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A Study of the Impact of Industrial Robot Application on Carbon Emissions

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Abstract: Technological advancements, particularly artificial intelligence, are deeply integrating with social and economic systems, making this trend irreversible. Industrial robots, born from this revolution, are reshaping industries and driving economic development towards environmental sustainability. AI has seeped into the fabric of society and economy, transforming industrial robots from mere tools to pivotal agents in promoting green, low-carbon economic transitions. Leveraging panel data from 2006 to 2019 across various industrial sectors, the empirical study reveals that industrial robots are instrumental in reducing carbon emissions and promoting a low-carbon operational framework within the industrial economy, with effects that are sustainable over the long haul. Mechanism tests indicate that human-machine coordination and energy efficiency are the primary mediating factors contributing to the emission reduction effect of industrial robots. Mechanism tests indicate that human-machine coordination and energy efficiency are the primary mediating factors contributing to the emission reduction effect of industrial robots. Heterogeneity analysis demonstrates that industrial robots exhibit a pronounced emission reduction effect in high-emission industries, low-technology industries, and smaller-scale industries. This research offers empirical support for achieving the "dual carbon" goals and provides valuable insights for policy development.

Keywords: Industrial Robots; Carbon Emissions; Human-Machine Coordination; Green Energy Use

INTRODUCTION

On the international stage of the 75th session of the United Nations General Assembly, the General Secretary solemnly promised the world an impressive and ambitious blueprint: the People's Republic of China will, with unprecedented determination and through a series of innovative and challenging policy initiatives, achieve milestones in carbon dioxide emission reduction by 2030, and accomplish carbon neutrality, a feat that will be a historic milestone, by 2060! The mission of carbon neutrality. It is worth pondering that as China's economic development miracle continues to unfold, the severe test of the ecological environment is becoming more and more prominent, and the wisdom of policy makers is being tested by the dialectical relationship between development and protection. In the midst of climate change and the scarcity of resources, it is of utmost importance to effect a transformation in economic development. This entails a restructuring of industries and a drive for innovation, striking a balance between economic benefits and the pursuit of sustainable energy, along with responsible environmental management, for the sake of both present and future generations. The Party Central Committee has actively implemented a series of policies to promote the "dual-carbon" goal and grasp the opportunities brought by this goal. As a key component of smart manufacturing, the application of industrial robots significantly affects carbon emissions and drives the intelligent transformation of the economy[[1]]. "Peak Carbon" and "Carbon Neutral" have become buzzwords. Businesses also see "dual carbon" targets as a turning point for investment and market opportunities in China in the coming decades. There's been quite the buzz about the hot-button issue of industrial carbon emissions lately. The conversation centers on both the external and internal industry factors[[2]]. These have been scrutinized more deeply in areas like policy influences, regional contexts, and variations across industries[[3]]. The diverse effects on carbon emissions have been thoroughly investigated.

Over the past decade, China's industrial robotics sector has witnessed remarkable advancements, positioning itself as a pivotal actor within the global arena of industrial automation. Based on the data from 2024, China possesses over 190,000 valid patents in the field of robotics, which represents approximately two-thirds (66.67%) of the global total. Consequently, China has secured its position as the leading nation in the global industrial robotics market for the eleventh year in succession. The deployment of industrial robots in China has spanned an extensive array of sectors, including but not limited to automotive manufacturing, electronics and electrical appliances, food processing, photovoltaics, and metalworking. It is expanding into new energy and other emerging fields. However, China's industrial robotics industry still faces several challenges, including a lack of skilled personnel, insufficient mastery of core technologies, and intensifying market competition. Going forward, as technology keeps advancing and the market matures even further, it's anticipated that the cost of industrial robots will come down considerably. And their extensive use in industrial production will give a push to the process of intelligence and automation[[4]].

