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Can industrial intelligence promote carbon emission efficiency? --empirical research based on the Yangtze River Economic Belt

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The rapid development of intelligent technology characterized by robots under the fourth scientific and technological revolution provides a favorable opportunity for the accurate decision-making of urban pollution control and the effective achievement of the goal of carbon emission reduction in China. This research uses the robot penetration rate as a representative and characteristic index of industrial intelligence development, based on panel data from 108 cities in the Yangtze River Economic Belt (YEB) from 2006 to 2020. It then uses panel quantile regression, spatial measurement, and threshold effect models to provide a more thorough theoretical and empirical discussion of the impact, mechanism, and spatial effect of industrial intelligence development on urban carbon emission efficiency (CEE). Urban CEE may be greatly increased with the use of industrial intelligence, and this finding remains true even after endogeneity and robustness tests are controlled; From an action mechanism perspective, industrial intelligence advances technology, optimizes industrial structure, and ultimately enhances regional CEE; There is a Matthew effect on the degree of development of carbon emission efficiency, and the impact of industrial intelligence on CEE is more pronounced in non-resource-based cities and the lower portions of YEB; Urban CEE increases positively with the spatial spillover impact of industrial intelligence development. The ability for regional sustainable development will be significantly increased if cross-regional cooperative prevention and control of environmental governance can be successfully achieved. This study verifies the enabling effect of industrial intelligence development on the improvement of urban CEE, and provides enlightenment for China to improve industrial intelligence development strategies and policies to achieve regional high-quality development.

KEYWORDS

industrial intelligence, carbon emission efficiency (CEE), Yangtze River Economic Belt (YEB), the matthew effect, high-quality development

Abbreviations: YEB, Yangtze River Economic Belt; CEE, Carbon emission efficiency; IFR, International Federation of Robotics.

1 Introduction

China's economy has expanded at an average annual pace of 9.4% since the reform and opening up, resulting in "The Chinese miracle". Yangtze River Economic Belt (YEB) is an important economic region in China, it crosses three Chinese regions and contributes more than 50% of China's annual economic growth, is a key strategic area for China's economic development. Nevertheless, the ecological environment of the provinces and cities along the Yangtze River is under peril due to the economy's fast development. Chinese President Xi Jinping has convened three meetings to emphasize the need to achieve high-quality economic development in China, and Chinese government put forward the commitment of independent emission reduction in the Paris Agreement in 2016 in an attempt to control greenhouse gas emissions. In 2020, China's carbon emissions per unit of GDP decreased by 48% compared with 2005, exceeding the target of 40%–45% promised to the international community, however, there is still a long way to go. Faced with the increasingly challenging situation of carbon dioxide emission reduction in China, YEB, as a pilot Chinese ecological civilization region and a link for the coordinated development of East, Central and West China, needs to shoulder the dual responsibilities of economic development and environmental protection. That is, to find a green growth path that takes into account both ecological environment and economic growth, and to realize the steady economic growth and "carbon peaking and carbon neutrality" goals. The key to achieving the above goals lies in YEB's ability to obtain maximum output with minimum material resource input and ecological resource cost, i.e., to improve YEB's urban carbon emission efficiency (CEE), which is directly related to the implementation of the national High-quality economic development and the realization of the future "carbon peaking and carbon neutrality" goals.

At this stage, a significant industrial intelligence development trend has emerged globally, which has a revolutionary effect on the economic activities of enterprises. This trend is brought about by the ongoing breakthroughs in information and communication, new materials, new energy (Graetz and Michaels, 2018). The White Paper on China's Industrial Intelligence in 2019 points out that industrial intelligence is the output increment brought by the use of artificial intelligence (AI), Internet of Things, Internet and other technologies in the primary, secondary and tertiary industries. It liberates manpower by replacing simple repetitive work, provides a brand-new human-computer interaction mode, and breaks through the limits of human beings to innovate new industrial species. It can be said that industrial intelligence is essentially subverting people's production and lifestyle. Through the automation of knowledge work, man-machine interaction and collaborative intelligence in product life cycle manufacturing activities, it realizes the optimization of product life cycle manufacturing process, thus promoting the optimization of industry factor endowment conditions and the innovation of production mode, and inevitably having a noticeable impact on urban CEE as the carrier of economic activities and industrial space. As a result, the widespread application of smart technologies in the industry holds great promise for the Chinese region to achieve the sustainable development goals (Vinuesa et al., 2020). It makes sense to bring the realistic background of industrial intelligence development into the policy consideration of improving the path of CEE, deeply reveal the influence effect and internal logic of industrial intelligence development on CEE, and discuss how industrial intelligence development can promote CEE.

2 Literature review

With the rise of Industry 4.0 Revolution, the impact of industrial intelligence on economy and society has aroused extensive discussion in academic circles (Goralski and Tan, 2022), and related research has produced substantial results on the economic growth effect and environmental impact effect of industrial intelligence respectively. Regarding the impact of industrial intelligence on economic growth, existing studies have come up with consistent and positive findings on the features of industrial intelligence that foster efficiency enhancement, technical innovation, and industrial revolution. For instance, labor can be supplemented and replaced in repetitive tasks and standardized processes by integrating artificial intelligence with manufacturing (Mikalef and Gupta, 2021); Labor productivity may be promoted to support economic growth, and intelligent production and management can be achieved by optimizing production control decisions through independent control (Kromann et al., 2020). Industrial intelligence can contribute to economic development by reshaping innovation processes, increasing the capabilities of R&D organizations and generating spillover effects through the application sector (Ding et al., 2023). Jin et al. (2022) pointed out that the application of artificial intelligence technology in greenhouse planting can predict greenhouse meteorological data, accurately guide agricultural production and reduce unnecessary production costs. Industrial intelligence brings intelligent industrialization innovation and industrial intelligence transformation, and at the same time, it can promote the intelligent reconstruction of industrial structure (Guo, 2019); The deep integration of artificial intelligence and traditional industries promotes the digital and intelligent transformation of traditional industries, accelerates industrial differentiation, and promotes the cross, penetration and integration of different industries (Graetz et al., 2022). However, some scholars have also put forward the adverse effects of industrial intelligence on economic growth, including labor market crowding out (Wang et al., 2022), unemployment (Acemoglu and Restrepo, 2019), blind expansion (Zhao et al., 2022) and so on.

