	7,450	5,531	3,817	3,612	2,566	1,364	872	130	2
Zhejiang	11,257	9,511	5,821	3,899	2,940	1712	1,591	1,210	751	580	110	8
Anhui	5,428	6,610	3,769	2,686	1,656	727	581	316	177	100	44	3
Fujian	3,703	3,440	2043	1,166	805	423	349	274	153	94	21	5
Jiangxi	1,228	938	607	438	255	120	111	70	44	48	6	0
Shandong	6,598	5,209	4,117	3,113	2,362	1,193	1,153	798	439	350	58	7
Henan	3,203	2,896	1833	1,041	803	362	328	259	141	87	16	5
Hubei	5,386	3,809	2,737	1,699	1,167	717	625	444	320	246	38	6
Hunan	2,988	2,622	1754	1,099	763	368	405	285	182	178	28	5
Guangdong	32,776	25,743	15,920	9,877	5,590	3,559	3,038	2,286	1,482	1,067	257	15
Guangxi	1,344	1,266	1,281	849	587	322	165	117	51	24	5	2
Hainan	217	175	110	68	61	21	12	12	8	3	0	0
Chongqing	2,935	2,289	1,689	1,329	823	500	401	258	174	131	33	1
Sichuan	6,054	6,218	4,008	3,011	2,278	1,083	908	523	319	211	39	3
Guizhou	743	603	384	281	265	88	60	35	22	12	3	1
Yunnan	1,034	800	498	334	231	122	110	65	51	45	11	2
Shaanxi	4,834	3,067	2,372	1,626	1,373	1,160	1,106	666	394	274	65	7
Gansu	494	350	236	156	140	84	111	64	27	23	6	0
Qinhai	99	65	91	84	6	10	5	2	1	3	0	0
Ningxia	189	250	180	109	47	19	16	8	8	1	0	0
Xinjiang	261	246	177	95	94	44	47	20	18	15	5	2

Table 8 presents the results of our model estimations. Two key findings emerge from Table 8. First, the coefficients for AI in models 8A-8F are all negative, indicating the consistent existence of a CRE attributed to AI development. Second, compared to the AI coefficients in models 8B, 8D, and 8F, the coefficients in models 8A, 8C, and 8E are not only highly significant but also have absolute values much larger than those in models 8B, 8D, and 8F. This suggests that the CRE of AI was greater during the period from 1997 to 2011 than during the period from 2012 to 2019. We can interpret this phenomenon from two perspectives. First, while AI development does lead to a CRE, this effect may require a longer period to be observable. Second, the rapid growth of AI may lead to carbon emission increases through increased electricity consumption, consumer rebound effect, and other channels, thereby reducing the CRE attributed to AI development.

5.3 Results of the nonlinear CRE test of AI

5.3.1 The nonlinear CRE of AI development

We can analyze the nonlinear impact of AI on CES based on the marginal effect of AI on CES, and the marginal effect of AI on CES can be estimated through the econometric model. Figure 2 shows related results based on Formula 3. Two findings can be obtained.

TABLE 5 The results of baseline regression.

Models variables	5A	5B	5C	5D	5E	5F	5G	5H	5I
	lncb	*lndcb*	*lnpcb*	*lncb*	*lndcb*	*lnpcb*	*lncb*	*lndcb*	*lnpcb*
lnAI	−0.0975***	−0.0896***	−0.0888***						
	(0.0256)	(0.0257)	(0.0257)						
lnstock				−0.0222	−0.0460*	−0.0459*			
				(0.0260)	(0.0269)	(0.0269)			
lninstall							−0.0249	−0.0421*	−0.0418
							(0.0246)	(0.0255)	(0.0255)
Observations	690	690	690	420	420	420	420	420	420
R^2	0.8459	0.6215	0.8255	0.8405	0.8278	0.8049	0.8407	0.8277	0.8047

*, **, *** represent the significance of parameter values at the 10%, 5%, and 1% levels, respectively. The same applies to the following tables. The values in parentheses represent t-values, and the same applies to the following tables. The econometric models include all the control variables listed in Equation (1), as well as provincial fixed effect and time fixed effect. The same applies to the following.

TABLE 6 The results of endogenous processing.