In the contemporary wave of industrial production, industrial robots, as a double-edged sword, are reshaping the carbon emission landscape of manufacturing in their own unique way [[5]]. It is worth pondering that the practice in the field of intelligent manufacturing has fully confirmed that these robots have demonstrated impressive emission reduction efficacy in high-carbon emission and highly intelligent industrial scenarios, a trend that is quietly changing the face of the traditional manufacturing industry [[3]]. Looking at the entire industrial chain, industrial robots not only replace traditional human labor, but also driven by technological innovation, through the optimization of production processes, improve energy efficiency and other multiple paths, for enterprises to reduce the emissions of environmental pollutants opens up new possibilities [[6]].

Furthermore, certain scholars express concerns regarding the potential adverse effects of industrial robot deployment. They posit that industrial robots represent a double-edged sword, suggesting that the higher concentration of robots in upstream industries could paradoxically exacerbate carbon emissions. This is attributed to the notion that such an increase may impose a burden on downstream industries, thereby inhibiting their scale expansion and innovation capabilities[[7]]. Research on the interplay between carbon emissions and industrial robots reveals controversial findings. While industrial robots enhance production efficiency, they also subtly alter energy consumption patterns, resulting in unpredictable non-linear changes in carbon emissions. This paradox highlights fundamental issues in modern industrial development that warrant further exploration. For example, the carbon emission reduction effect of industrial robots is not significant in resource-based cities, cities with low digitalization levels, and central and western regions.Overall, industrial robots significantly contribute to fostering the industry's shift towards a low-carbon future.To maximize its emission reduction effect, it is necessary to formulate differentiated policies according to local conditions and to strengthen core technology research and development and industrial intelligent upgrading[[8]]. Simultaneously, the government ought to spur manufacturing enterprises to bring in industrial robots by providing financial and policy backing. Moreover, it should boost investment in human capital education to nurture and attract high-caliber innovative and highly proficient talents.

This paper, through a comprehensive literature review, uncovers the multifaceted influences of industrial robots on socio-economic activities. Initially, it expands the scope of research concerning the socio-economic repercussions of industrial robot applications, which have predominantly centered on economic growth[[9]], employment[[10]], regional economic inequality, and operational aspects of businesses. In contrast, this study delves into the environmental ramifications of industrial robots from an industry-specific viewpoint, introducing a fresh and intellectually stimulating academic query that enriches the discourse on the socio-economic implications of industrial automation. Additionally, the study addresses a lacuna in the academic corpus concerning the enhancement of industrial carbon-cutting tactics. While existing research has investigated the socio-economic effects of smart manufacturing through economic growth, labor market dynamics, productivity gains, and global value chains, the part that industrial robots play in carbon reduction strategies has not received sufficient attention. This study is based on an in-depth analysis of the practical application of industrial robots in specific industries, and attempts to explore an innovative path that can both promote industrial upgrading and realize green development between the seemingly opposing poles of economic benefits and environmental protection.

HYPOTHESIS DEVELOPMENT

Industrial Robot Applications and Carbon Emissions

With the implementation of the "dual carbon" objective, industrial robots influence carbon emissions in various ways while facilitating the economy's intelligent transformation. Research on the impact of industrial robot application on carbon emissions is more complex, and the effect size of its impact varies in different directions and channels, which is difficult to judge intuitively[[12]]. Based on this, in exploring the complex issue, this study focuses on two intertwined and independent dimensions: the shifting trends in overall carbon emissions and the underlying transformation of carbon intensity. This perspective not only reflects an in-depth understanding of the nature of the problem, but also highlights the subtle but close correlation between technological development and environmental protection in the realm of climate change.

The application of robots in various industries to replace manual operations in the production process not only effectively improves the safety of high-risk workers, but also enhances energy efficiency in industrial production and further reduces pollution emissions per unit of output. On the one hand, the utilization of industrial robots gives a boost to investment in research and development (R&D). This, in turn, spurs the development of new technologies and makes a substantial contribution to enhancing energy use efficiency, thereby reducing the overall volume of carbon emissions[[13]]; on the other hand, the use of robots in various industries to replace manual operations reduces many of the environmental pollution problems that are caused by the low efficiency of manpower. Furthermore, the deployment of robots to supplant low-skilled labor contributes to the optimization of the workforce structure, thereby effectively curbing the intensity of carbon emissions[[14]].Hence, the research hypothesis is formulated:

Hypothesis 1: Industrial robotics applications can curb carbon emissions.