Existing studies mainly used the Divisia index method to decompose carbon dioxide emissions in order to analyze the factors affecting carbon emissions (Raza et al., 2021), or mainly studied the impact of the traditional production factors on carbon emissions (Raza and Lin, 2022; Raza and Li, 2023). The current study on the effects of industrial intelligence on the environment is mainly focused on the industrial sector. It has conducted both theoretical and practical research on the potential avenues through which industrial intelligence could support low-carbon and green development, with a focus on energy efficiency enhancement, innovation in green technologies, and industrial structure optimization. It is believed that industrial intelligence can integrate intra-industry and inter-industry knowledge and cross-enterprise cooperative innovation (Barbieri et al., 2020), and accelerate knowledge spillover and creation; Promote the absorption and creation of knowledge within enterprises, optimize the decision-making of equipment and materials use (Zhang et al., 2023). The application of artificial intelligence in the industrial field helps to improve energy efficiency and reduce related pollutants (Sarkar and Sarkar, 2020). According to Yuan et al. (2022), industrial intelligence has the potential to enhance production processes, provide real-time feedback and optimization of production information, minimize energy waste, shorten equipment response times, and drastically close the gap between companies and the most energy-efficient ones; Neural network and machine learning applications can forecast waste production and encourage waste recycling, increasing energy efficiency and lowering emissions of pollutants (Kopka and Grashof, 2022). Additionally, the use of industrial intelligence can help modernize and restructure the industrial structure, advance the growth of clean industries, and remove outdated production capacity (Shen and Yang, 2023); The energy industry may effectively foster the growth of new energy industries, decrease industrial pollution emissions (Du et al., 2021). Some scholars have reservations about whether industrial intelligence can improve the environment. The reason is that although artificial intelligence technology is developing rapidly, only some regions and a small number of enterprises have matching human capital and corresponding intelligent infrastructure at present. In addition, the lag of technology diffusion and the formation of social group consciousness take a long time, which easily makes the production efficiency improvement brought by artificial intelligence technology not obvious, and even crowds out the investment of other departments and easily causes unnecessary waste of resources (Du and Lin, 2022; Liu et al., 2022). In the long run, these regions with relatively backward basic conditions cannot share the knowledge dividend brought by artificial intelligence technology equally, which hinders the green development of regional economy, and eventually leads to the Matthew effect that the stronger the strong and the weaker the weak. According to Czarnitzki et al. (2023) and Liu et al. (2020), industrial intelligence has a "U-shaped" impact on economic intense transformation. Some experts believe that human conduct has a crucial part in determining the direction of environmental change, and that the application mode of industrial intelligence affects this.

In summary, Research exploring the environmental impact effects of industrial intelligence needs to be fleshed out as the trend towards industrial intelligence increases globally; furthermore, existing research has focused mainly on the environmental impacts of intelligent developments in the industrial sector. However, the problem of carbon emissions from primary and tertiary industries in China is equally serious. For example, from 2011 to 2018, China's tertiary industry carbon dioxide emissions increased by 51.24%, and total agricultural carbon emissions accounted for 17% of total greenhouse gas emissions, higher than the global average of 11% (Gai and Yang, 2023). Because of the numerous problems caused by the depletion of global resources and the mounting demand on enterprises to reduce carbon emissions, it is therefore not sufficient to examine the effects of industrial intelligence on productivity, economic growth, and carbon emissions in isolation. Therefore, even if the secondary industry, including the industrial sector, is the main source of carbon emissions, the growth of carbon emissions from other industries cannot be ignored. It is imperative to study how industrial intelligence affects carbon emission from the perspective of coordinated development of various industries. The theory and methodology of the green total factor productivity (GTFP) index in environmental economics are based on the TFP. GTFP is a significant indicator of the joint performance of economic growth and environmental optimization, represents the ability of the economic system to generate economic output while maintaining environmental quality and ecological balance through production factors like labor, capital, and energy (Zhan and Li, 2022). Only Tang and Chi (2022), Meng and Zhao (2023), and Qian et al. (2023) have examined the connection between industrial intelligence and green economic efficiency in the literature that is now in existence. This relationship has to be further refined.

For the reasons listed above, the penetration rate of industrial robots is used in this article as a representative and distinctive indicator of the growth of industrial intelligence, and conducts a theoretical and empirical analysis on the impact and mechanism of CEE of cities empowered by industrial intelligence, based on panel data of 108 cities in Chinese YEB from 2006 to 2020. The possible marginal contributions of this research include: Firstly, this research enriches the research on the relationship between industrial intelligence and the coordinated development of economy and environment, and provides theoretical and empirical evidence from China for exploring the path of improving urban CEE from the perspective of digital technology. Secondly, this research analyzes the heterogeneous impact effect of industrial intelligence on CEE in YEB from the perspectives of geographical location, resource endowment and CEE, and provides more detailed empirical conclusions for policy recommendations. Thirdly, this research verifies the spatial spillover effect of industrial intelligence on urban CEE, and provides theoretical support for the implementation of cross-regional pollution control policies. Fourthly, this research discusses the threshold effect of human capital on the impact of industrial intelligence on CEE, which has important policy implications for breaking the "Matthew effect" between regions and giving full play to the role of human capital in environmental governance. Section 2 is literature review. Section 3 elucidates the theoretical analysis and provides research hypotheses. Section 4 details the methodologies and variable descriptions. Section 5 presents the empirical results. Section 6 is the discussion of empirical results. Section 7 provides conclusion, policy implications and limitations.

3 Mechanism analysis and hypothesis

3.1 Analysis of the direct impact of industrial intelligence on urban CEE

Technologies such as machine learning, intelligent robots, computer vision, and deep learning are important forms of artificial intelligence (Liu et al., 2020). With the free flow of cross-border capital in recent years, the application of artificial intelligence technology in industries in emerging economies has been accelerated (Ma et al., 2023). The application of artificial intelligence in the primary industry can transform the traditional production mode of agriculture into an intelligent production model, realize precision planting and breeding, and achieve the goal of low-carbon agricultural development. The integration of artificial intelligence and manufacturing will help break through the limitations of manual supervision process, realize the digital control of the whole production process, and reduce the greenhouse gas emissions of the entire industrial chain (Wang et al., 2023). Industrial intelligence can also optimize urban industrial production conditions, improve the purification accuracy of waste through robot operation, and provide a more scientific and effective basis for enterprise pollution control decisions through pollution data mining and analysis. The application of artificial intelligence technology in the tertiary industry can reduce the carbon emissions of transportation and life services, and improve the CEE of the tertiary industry. Therefore, the following assumptions are put forward:

H1: Industrial intelligence can promote the improvement of urban CEE.