Models variables	6A	6B	6C	6D
	lnAI	*lncb*	*lndcb*	*lnpcb*
lnAI		−0.2965***	−0.2796***	−0.2746***
		(0.0646)	(0.0645)	(0.0646)
L.lnAI	0.3965***			
	(0.0347)			
Observations	660	660	660	660
R^2	0.9741	0.8305	0.5884	0.8116
Anderson canon. corr. LM statistic		112.92***	112.93***	112.92***
Cragg-Donald Wald F statistic		130.38***	130.38***	130.38***
Anderson-Rubin Wald test		23.00***	20.34***	19.50***

TABLE 7 The results of spatial heterogeneity analysis.

Models variables	Eastern region	Central region	Western region	Eastern region	Central region	Western region	Eastern region	Central region	Western region
	7A	7B	7C	7D	7E	7F	7G	7H	7I
	lncb	*lncb*	*lncb*	*lndcb*	*lndcb*	*lndcb*	*lnpcb*	*lnpcb*	*lnpcb*
lnAI	−0.0911***	−0.0972***	−0.0963*	−0.1074***	−0.0990***	−0.0886	−0.1131***	−0.1008***	−0.0803
	(0.0284)	(0.0364)	(0.0539)	(0.0284)	(0.0367)	(0.0542)	(0.0287)	(0.0367)	(0.0543)
Observations	253	184	253	253	184	253	253	184	253
R^2	0.9517	0.9380	0.8302	0.8966	0.8380	0.5555	0.9369	0.9353	0.8128

Firstly, As illustrated in Figure 2, the marginal effect of AI on CES consistently remains below zero and passes the significance test in each subplot. The results mean that the net effect of AI on CES is negative, and Hypothesis 1 can be supported again. Secondly, it can also be observed that with increasing AIDL, the absolute value of the marginal effect in each subplot grows. The results mean that the CRE of AI follows a nonlinear trend, and a higher AIDL correspond to a more significant CRE. In other words, improving the AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thus, Hypothesis 2 can be supported.

TABLE 8 The results of time heterogeneity analysis.

Models variables	1997–2011	2012–2019	1997–2011	2012–2019	1997–2011	2012–2019
	8A	8B	8C	8D	8E	8F
	lncb	*lncb*	*lndcb*	*lndcb*	*lnpcb*	*lnpcb*
lnAI	−0.1270***	−0.0126	−0.1220***	−0.0215	−0.1211***	−0.0226
	(0.0334)	(0.0227)	(0.0334)	(0.0228)	(0.0335)	(0.0228)
Observations	450	240	450	240	450	240
R^2	0.7625	0.6035	0.4306	0.9010	0.7414	0.5616