Mechanisms of action of industrial robot applications affecting carbon emissions

i. Man-machine matching degree

The effects of human-machine interaction and energy utilization act as mediating factors in the process by which industrial robots are applied to mitigate carbon emissions. Specifically, The extensive use of industrial robots in manufacturing, logistics and warehousing, precision machining, stamping automated production lines, and enterprise management's internal control can improve the matching degree of man-machine and the efficiency of energy use in the industry, thus enhancing carbon emission reduction in the industry.

Industrial robotics applications help to improve human-robot matching. Existing literature suggests that mobile industrial robots can efficiently collaborate with operators to complete tasks in shared spaces and autonomously follow target pedestrians through strong sensing and planning capabilities, thus safeguarding operator safety[[15]]. On the one hand, the improvement of human-machine matching implies the optimization of labor structure and work arrangement, working more efficiently and collaboratively with human operators, gradually improving the green innovation capability of the industry, which in turn promotes green production and effectively reduces the pollution emission of the industry. On the other hand, in the automotive manufacturing industry, poor human-machine matching leads to low production efficiency, which in turn affects carbon emissions. Poor human-machine matching leads to poor safety systems and low production efficiency at the production site, which not only affects product quality but also increases carbon emissions[[16]].

Moreover, according to previous research on artificial intelligence and carbon emissions, it was found that the human-machine matching degree will effectively reduce carbon emissions through green technology innovation[[17]].Specifically, it has been shown in the literature that human-machine collaboration can effectively constrain greenhouse gas emissions. In this paper, the human-machine matching degree is selected as an indicator to measure human-machine collaboration in the industry. Based on this, the hypothesis is formulated:

Hypothesis 2a: Industrial robotics applications reduce carbon emissions by enhancing human-machine fit.

ii. Energy efficiency

Global climate change highlights industrial robots as a symbol of productivity and energy efficiency, crucial for carbon emission control. The IEA's study underscores energy efficiency's pivotal role in carbon reduction, offering strong theoretical backing for robots in environmental protection.Enhancing energy efficiency has been demonstrated to be a potent strategy for mitigating carbon emissions[[17]]. On the one hand, boosting productivity means we can cut down on energy use without skimping on output, which in turn slashes our carbon footprint. Plus, tweaking the energy mix, enhancing energy efficiency, and giving a nod to renewable sources can make a big dent in emissions. On the flip side, when we step up energy efficiency, we're not just boosting productivity; we're also giving the economy a shot in the arm and paving the way for a more ambitious carbon-cutting agenda.From this, the hypothesis is formulated:

Hypothesis 2b: Industrial robotics applications constrain carbon emissions by improving energy use efficiency.

The impact of industrial robot deployment on carbon emissions shows obvious industrial heterogeneity.

High-carbon-emitting industries have high energy consumption and complex industrial structures, and there are significant differences in carbon emission efficiencies within the same industry[[18]]. Some industries, despite their large scale, may have lower carbon emission intensity through technological progress and energy efficiency improvement[[19]]. Many high-carbon emitting industries are less efficient in terms of carbon emissions due to lower technological levels or failure to effectively apply energy-efficient technologies[[20]]. Integrating industrial robots can boost energy efficiency and streamline the industrial landscape by way of the artificial substitution phenomenon, making their deployment particularly impactful in such sectors.

Industries with minimal reliance on high-tech, such as the textile and garment sector, leather goods production, woodworking, papermaking, and various other manufacturing fields, are generally considered low technology-intensive. These industries generally face a lack of innovation and independent R&D capabilities, as well as constraints from insufficient government attention and the enterprise financing environment, which together have led to inefficiencies and homogeneous competition. Such industries are usually predominantly labor-intensive, which means that they have a high demand for labor and lack the incentive for technological upgrading due to long-term reliance on low-cost labor. Intelligent robots in industrial settings ease labor shortages for low-skilled jobs and inadvertently reduce greenhouse gas emissions by optimizing energy use and increasing productivity.