3.2 Analysis of the indirect impact of industrial intelligence on urban CEE

3.2.1 Analysis of technological progress channel

The endogenous growth theory states that the advancement of technology is the primary driver of steady economic growth, and Grossman and Krueger (1991) confirm the key role of technological effect in improving environmental pollution. In the context of industrial intelligence, the traditional labor force is liberated from tedious process work to focus on innovation as well as more valuable strategic activities (Li, 2023), the use of intelligent equipment often requires a high level of knowledge, prompting enterprises to introduce high-quality talent, and to achieve scientific and technological progress through the human capital effect and technological complementary effect (Yu et al., 2022). In addition, AI technology can reduce the cost of information transfer between enterprises, enable enterprises to learn and imitate advanced production technology, expand the capital stock of public knowledge, and drive the technological innovation of upstream and downstream enterprises (Nishant et al., 2020). The use of intelligent technology enables enterprises to continuously improve the added value of their products and gradually replace low value-added enterprises in the industrial value chain, while other enterprises that have not undergone intelligent transformation will continuously update their production technology and management experience through learning and imitation in order to avoid being eliminated (Bernard et al., 2019). Urban industrial energy efficiency can be effectively increased through technological advancements in the areas of industrial resource recycling efficiency, green technology and equipment product supply, and green transformation level of production process. Therefore, the following assumptions are put forward:

H2: Industrial intelligence promotes urban CEE through the channel of technological progress.

3.2.2 Analysis of industrial structure optimization channel

In the process of the intelligent development of industry, digital technology and digital elements are widely applied in all fields of cities' economy and society, and the rapid development of modern information technology promotes the deepening of the integration of the digital economy and the real economy, giving rise to a series of new products, new technologies and new forms of business, and promotes the continuous upgrading of the industrial structure in the direction of high-end digitization, greening and low-carbonization (Furman and Seamans, 2019). In addition, industrial intelligence can prompt traditional industrial enterprises to gradually eliminate backward production capacity and carry out transformation and upgrading, which is not only an important path to break the dilemma of high pollution, high energy consumption and high emission in the field of industrial economy, but also a typical feature of the optimization and upgrading of industrial structure (Waltersmann et al., 2021). Industrial structure upgrading in the process of industrial intelligent development can accelerate the development of greening and low-carbonization in the whole field of social economy and realize the improvement of CEE. Therefore, this research proposes the following research hypothesis.

H3: Industrial intelligence promotes urban CEE through the channel of industrial structure optimization.

3.2.3 Spatial effect analysis

According to the theory of economic geography, the flow of production factors can gradually break down interregional market segmentation and change the spatial isolation of individual development. This leads to a certain spatial spillover effect in interregional production activities. Digital technologies such as artificial intelligence and big data carried by industrial intelligence can break the geographical distance barrier of information technology transmission, improve the mobility and accessibility of data, and alleviate the barriers of technical exchange between regions, which makes the regions that actively improve the level of industrial intelligence have certain enlightening and learning effects on neighboring regions after achieving economic growth and environmental protection achievements (Vial, 2019), thus promoting the improvement of CEE in neighboring regions. If the spatial spillover effect is disregarded, the overall benefit of industrial intelligence on CEE may be underestimated. Based on this, this research proposes the following research hypothesis.

H4: Industrial intelligence may have spatial spillover effects on carbon efficiency in neighboring regions.

4 Methodology and variable definitions

4.1 Model setting

The empirical research in this paper aims to effectively identify the impact of industrial intelligence on urban CEE, so we set the following benchmark regression model based on the above theoretical mechanism analysis and research hypotheses:

$$CEE_{it} = \beta_0 + \beta_1 IRobot_{it} + \gamma C_{it} + \mu_i + \lambda_t + \xi_{it} \tag{1}$$

Where CEE_{it} represents the CEE of city i in the year of t, and the core explanatory variable $IRobot_{it}$ denotes the robot application degree of city i in the year of t. The estimated coefficient β_1 before $IRobot_{it}$ portrays the effect of changes in industrial intelligence on urban CEE, if $\beta_1 > 0$, it indicates that urban industrial intelligence improves urban CEE. Meanwhile, in order to make the empirical results more robust, this research controls as much as possible other factors affecting the urban CEE, which mainly include: the intensity of environmental regulation, the level of urbanization, foreign direct investment, the size of the population, the government intervention, and the level of financial development. In addition, in order to eliminate the possible interference of unobservable and time-varying factors at the city level on the regression results, the city fixed effect μ_i and year fixed effect λ_t are added into the model, ξ_{it} is random error terms.

To further discuss the spatial spillover effect of urban industrial intelligence on urban CEE, the spatial interaction terms of the explanatory variables are introduced into Eq. 1 to construct the following spatial measurement model:

$$GEEV_{it} = \beta_0 + \rho WGEEV_{it} + \beta_1 IRobot_{it} + \delta WIRobot_{it} + \gamma_1 C_{it} + \gamma_2 W \times C_{it} + \mu_i + \nu_t + (1-\lambda W)^{-1}_{\varepsilon_{it}} \tag{2}$$

In Eq. 2, W is the spatial weight matrix, which is constructed by the geographical structure difference distance between two cities. On account of the limitation of constructing the weight matrix only by geographical distance, subsequent spatial econometric regressions were performed using the adjacency matrix and the economic distance matrix respectively to ensure the robustness of the results. ρ is spatial autocorrelation coefficient, δ is the spillover effect of industrial intelligence, γ_2 is the spillover effect of control variables. According to whether the values of ρ, δ, γ_1 and λ are significantly 0, spatial econometric models can be divided into three categories: if $\rho = \delta = \gamma_1 = 0$, the models are spatial error models (SEM); If $\delta = \lambda = 0$, the model is spatial lag model (SLM). If $\lambda = 0$, the model is spatial Durbin model (SDM). Later, the above models will be selected through further inspection.