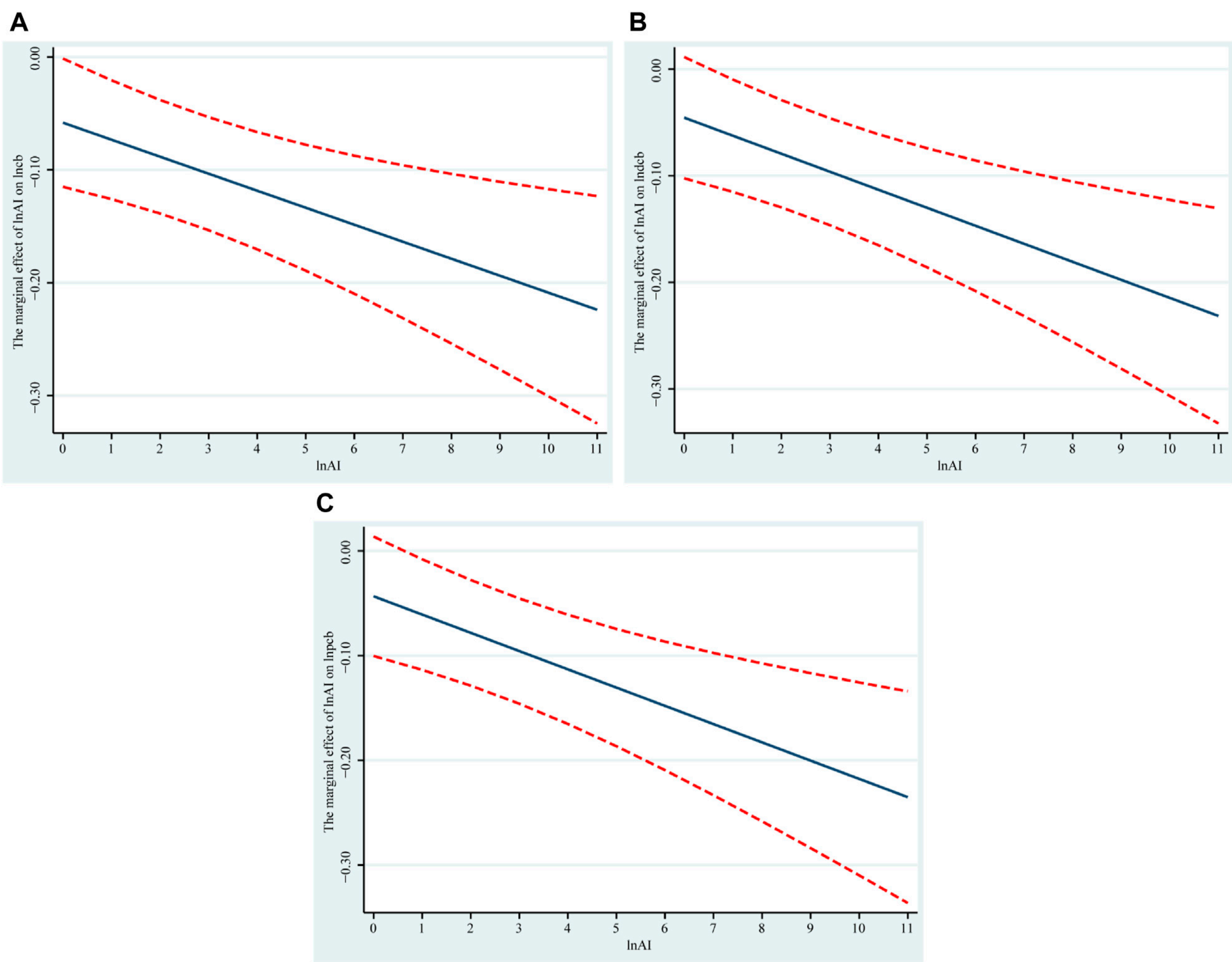

FIGURE 2
(A–C) respectively show the marginal effect of AI on the total CES, carbon intensity, and per capita CES. The blue line in each picture describes the trend of the marginal effect of AI on CES, and the red curve in each picture represents a 95% confidence interval.

5.3.2 The nonlinear CRE of AI due to changes in other factors

Even if the AIDL remains constant, improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. Figure 3 presents related results based on Formula 4–9. Three valuable discoveries can be gleaned. Firstly, as illustrated in Figure 3, within the range of distributions for other factors, the marginal effect of AI on CES is significantly negative in each subplot. The results mean that the net effect of AI on CES is negative, and Hypothesis 1 can be supported again. Secondly, it can also be observed from