Industry size shows annual sales revenue, number of employees, and production volume, and enterprises in low-scale industries are below a certain standard. Due to financial and technological constraints, enterprises in low-scale industries often lack sufficient innovative capacity for technological upgrading and product innovation, thus affecting their long-term development[[19]]. Their deficiency in green innovation skills will result in heightened carbon emissions. Integrating industrial robots into these businesses can greatly accelerate technological advancements and proves to be far more efficient in conserving energy and cutting down on emissions than large-scale operations. In light of the preceding information, the hypothesis is suggested:

Hypothesis 3: The application of industrial robots significantly affects carbon emissions, with a pronounced impact on sectors with high emissions, low tech intensity, and small scale operations.

METHODS

i.Sample and data sources

Since comprehensive data on China's sub-industry's robotic inventory provided by the International Federation of Robotics (IFR) is only available starting from 2006, the sample for the study is drawn from the records of 18 industrial sectors covering the period from 2006 to 2019.This approach guarantees the thoroughness and reliability of the variables examined. The data mainly comes from 3 sources: first, the global industrial robot data published by IFR for sub-industries; second, the China Energy Statistical Yearbook which provides different energy consumption and energy discounting coefficients for each industry. Carbon emission coefficient IPCC 2006 measured data provided. The third is the China Industrial Statistical Yearbook, which provides economic indicators for each industry in the industry and lays the foundation for calculating the relevant economic variables for each industry. The data for 2017 and 2018 are from the China Input-Output Tables. Moreover, information on control factors like governmental involvement, the population's scale, foreign direct investment, and research and development spending is primarily gathered from the China Statistical Yearbook, the China Science and Technology Statistical Yearbook, as well as the respective provincial statistical yearbooks from past years.

ii.Variable constructions

Dependent variable - level of carbon emissions

This paper assesses the carbon emission levels of explanatory variables primarily through carbon emissions and their emission intensity metrics. The carbon emissions of various energy consumption are calculated using the calendar year consumption data of each industry and the carbon emission coefficients of various energy sources. The total carbon emissions are calculated in the following form:

$$tce = \sum tce_i = \sum (E_i \times \delta_i \times \eta_i) \quad (1)$$

Where: tce is the total carbon emissions of an industry; tcei is the carbon emissions generated by the ith energy consumption of an industry; E_i is the ith energy consumption of the industry; δ_i is the discount factor of the ith energy; η_i is the carbon emission factor of the ith energy.

Carbon intensity is calculated by dividing total carbon emissions by the overall industrial output value for each industry.

Independent variable - industrial robot applications

Based on detailed data published by the International Federation of Robotics (IFR), this study analyzes the actual operating stock of robots in various industrial sectors to present a clear and three-dimensional picture of industrial automation. It is worth mentioning that the key indicator of robot inventory not only accurately reflects the actual penetration of industrial robots, but also provides a unique insight into the process of industrial upgrading.

Control variables

This paper introduces energy intensity(er), population size (pop), foreign direct investment (fdi), government intervention(gov), R&D(rd), and industry structure (is) as control variables. From the perspective of multi-dimensional construction of measurement standards, this study adopts a series of sophisticated indicator systems: the ratio of industrial energy consumption in total industrial output becomes a key indicator of energy intensity; the average value of employees in each industry reflects the specific distribution of the population size; the actual utilization of foreign direct investment not only mirrors the level of external openness but also indicates the industry's attractiveness; the proportion of government general budget expenditure to GDP shows the extent of administrative intervention; the scale of internal expenditure on R&D undoubtedly highlights the strength of innovation investment; In this intricate framework of metrics, the share of each industry's overall output relative to the total industrial output has emerged as a crucial lens for understanding the industry's structure(is).