4.2 Variable definitions

4.2.1 Core explanatory variable: urban industrial intelligence level (*lnirobot*)

Referring to the methods of Acemoglu and Restrepo (2019), Xu and Song (2023), this research construct the robot application index at the city level using the industrial employment structure of the city, the number of working-age laborers in the city and the number of robots at the industry level. This method comprehensively considers the characteristics of urban labor force, the scale characteristics of industrial labor force and the application scale of urban robots, and is more scientific compared with the direct use of the robot data. Specific measurement formula is shown in Eq. 3:

$$IRobot_{it} = \sum_j \frac{Emp_{si,t}}{\sum_j Emp_{ji,t}} \times \frac{Robots_{jt}}{Labor_{i,t}} \tag{3}$$

In Eq. 3, i means city, j denotes industry, t means year, s represents different sectors among the three industries, and based on data availability, six industries including agriculture, mining, manufacturing, electricity, gas, water and gas supply, construction and education are selected. $Robots_{jt}$ indicates the number of robots used in various industries in China from 2006 to 2020, $Labor_{i,t}$ denotes the total number of people employed in the three industries in year t of city i, $Emp_{si,t}$ indicates the amount of laborers in the above six industries in year t of city i, and $\sum_j Emp_{ji,t}$ denotes the total number of people employed in the three industries in year t of city i. To facilitate reporting the research results, we multiply $IRobot_{it}$ by 0.1.

4.2.2 Explained variable: *CEE*

Referring to the existing literature (Sun and Huang, 2020; Yu and Zhang, 2021), this research adopts total factor productivity (TFP) to measuring CEE, in which input indicators mainly include resources and factors, expected output indicators mainly include economic and environmental indicators, and non-expected output indicator are carbon dioxide emissions. The specific input-output indicators are shown in Table 1.

Due to the lack of detailed urban energy consumption data, this research draws on the methodology of Chen et al. (2020) and uses NPP-VIRS nighttime lighting data to derive carbon emission data for Chinese cities. In recent years, measuring carbon emissions based on NPP-VIIRS night light data has been widely used in economic research (Zhang et al., 2019; Ismael, 2021). The basic logic is that the higher the brightness of lights at night, the more active the city's night-time economic activities are, and the higher the energy consumption will be. Specifically, considering the accuracy of the downscaling model inversion, a linear model is adopted to fit the carbon emission data, and the results of the correlation test between the carbon emission estimates and the statistical values of each province are shown in Figure 1. There is a linear correlation between carbon emission estimates and statistics, and the goodness of fit R^2 is about 0.8, indicating that the method of deduction of carbon emissions by night light data is scientific and effective.

4.2.3 Tool variables: U.S. Robot use (*AMIRobot*)

Considering that cities with higher CEE often have a higher level of digital infrastructure, which in turn facilitates local industries to undergo smart transformation and enhance industrial intelligence, so there may be a problem of two-way causality. Therefore, this research uses U.S. industry-level robotics data to construct the instrumental variable $AMIRobots_{it}$ as shown in Eq. 4 for the following reasons: Firstly, although the application level of American robots is ahead of China in the sample period, the stock and penetration of robots are close to that of China in the same period; Secondly, the application level of robots in the United States is in a leading position in the world, and its development trend can reflect the trend of technological progress to a certain extent; Thirdly, the labor market in the United States has a high level of development, which makes it easier to meet exogenous conditions (Huang et al., 2023; Zhao et al., 2024).

$$AMIRobots_{it} = \sum_j \frac{Emp_{si,t}}{\sum_j Emp_{ji,t}} \times \frac{ARobots_{jt}}{Labor_{i,t}} \tag{4}$$

4.2.4 Control variables

Referring to relevant studies (Du et al., 2022; Huang et al., 2023), this study includes the following control variables. Environmental

TABLE 1 Input and output variables of CEE measurement.

Indicators	Composition	Measurement
input	Labor input	Number of employees
	Capital investment	Capital stock
Expected output	GDP	Annual regional real GDP
Unexpected output	Carbon dioxide emissions	Fitting according to night light data

regulation (er), referring to the study of Zhang and Chen (2021), measured by the ratio of environmental word frequency in in city government reports to the total word frequency in city government reports. Population size (pop), measured by the natural logarithm of the resident population at the end of the year. Foreign direct investment (fdi), expressed as the proportion of foreign capital actually used to GDP. Government intervention (gv), measured by the proportion of government fiscal expenditure to GDP. Financial development (fin), expressed by the proportion of deposit and loan balance of financial institutions to GDP. The level of urbanization ($urban$), measured by the ratio of urban resident population to rural resident population.

4.2.5 Mechanism variables

In accordance with the above analysis, the mechanism effects of this research mainly include technological progress and industrial structure optimization. Technological progress variables are expressed as the number of green innovation ($lngpt$) and quality of green innovation ($lngpq$), measured by the logarithm of the total number of urban green patent applications and the logarithm of the total number of urban green invention patent applications, respectively. Also, to facilitate the reporting of regression results, the final value of the indicators is multiplied by 0.1. Optimization of industrial structure variables are expressed as rationalization and upgrading of industrial structure. The former is measured by the ratio of output of the tertiary industry to that of the secondary industry (ind), and the latter is measured by the (TL), where the smaller the Theil index, the more rational the industrial structure and the greater the coordination between industrial sectors. Tables 2, 3 are variable description and descriptive statistical analysis respectively.

4.2.6 Data sources

The robot data comes from International Federation of Robotics (IFR), a database that shows the annual increase and inventory of robots in manufacturing, agriculture and certain service industries in 75 countries. Other variables were derived from the National Intellectual property Patent database and the China City Statistical Yearbook.

5 Analyses and empirical findings

5.1 Baseline regression analysis

Table 4 displays the results of the baseline regression. It is evident from columns (1) to (4) that industrial intelligence positively affects urban CEE in YEB, and the effect is significant at the 1% significance level, proving that industrial intelligence can significantly promotes urban CEE, and Hypothesis 1 is confirmed.

TABLE 2 Variable descriptions.