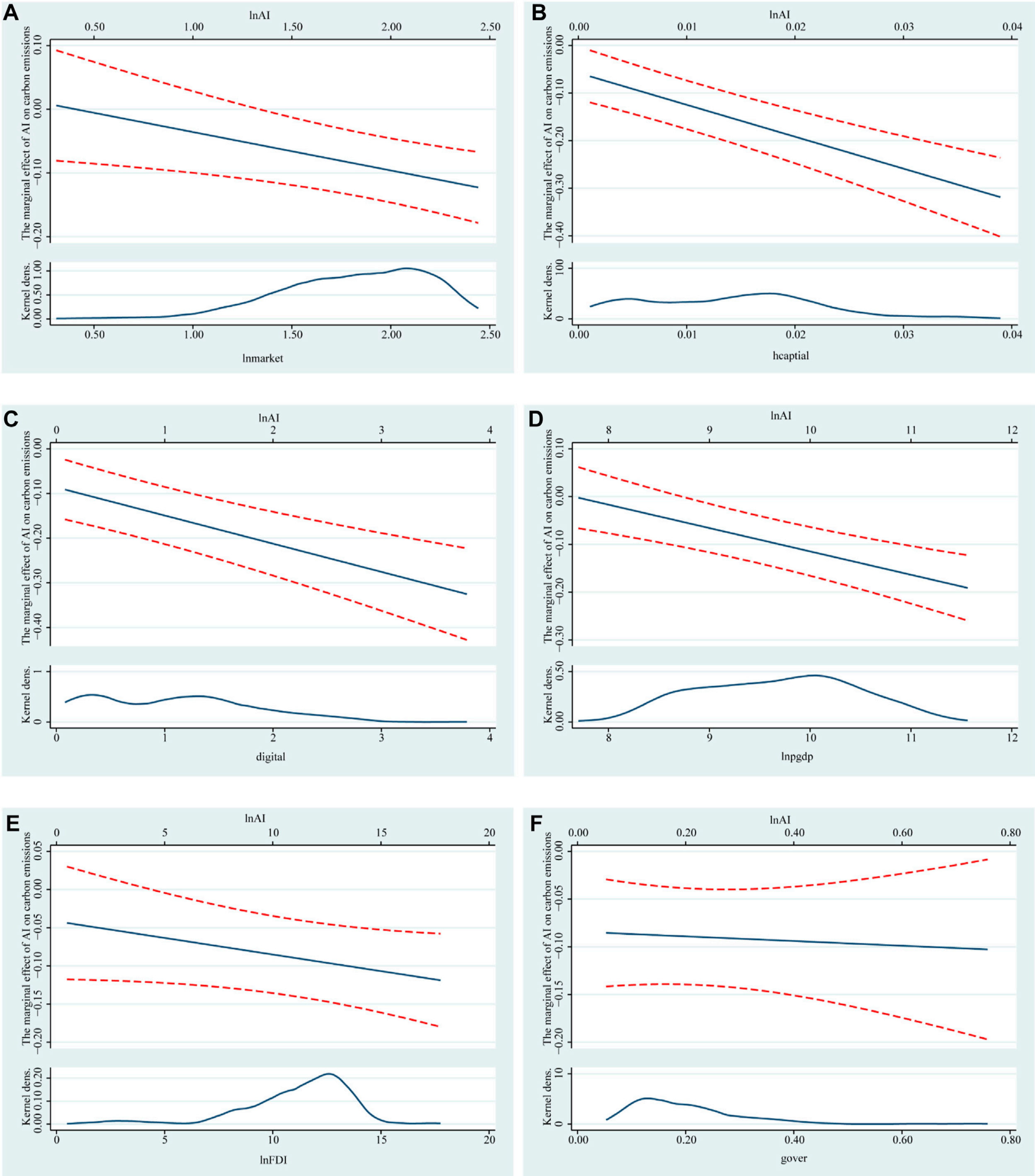

FIGURE 3
(A–F) respectively show the marginal effect of AI on carbon intensity when improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention. The blue line in each picture describes the trend of the marginal effect of AI on CES, and the red curve in each picture represents a 95% confidence interval. The bell-shaped curve in each picture depicts the distribution density of each variable.

Figure 3 that with the improvement in the level of these factors, the absolute values of the marginal effect of AI on CES demonstrate a rising pattern. The results imply that these factors can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thus, Hypothesis 3 can be supported. Thirdly, it is important to highlight that the absolute values of the marginal effect of AI on CES in Figures 3B, C escalate more rapidly in comparison to Figure 3A, D–F. The outcomes imply that, among these factors under examination, human capital and digital infrastructure exert a more pronounced influence on magnifying the marginal CRE of AI. One possible reason is that innovation capability and data can play crucial roles in the innovation and application of AI technologies. Compared to other factors, human capital serves as a significant support for technological innovation, and digital infrastructure is a critical foundation for data collection and processing.