Table 1 Descriptive statistics

variable	N	mean	SD	min	max
lntce	252	2.713	2.189	-2.996	7.129
cei	252	0.258	0.502	0	3.31
lnrob	252	5.657	3.381	0	12.364
er	252	0.31	0.304	0.02	1.76
lnpop	252	5.404	1.856	-4.605	6.81
lnfdi	252	8.511	1.001	5.749	12.057
gov	252	0.208	0.236	0.01	0.98
lnrd	252	11.078	1.301	8.12	14.269
is	252	0.186	0.125	0.01	0.52

iii.Model specification

This study uses a particular benchmark model to examine the impact of industrial robots on carbon emissions in the industrial sector:

$$\ln ce_{it} = \delta_i + \beta_1 \ln rob_{it} + \sum control_{it} + \varepsilon_{it} \tag{2}$$

Where t represents time, the time span of this paper is 2006-2019 i represents a certain industry in the industrial segmentation, and this paper divides the industrial industry into 18 segments; ce_{it} represents the industry carbon emissions in year t of the ith industry; rob_{it} is the operating stock of industrial robots in year t of the ith industry, which serves as an indicator of industrial intelligence advancement; $\sum control_{it}$ represents the other selected $\varepsilon_{it}$is the random disturbance term.

RESULTS

i.benchmark regressions

Carbon emissions are the dependent variable

Per Table 2's data, after accounting for industry-specific and yearly variations and incrementally introducing additional factors, a 1% uptick in industrial robots' usage tends to trim the industry's carbon footprint by an average of 0.12%. The application of industrial robots in the field of carbon emissions management has shown a non-negligible regulatory role. In-depth analysis of the current industrial production pattern, the deep integration of robotics technology not only reshapes the traditional energy structure system, but also builds a barrier to reduce carbon emissions in an invisible way. It is noteworthy that this unique constraint mechanism confirms the theoretical framework of Hypothesis 1, providing strong evidence for our understanding of the complex link between industrial robots and carbon emissions.

Table 2 Regression results with total carbon emissions as the explanatory variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnrob	-0.120**	-0.137***	-0.132***	-0.116***	-0.112**	-0.114***	-0.121***
	(-2.35)	(-2.85)	(-2.79)	(-2.65)	(-2.55)	(-2.60)	(-2.76)
er		1.496***	1.731***	1.510***	1.388***	1.422***	1.387***
		(5.35)	(6.02)	(5.62)	(4.88)	(5.02)	(4.88)
lnpop			-0.126***	-0.051	-0.060	-0.057	-0.065
			(-2.80)	(-1.19)	(-1.37)	(-1.32)	(-1.49)
lnfdi				0.545***	0.579***	0.604***	0.507***
				(6.13)	(6.26)	(6.48)	(4.36)
gov					0.807	0.778	0.635
					(1.30)	(1.26)	(1.02)
lnrd						0.065*	0.060
						(1.79)	(1.65)
is							1.798
							(1.38)
Constant	4.574***	3.570***	4.216***	-0.150	-0.933	-1.783	-1.213
	(15.60)	(10.69)	(10.50)	(-0.19)	(-0.93)	(-1.61)	(-1.03)
Observations	252	252	252	252	252	252	252

R^2	0.896	0.908	0.911	0.924	0.925	0.926	0.927
Industry/year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes:(1) ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively; (2) t-values adjusted for cluster robust standard errors are in parentheses. Same below.

Carbon intensity are the dependent variable

Examining Table 3, we observe that when industry-specific constants are accounted for and additional variables are introduced incrementally, there's a discernible trend. In the industrial sector, for every one percent increase in the application of robots, the carbon footprint can be reduced by 0.019%, which reflects the far-reaching impact of scientific and technological innovation on environmental protection. Looking at the development of industrial robots in China, it is remarkable how well they have mitigated carbon emissions. With the deep integration of intelligent manufacturing equipment, the energy structure of the industrial production system is experiencing an unprecedented optimization and restructuring, which directly contributes to the total carbon emissions continue to go down. Industrial robots on the carbon emissions intensity of the inhibition effect, not only confirmed the initial theoretical assumptions, but also more low-carbon transformation of the industry in the future to point out the direction.