	Variable name	Abbreviation	Measure of variable
Dependent variable	Carbon emission efficiency	CEE	total factor productivity
Independent variable	industrial intelligence	$lnirobot$	Robot permeability
Control variable	Environmental regulation	er	the ratio of environmental word frequency in in city government reports to the total word frequency in city government reports
	Population size	pop	the natural logarithm of the resident population at the end of the year
	Foreign direct investment	fdi	the proportion of foreign capital actually used to GDP
	Government intervention	gv	the proportion of government fiscal expenditure to GDP
	Financial development	fin	the proportion of deposit and loan balance of financial institutions to GDP
	The level of urbanization	$urban$	the ratio of urban resident population to rural resident population
Instrument variable	American industrial intelligence	$AMIRobot$	Robot penetration in U.S
Mediating variable	Number of green innovations	$lngpt$	the logarithm of the total number of urban green patent applications the logarithm of the total number of urban green invention patent applications measured by the ratio of output of the tertiary industry to that of the secondary industry Theil index
	Green innovation quality	$lngpq$	
	upgrading of industrial structure	ind	
	rationalization of industrial structure	TL	

TABLE 3 Descriptive statistics.

	N	Mean	S.D.	Min	Max
CEE	1,620	0.998	0.039	0.701	1.354
$lnirobot$	1,620	0.439	0.178	0.049	1.147
er	1,620	0.003	0.001	0.004	0.012
$urban$	1,620	0.510	0.146	0.118	0.896
fdi	1,620	0.019	0.018	0.003	0.108
pop	1,620	5.886	0.632	4.152	8.047
gv	1,620	0.031	0.016	0.010	0.131
fin	1,620	0.892	0.510	0.213	3.664
$AMIRobot$	1,620	6.251	2.261	0.178	17.521
$lngpt$	1,620	0.431	1.804	0.051	0.923
$lngpq$	1,620	0.268	1.945	0.039	0.803
ind	1,620	0.374	0.132	0.245	4.932
TL	1,620	0.218	0.165	0.001	1.791

Source: International Federation of Robotics (IFR), national intellectual property patent database, the China City Statistical Yearbook.

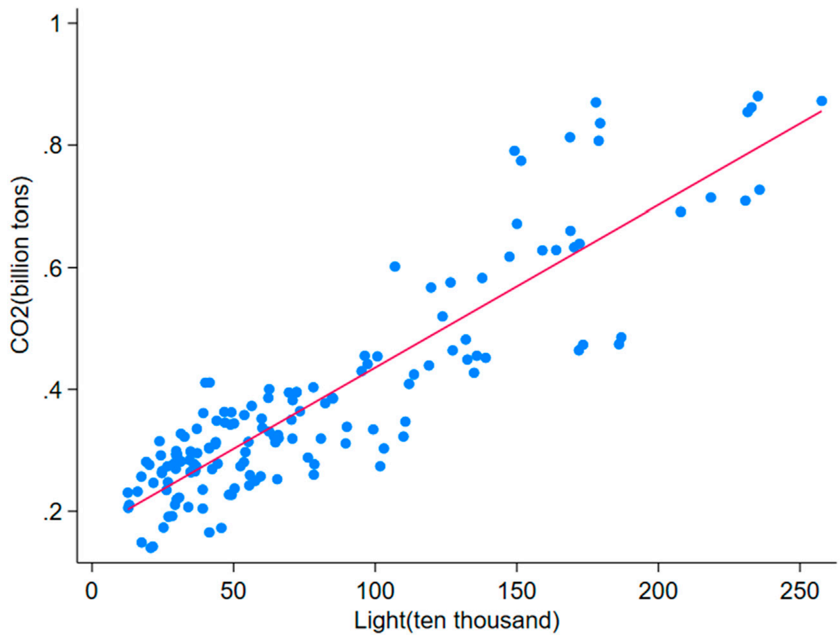

FIGURE 1
Carbon emission fitting.

5.2 Robustness test

5.2.1 Endogenous treatment

This research takes the U.S. robotics data measured in Eq. 4 as an instrumental variable for the regression, and the results are shown in Table 5. The Anderson LM test is significant at the 1% level, and the value of Cragg-Donald Wald F statistic is 76.364, which is greater than the critical value of 16.38 corresponding to the maximal IV size at the 10% critical value of the Stock-Yogo test, so it can be considered that this instrumental variable is appropriate. After considering endogeneity, the second-stage regression results show that the regression coefficient of the impact of industrial intelligence on urban CEE is significantly positive at the 1% significance level, which is consistent with the baseline regression results but larger than the baseline regression coefficients, which indicates the robustness of the baseline regression results, and suggests that

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TABLE 4 Baseline regression results.

	(1) *CEE*	(2) *CEE*	(3) *CEE*	(4) *CEE*
lnirobot	0.041***	0.057***	0.046***	0.057***
	(0.011)	(0.012)	(0.013)	(0.015)
er		0.699***	0.702***	0.707***
		(0.117)	(0.118)	(0.117)
urban		−0.041	−0.029	−0.026*
		(0.026)	(0.027)	(0.014)
fdi			−0.177**	−0.172**
			(0.077)	(0.077)
pop			0.026*	0.030**
			(0.014)	(0.015)
gv				−0.178*
				(0.093)
fin				−0.008
				(0.005)
cons	0.982***	0.997***	0.840***	0.827***
	(0.008)	(0.009)	(0.088)	(0.090)
year	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620
R^2	0.041	0.042	0.047	0.051

Note: Robust standard errors are shown in brackets. *, **, **** represent significant levels of 10%, 5%, and 1%, respectively. The following tables are the same.

TABLE 5 Regression results of instrumental variables.

2SLS		2SLS	
Variable	*lnirobot*	Variable	*CEE*
IV	0.504***	*lnirobot*	0.199***
	(0.064)		(0.070)
cons	Yes	*cons*	Yes
year	Yes	*year*	Yes
city	Yes	*city*	Yes
N	1,620	*N*	1,620
R^2	0.038	R^2	0.040
Anderson LM	60.115		
	[0.000]		
Cragg-Donald Wald F	62.315		
	[16.38]		

Note: () is a robust standard error; P in []; {} is the critical value at 10% level of Cragg-Donald Wald F statistical weak identification test; Regression results of related commands in two-stage least square method do not report constant terms.

TABLE 6 Robustness test results.