5.4 Discussion

The above results can be discussed from two perspectives. The first perspective is the CRE of AI. The findings in this study indicate that AI can reduce CES, further confirming existing research viewpoints (Li et al., 2022). However, in contrast to existing research, this study also reveals that using the quantity of industrial robots to measure AIDL might underestimate the CRE of AI. The second perspective is the nonlinear CRE of AI. There has been limited focus in existing research on the nonlinear CRE of AI, whereas this paper places particular emphasis on this aspect. The results in this study suggest that increasing AIDL can amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. However, some scholars have proposed that the impact of industrial robots on CES exhibits an inverted U-shaped relationship (Liu et al., 2024). This result indicates that increasing AIDL will first raise the CES before eventually reducing CES. This result differs somewhat from the findings of this paper. The discrepancy may be due to the different methods used to measure AIDL in the two studies. Additionally, the results in this study suggest that even if the AIDL remains constant, changes in other factors can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. While existing research has indicated that enhancing technological absorption capacity can strengthen the CRE of AI (Li et al., 2022), this study suggests that there are additional factors, including marketization, human capital, digital infrastructure, economic development, openness, and government intervention, can amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. Another novel finding relative to existing research is human capital and digital infrastructure can play the most significant role in amplifying the CRE of AI.

6 Conclusion and implications

6.1 Conclusion

The principal findings are as follows. Firstly, during the study period, the number of AI patents in China has shown a continuous growth trend. Since 2012, the growth of AI patents in China has accelerated, especially after 2014, when the number of AI patents in China entered a stage of rapid growth. Secondly, the provinces with a high level of economic development and technological innovation capability, such as Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Henan, Hubei, Hunan, Shaanxi, Sichuan, and Chongqing, possess a larger number of AI patents. Thirdly, although AI can exert both positive and negative impacts on CES, the CRE of AI is more substantial. This conclusion holds true even after considering robustness, endogeneity, and spatial heterogeneity. It is worth noting that employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate measurement of the AI's CRE. Fourthly, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. Fifthly, the CRE of AI was greater during the period from 1997 to 2011 than during the period from 2012 to 2019. Sixthly, improving the AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Lastly, even if the AIDL remains constant, changes in other factors such as marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI.

6.2 Implications

Based on the aforementioned conclusions, the following policy recommendations can be formulated. Firstly, facilitating AI technology innovation and leveraging AI for carbon reduction. AI can reduce CES, and improving the AIDL can magnify the marginal CRE of AI. Thus, the government should prioritize the development and utilization of AI. The enterprises should expedite the application of AI in various activities, including green energy production, the production of environmentally friendly products and services, carbon emission monitoring, carbon market trading, carbon sink management, and carbon capture technology innovation. Secondly, when assessing the CRE of AI, it is essential to utilize AI patent data and take into account the nonlinear CRE of AI. Employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate measurement of the AI's CRE, and the CRE of AI exhibits a nonlinear characteristic. Thus, government and research institutions should take these influences into account when assessing the CRE of AI. Lastly, optimizing the economic and social environment is crucial to fully unleash the carbon reduction potential of AI. Even if the AIDL remains constant, changes in other factors such as marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the CRE of AI. Thus, the government, in the process of utilizing AI for carbon reduction, should not confine its focus solely to the development of AI but also consider the impact of other factors. For example, the government and other relevant stakeholders should refine the marketization, human capital, digital infrastructure, economic development, openness, and government intervention to amplify the CRE of AI.

The main potential challenges and practical considerations in implementing the recommended policies are follows: first, promoting AI development requires ensuring data security. However, managing and protecting data securely is a challenge. The government can introduce strict data privacy and security laws to ensure the protection of data. Second, as AI technology becomes more advanced, ethical and moral questions arise, such as the use of AI in decision-making processes that affect human lives. The government should establish ethical frameworks and guidelines for AI use. This can ensure that AI is used responsibly and does not harm human interests.

6.3 Limitations

The limitations in this study are as follows. Firstly, the research conclusions are drawn based on Chinese data, and the processes of CES and AI development in China may differ from other countries. Therefore, some research findings may not be applicable in other nations. Secondly, this paper only considers the roles of some factors, including marketization, human capital, digital infrastructure, economic development, openness, and government intervention, in amplifying the CRE of AI. There may be additional factors that can amplify the CRE of AI. Lastly, this article analyzes the impact of AI on CES using traditional panel econometric models. However, the impact of AI on CES may exhibit a spatial spillover effect, which suggests that the models used in this article still requires further improvement. In the future, a spatial panel econometric model will be employed to analyze the spatial spillover effect of AI on CES.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XW: Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. TX: Data curation, Investigation, Software, Supervision, Validation, Visualization, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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