Table 3 Regression results with carbon emission intensity as explanatory variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnrob	-0.028***	-0.021***	-0.012	-0.019***	-0.019***	-0.019***	-0.019***
	(-7.13)	(-5.29)	(-1.18)	(-4.45)	(-4.29)	(-4.20)	(-4.21)
er		0.266***	0.176***	0.212***	0.210***	0.205***	0.211***
		(4.77)	(2.84)	(3.57)	(3.52)	(3.40)	(3.46)
gov			0.415***	0.270**	0.277**	0.284**	0.291**
			(3.14)	(2.50)	(2.45)	(2.49)	(2.54)
lnpop				0.003	0.004	0.003	0.004
				(0.38)	(0.41)	(0.41)	(0.46)
lnfdi					0.004	0.003	0.013
					(0.21)	(0.16)	(0.53)
lnrd						-0.005	-0.004
						(-0.66)	(-0.57)
is							-0.194
							(-0.69)
Constant	0.460***	0.330***	0.103	0.130	0.091	0.151	0.101
	(11.04)	(6.83)	(0.88)	(1.43)	(0.44)	(0.67)	(0.43)
Observations	252	252	252	252	252	252	252
R^2	0.913	0.920	0.925	0.923	0.923	0.923	0.923
Industry/year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

ii. robustness test

This study ensures the robustness of its findings by adopting the more time-sensitive measure of annual new industrial robots installed (lnnrob) as the core independent variable, thereby superseding the previous metric of operational industrial robot inventory. This replacement of the indicator is strongly confirmed by the robustness test in Table 4: there is still a significant negative correlation between the application of industrial robots and the total carbon emissions and carbon intensity, which is a thought-provoking finding. This aligns with the outcomes of the initial regression analyses, thereby providing additional support for Hypothesis 1.

Table 4 Robustness test results

variable	(1) lntce	(2) lntce	(3) cei	(4) cei
lnnrob	-0.098**	-0.111***	-0.027***	-0.017***
	(-2.48)	(-3.29)	(-6.24)	(-3.64)
constant term (math.)	4.673***	-1.292	0.444***	0.136
	(16.91)	(-1.11)	(10.49)	(0.57)
control variable	No	Yes	No	Yes
Industry/year FE	Yes	Yes	Yes	Yes
Observations	252	252	252	252
R^2	0.896	0.980	0.909	0.922

iii.endogeneity test

Throughout the in-depth investigation of the correlation between industrial robots and carbon emissions, the author has taken the unique dimension of the U.S. industrial robot operating inventory (lnrobus) into the research field of vision, and analyzed it in detail through two-stage least squares regression, in order to provide more persuasive evidence for the baseline regression results. It is posited that while the U.S. industrial robot usage does not exert a direct influence on China's industrial carbon emissions, it serves as a suitable proxy for the technological adoption patterns that may be relevant to Chinese industries (meeting the criteria for relevance and exclusivity).

The results of instrumental variable analysis are presented in Table 5. Here, models (1) and (3) illustrate the initial stage outcomes concerning total carbon emissions and carbon intensity, respectively. The data reveals that the instrumental variables exert a significant and positive influence on the primary explanatory variables, boasting F-values of 135.564 and 403.04, which confirms the strong correlation of these instrumental variables. In model (4), we observe the results from the second stage concerning carbon emission intensity after incorporating the instrumental variable related to the U.S. industrial robot operating inventory.Of particular interest is the fact that the coefficient of industrial robot utilization, which is the core explanatory variable, still maintains a significant negative relationship, with a negligible difference from the baseline regression.This finding not only confirms the reliability of the study, but also reveals a deeper fact that cannot be ignored: with the expansion of industrial robot deployment, the carbon emission intensity of China's industrial sector shows a clear downward trend.