	(1)	(2)	(3)
	Alternate explanatory variable	One-stage lag	Tailing treatment
lnirobot	0.010**	0.063***	0.050***
	(0.004)	(0.017)	(0.011)
cons	0.666***	0.831***	0.848***
	(0.096)	(0.098)	(0.072)
controls	Yes	Yes	Yes
year	Yes	Yes	Yes
city	Yes	Yes	Yes
N	1,620	1,620	1,620
R^2	0.042	0.051	0.055

failing to take into account endogeneity underestimates the effect of industrial intelligence on urban CEE.

5.2.2 Alternate explanatory variable

We re-run the regression using the incremental robot data as explanatory variables. Logically, if the stock of robots in the urban industrial subsector can have a positive impact effect on the urban CEE, the incremental robots in the urban industrial subsector can have a positive effect as well. The International Federation of Robotics (IFR) reports both the stock data and incremental data of robot use in China. The regression results are shown in column (1) of Table 6. After regressing with incremental data as an explanatory variable, the coefficient value is still significantly positive, indicating the robustness of the benchmark regression results.

5.2.3 Lagging one-stage regression treatment

Considering that there may be a time lag in the role of industrial intelligence in improving CEE in cities, the following regression is conducted with the core explanatory variables of urban robot application rate lagged by one period, and the results are shown in column (2) of Table 6. The coefficient value in front of the explanatory variables is still significantly positive, which verifies the robustness of the baseline regression results.

5.2.4 Tailing treatment

In order to exclude the influence of extreme outliers, this research shrinks all the extreme outliers of continuous variables at the upper and lower 1%, and then reruns the regression estimation, and the results are shown in column (3) of Table 6, which shows that industrial intelligence positively influences urban CEE at the 1% significance level, verifying the robustness of the baseline regression results.

5.3 Heterogeneity analysis

5.3.1 Regional heterogeneity analysis

The YEB in China is a vast area, and each city has different degrees of economic development and industrial intelligence development level. For example, Zhejiang, Jiangsu, Anhui, Shanghai in the downstream area of the YEB are the largest digital economy regions in China, with the scale of the integrated circuit industry accounting for 58.3% of China, and their AI industry accounting for 33.0% of AI industry in China. Furthermore, the market competition in the downstream area of YEB is better with fewer constraints to the development of industrial intelligence compared with other areas of YEB. Therefore, this research then divides the samples into two sub-samples of upstream and midstream, downstream regions to investigate the regional heterogeneity of the impact of industrial intelligence on urban CEE in YEB, and the results are shown in Columns (1) to (2) of Table 7. The results show that industrial intelligence in the upstream and midstream regions of the YEB does not have a significant effect on urban CEE, but industrial intelligence in the downstream region of the YEB significantly and positively improves urban CEE.

5.3.2 Resource endowment heterogeneity analysis

We then divide the samples into resource cities and non-resource cities to investigate the differential impact of industrial intelligence on CEE in YEB under the condition of heterogeneity of resource endowment, and the results are shown in Columns (3) to (4) of Table 7 It shows that the impact coefficients of industrial intelligence on the non-resource cities are significantly positive, and the impacts on the resource cities are not significant. The reason may be that, the economic growth of resource cities relies heavily on value-added, low technological level and high energy consumption based on the theory of "resource curse" and "comparative advantage trap", which restricts the enhancement of CEE of resource cities in the YEB empowered by industrial intelligence.

5.3.3 CEE heterogeneity analysis

We then use panel quantile regression to test the heterogeneous effect of urban industrial intelligent development on CEE at different CEE levels. Table 8 shows that the regression results are not significant only for the samples at the 10% quartile level, which indicates that the development of industry intelligent has a positive effect on the improvement of urban CEE in most cases. Moreover, there is a "marginal increase" in the impact coefficient as the quartile

TABLE 7 Heterogeneity analysis I.

variable	Regional heterogeneity		Resource heterogeneity	
	Upstream and Middle region (1)	lower reaches (2)	Resource-based city (3)	Non-resource-based cities (4)
lnirobot	0.047	0.084**	0.062	0.067***
	(0.043)	(0.032)	(0.041)	(0.020)
cons	0.651***	1.003***	0.632***	0.851***
	(0.172)	(0.112)	(0.174)	(0.108)
controls	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes
N	1,005	615	465	1,155
R^2	0.047	0.066	0.072	0.032

TABLE 8 Heterogeneity analysis II.

	10%	25%	50%	75%	90%
lnirobot	0.040	0.049***	0.057***	0.066***	0.075***
(0.025)	(0.017)	(0.014)	(0.018)	(0.027)	
controls	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620	1,620

TABLE 9 Threshold effect results.

	F Value	*p*-Value	10%	5%	1%
Single threshold	18.80**	0.012	10.885	13.238	19.213
Double threshold	3.95	0.746	11.095	14.391	23.700
Triple threshold	4.92	0.576	11.720	14.231	23.898
Threshold interval				*CEE*	
$lnirobot\,(dig \leq 9.135)$				0.057 (0.049)	
$lnirobot\,(dig > 9.135)$				0.118*** (0.020)	
controls				Yes	
year				Yes	
city				Yes	
N				1,620	
F				12.12	

rises, that the estimated coefficient at the 25% quantile is significantly smaller than the estimated coefficient at the 90% quantile, which indicates that the empowering effect of industrial intelligence is more obvious for cities with higher levels of CEE, and there is the "Matthew effect" of carbon reduction in cities.

5.4 Expanded research

5.4.1 Threshold effect analysis

We then take the level of urban digital human capital as a threshold variable to further explore the threshold effect of industrial intelligence on CEE in the YEB. Specifically, the number of employees in the sectors of information transmission, computer services and software are used to measure urban digital human capital. The results in Table 9 show that when the level of digital human capital is lower than the threshold value of 9.135, the CEE effect brought by industrial intelligence is not significant, when the level of digital human capital is greater than the threshold value of 9.135, the regression coefficient is 0.118 and passes the test of 1% significance level. It can be seen that there is a digital human capital threshold for the CEE effect of industrial intelligence in YEB, and industrial intelligence has a significant positive effect on CEE only when it crosses the threshold of digital human capital, and the effect value will show an upward trend with the improvement of the digital human capital level.

5.4.2 Spatial spillover effect analysis

We further explore whether the effect of industrial intelligence on urban CEE in YEB has spatial spillover effects. We first test the spatial autocorrelation of industrial intelligence and urban CEE variables. The $Moran's$ index was used to verify the spatial autocorrelation of the main variables under the geographic distance matrix. As shown in Table 10 that industrial intelligence and urban CEE are significantly positive at the 1% significance level from 2006 to 2020, indicating that the level of industrial intelligence and urban CEE in YEB have significantly positive spatial autocorrelation. The spatial econometric model is further used to identify whether industrial intelligence has a spatial spillover effect on the urban CEE, and the Hausman test as well as the LR and LM tests show that the Spatial Durbin Model (SDM) should be used for the estimation of the spatial spillover effect. In order to ensure the robustness of the regression results, the neighbor matrix and economic distance matrix are also added for spatial econometric regression. The final results of the spatial econometric regression are shown in columns (1)–(3) of Table 11, that the autoregressive

TABLE 10 Moran's I test.

Variable	2006	2008	2010	2012	2014	2016	2018	2020
CEE	0.162***	0.161***	0.168***	0.166***	0.175***	0.166***	0.178***	0.171***
	(4.352)	(4.256)	(4.235)	(4.332)	(4.193)	(4.575)	(4.346)	(4.258)
lnirobot	0.121***	0.106***	0.101***	0.083**	0.088**	0.091**	0.073**	0.078**
	(2.735)	(2.643)	(2.591)	(2.382)	(2.433)	(2.426)	(2.143)	(2.123)

Note: Z statistics are in brackets here; *** indicates significant at the level of 1%.

TABLE 11 Regression results of spatial Durbin model.

	Inverse distance matrix	Adjacency matrix	Economic distance matrix
$W \times lnirobot$	0.031*** (0.013)	0.023* (0.013)	0.016** (0.007)
ρ	0.115*** (0.029)	0.254*** (0.012)	0.043*** (0.016)
LR_direct	0.035** (0.018)	0.014** (0.006)	0.084** (0.038)
LR_Indirect	0.182** (0.093)	0.055*** (0.018)	0.127* (0.069)
LR_Total	0.217* (0.126)	0.069** (0.034)	0.211** (0.104)
$W \times Controls$	Yes	Yes	Yes
year	Yes	Yes	Yes
city	Yes	Yes	Yes
N	1,620	1,620	1,620
R^2	0.036	0.073	0.054

coefficient of the urban CEE is positive at the 1% significance level, and the coefficient of the spatial weighting term W is significantly positive, which indicates that the CEE in YEB is not only affected by the local industrial intelligence level, but also by the industrial intelligence level of the neighboring regions.

5.5 Mechanism analysis

Based on the above theoretical analysis and hypothesis, this research examines the mediating mechanisms through which industrial intelligence affects urban CEE from the perspectives of technological progress and industrial structure optimization, respectively. We set up the mediated effect test model as shown in Eqs 5, 6:

$$Medi_{it} = g_0 + g_1 IRobot_{it} + g_2 C_{it} + m_i + l_t + x_{it} \tag{5}$$

$$GEEV_{it} = \alpha_0 + \alpha_1 IRobot_{it} + \alpha_2 Mediator_{it} + \alpha_3 C_{it} + \mu_i + \lambda_t + \xi_{it} \tag{6}$$

$Medi_{it}$ is the mediator variable, which represents the variables of technological progress and industrial structure optimization respectively. Eq. 5 is used to test the effect of industrial intelligence on the mediator variable, and Eq. 6 is used to test effect of the mediator variable in the process of industrial intelligence affecting urban CEE. In addition, to improve the precision of the mediation effect test, this research uses the Bootstrap method to test the significance of the mediation effect, and the results of the Bootstrap test (500 samples) are also reported in Tables 12, 13

1. Mechanism test of technological progress. Theoretically, industrial intelligence can not only enhance the technological innovation ability of related industries, but also enhance the green technology efficiency of other industries through the inter-industry "demonstration effect", thus generating vertical technology spillover effects, which will help to improve the overall scientific and technological level of the city, and ultimately contribute to the enhancement of the efficiency of the city's carbon emissions. The results in columns (1) and (2) of Table 12 show that industrial intelligence can significantly promote urban green innovation, regardless of whether the explanatory variables are the quantity of green innovation ($lngpt$) or the quality of green innovation ($lngpq$). The results in columns (1) and (2) of Table 13 show that the technological progress variables characterized by both dimensions have a significant contribution to urban CEE, and the coefficients of the cross-multiplier terms of the Bootstrap test are all significantly positive, which indicates that industrial intelligence can enhance the urban CEE through the pathway of technological progress, and accordingly, Hypothesis 2 is verified.
2. Mechanism test of industrial structure optimization. Theoretically, industrial intelligence uses various advanced technologies such as edge computing, digital simulation, artificial intelligence, etc., which can eliminate energy waste

TABLE 12 Mechanism analysis I.

	(1) *lngpt*	(2) *lngpq*	(3) *ind*	(4) *TL*
lnirobot	0.529***	0.427***	1.022***	−0.061**
	(0.029)	(0.095)	(0.152)	(0.016)
cons	−2.711	−8.321**	0.484	0.623
	(1.866)	(3.821)	(0.853)	(0.541)
controls	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620
R^2	0.872	0.598	0.471	0.541

TABLE 13 Mechanism analysis II.

	(1) *CEE*	(2) *CEE*	(3) *CEE*	(4) *CEE*
lnirobot	0.053***	0.049***	0.048***	0.054***
	(0.012)	(0.016)	(0.013)	(0.018)
lngpt	0.008**			
	(0.004)			
lngpq		0.019**		
		(0.008)		
ind			0.009*	
			(0.005)	
TL				−0.049**
				(0.024)
cons	0.826***	0.830***	0.823***	0.836***
	(0.089)	(0.091)	(0.089)	(0.090)
controls	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
city	Yes	Yes	Yes	Yes
N	1,620	1,620	1,620	1,620
Bootstrap	0.004***	0.008**	0.009**	0.003**
	(z = 2.73)	(z = 2.13)	(z = 2.04)	(z = 2.33)
R^2	0.050	0.048	0.052	0.055

in the production and manufacturing system, improve resource utilization efficiency and the degree of inter-industry synergy, and contribute to the improvement of the urban CEE. The results in columns (3) and (4) of Table 12 show that industrial intelligence can significantly promote industrial structure upgrading (*ind*) and industrial structure rationalization (*TL*), and the results in columns (3) and (4) of Table 13 show that the industrial structure upgrading (*ind*) and industrial structure rationalization (*TL*) can significantly improve the urban CEE, that the optimization of industrial structure plays a mediating role in the process of industrial intelligence affecting urban CEE, and Hypothesis 3 is verified.

6 Discussion

In this research, we have verified through theoretical and empirical research that industrial intelligence has a positive effect on improving CEE, and this conclusion remains valid after a series of robustness tests. We now discuss the main findings below.

First of all, this research constructs a linear regression model by taking CEE as an explanatory variable, taking industrial intelligence level as an explanatory variable, and adding a series of control variables. The regression results show that CEE increases significantly as the level of industrial intelligence increases. Among the control variables, only the level of financial development is not significant in the final regression results.

Secondly, this research proves the robustness of the benchmark regression results by a series of robustness testing methods, including instrumental variable method, replacement of explanatory variables, lag of explained variables, tail reduction treatment, etc.

Thirdly, this research carry out heterogeneity analysis from the perspectives of the level of regional economic development, regional resource richness and CEE level. It is found that the carbon emission reduction effect of industrial intelligence only exists in the lower reaches of the Yangtze River and non-resource-based cities (Mao et al., 2023). At the same time, through quantile regression method, it is found that there exists a “Matthew effect” in promoting industrial intelligence to improve CEE (Wang et al., 2024).

Fourthly, this research takes the level of urban digital human capital as a threshold variable to further explore the threshold effect of industrial intelligence on CEE in the YEB, by using the threshold effect model, it is found that only when the level of human capital breaks through a certain threshold value can industrial intelligence significantly promote the improvement of CEE (Tian et al., 2024).

Fifthly, this research also tests the spatial spillover effect of industrial intelligence affecting CEE by building a spatial econometric model and conducting a relevant regression analysis (Lin and Xu, 2024). The results of the application of the inverse distance matrix, the economic distance matrix and the nested matrix all indicate that, the improvement of CEE brought about by industrial intelligence has a certain spatial spillover effect.

7 Conclusion and policy implications

7.1 Conclusion

This research comprehensively uses panel econometric model, mechanism test model, tool variable method, and spatial econometric model to analyze and identify the mechanism and effect of industrial intelligence on CEE in YEB. The results found that: 1. YEB’s CEE improves greatly with the development of industrial intelligence, and this conclusion remains steady during a series of robustness tests; 2. Technological progress and industrial structure optimization are intermediary mechanisms for industrial intelligence to promote CEE growth; 3. The impact of industrial intelligence on reducing carbon emissions is especially noticeable in the downstream region of the YEB, non-resource-based cities, and cities with higher CEE; 4. The growth of urban industrial intelligence has had a substantial beneficial impact on nearby cities' CEE; in other words, there is a positive spatial spillover effect from the development of industrial intelligence on the enhancement of urban CEE; 5. There is a digital human capital threshold for the CEE effect of industrial intelligence in YEB, promote urban digital human capital will help to enhance the driving effect of industrial intelligence on carbon emission reduction in YEB.

7.2 Policy implications

Firstly, accelerating the development of industrial intelligence in cities in YEB is an important path to realize the green transformation and upgrading of the regional economy, the government should promote the integration of intelligent development models with traditional industries, build green production and service models, and apply policies to create a fair competitive market environment. The government should also increase its investment in the fields of science, technology, engineering and mathematics to train the professionals needed for the smart industry and provide strong talent support for industrial intelligence.

Secondly, the pace of technological innovation should be accelerated to enhance the driving force of industrial intelligence to empower urban CEE. The government should establish a sound innovation ecosystem, including research and development centers and incubators to promote close cooperation and knowledge transfer between academia, industry and the government. The government should also strengthen basic and applied research, encourage enterprises to carry out research in areas such as new materials, biotechnology and information technology, optimize the incentive mechanism for innovation and improve the intellectual property protection system, thereby protecting the interests of innovators and encouraging more technological innovation activities.

The Government should clarify the positioning of urban development and industrial layout in accordance with regional characteristics, so as to avoid disorderly competition and duplicative construction in cities. The government should also liberalize market access, attract foreign investment into advanced industries and services, and promote the development of an export-oriented economy. In addition, the Government should foster strategic emerging industries and accelerate the development of industrial digitalization, networking and intelligence.

Fourthly, attention should be paid to the "spatial spillover effect" of industrial intelligence on the urban CEE. Each region should form a synergistic development idea, and synergize the development of infrastructure interconnection and interoperability, data resource opening and sharing, ecological environment joint prevention and joint treatment, and public services universal sharing, etc. Each region should also give full play to its comparative advantages by clarifying the boundaries of the rights and responsibilities of the cooperating parties, improving the docking implementation mechanism, innovating the market-oriented operation mechanism, and strengthening the integration and linkage of the industrial chain, so as to realize the complementary advantages and synergy of industrial intelligence.

7.3 Limitations and future research

This study also has some limitations, which can be improved in some aspects in the future. Firstly, the time period of this study is from 2006 to 2020 due to the data limit. Considering that the COVID-19 epidemic in China lasted for 3 years from the end of 2019 to the end of 2022, and the digital economy was booming during this period, the sample can be expanded in subsequent studies. Secondly, this research mainly focuses on the macro level of the city, and the discussion on the micro level is insufficient. Considering that artificial intelligence has a significant impact on the production activities of enterprises and the consumption habits of the public, it is necessary to combine macro and micro perspectives. Thirdly, this research investigates the influence mechanism of industrial intelligent development on CEE from perspectives of technological innovation and industrial structure optimization, further research needs to explore other economic and social variables that may be the mechanisms by which industry intelligence acts on CEE.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://www.stats.gov.cn/.

Author contributions

XX: Conceptualization, Data curation, Formal Analysis, Visualization, Writing–original draft. MC: Conceptualization, Funding acquisition, Project administration, Supervision, Writing–review and editing. AZ: Data curation, Resources, Software, Supervision, Writing–original draft. YW: Data curation, Investigation, Visualization, Writing–review and editing.

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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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