Table 5 Endogeneity test results

variable	Total carbon emissions		Carbon intensity	
	Phase I (1) lnrob	Phase II (2) lntce	Phase I (3) lnrob	Phase II (4) lntce
lnrobus	0.542***		1.1398***	

	(11.64)		(20.08)	
lnrob		-0.0482 (-0.74)		-0.0207*** (-3.88)
Constant	-4.814*** (-3.22)	-1.2201 (-1.12)	-13.1909*** (-6.41)	0.0826 (0.36)
F	135.564	71.80	403.04	113.45
control variable Industry/year FE	Yes	Yes	Yes	Yes
Observations	252	252	252	252
R^2	0.388	0.926	0.640	0.923

iv.mechanism test

In the last section, we touched on how industrial robots have influenced carbon emissions in their entirety. Now, in this section, we're going to delve into the intricacies by introducing two key mediating factors: "hmatch" and the "level of industry economic development." We aim to uncover the underlying dynamics at play. The selection and calculation of the mediating variables are as follows: (1) Human-machine match (hmatch): industrial robots can improve productivity, reduce energy waste, and reduce indirect carbon emissions by reducing labor demand and replacing traditional energy-intensive equipment.It is calculated from the robot inventory and the level of human capital (the proportion of R&D staff to total workforce in each industry); (2) energy use efficiency (lnei): The proportion of log GDP to overall energy usage. In this paper, we refer to the recursive equation of Wen Zhonglin and Ye Baojuan (2014) for research and add the Sobel test and Bootstrap method test (take samples 500 times). The model is constructed as follows:

$$hmatch_{jit} = \alpha + \beta \ln rob_{jit} + \sum \varphi_j X_{jit} + \theta_j + \mu_t + \varepsilon_{jit} \quad (3)$$

$$\ln ei_{jit} = \alpha + \beta \ln rob_{jit} + \sum \varphi_j X_{jit} + \theta_j + \mu_t + \varepsilon_{jit} \quad (4)$$

$$\ln tce_{jit} = \alpha + \beta hmatch_{jit} + \sum \varphi_j X_{jit} + \theta_j + \mu_t + \varepsilon_{jit} \quad (5)$$

$$\ln tce_{jit} = \alpha + \beta \ln ei_{jit} + \sum \varphi_j X_{jit} + \theta_j + \mu_t + \varepsilon_{jit} \quad (6)$$

Table 6 presents the results of the regression analysis, highlighting positive and statistically significant coefficients associated with the integration of industrial robots in human-robot collaboration. The incorporation of these robots significantly boosts the efficiency of skilled workers when working alongside robotic systems. Such enhanced collaboration not only streamlines the processes across industrial production, management, and transportation but also aids in addressing the issue of declining productivity, thereby effectively curbing carbon emissions. Column (2) demonstrates that utilizing industrial robots can greatly enhance the alignment between human workers and robotic systems. This enhancement streamlines industrial labor complexities, promotes sustainable production, and reduces total carbon emissions, thereby confirming Hypothesis 2a.

From another perspective, industrial robots have a greater potential to promote not only the human-robot matching effect but also energy efficiency[**Error! Reference source not found.**]. Through the optimization of energy allocation, industrial robots play a crucial role in substantially reducing the carbon intensity of companies and enhancing energy use efficiency. As clearly demonstrated in Table 6, the growing utilization of industrial robots leads to a significant improvement in energy efficiency. This improvement stems from the robots' ability to optimize operational patterns, incorporate energy-efficient equipment, and achieve more precise and scaled production. Column (5) reveals a highly negative correlation between energy usage efficiency and total carbon emissions, indicating that higher energy efficiency is more effective in curbing carbon pollution, thus validating Hypothesis 2b.

Table 6 Results of the industrial robot application's mechanism assessment on carbon emissions impact

variable	(1) lntce	(2) hmatch	(3) lntce	(4) lnei	(5) lntce
lnrob	-0.1213*** (-2.7581)	2.6171*** (3.5068)		0.0815*** (4.1882)	
hmatch			-0.0070* (-1.7353)		
lnei					-0.9642*** (-6.8842)
Sobel test		Mediating variable: human-machine fit -0.037*** Mechanisms are effective		Intermediary variable: economic development of the industry -0.054*** Mechanisms are effective	
Bootstrap Inspection		Direct effect established Indirect effects are established		Direct effect established Indirect effects are established	
control variable	Yes	Yes	Yes	Yes	Yes
Industry/year fixed	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252
Adjusted R^2	0.914	0.814	0.915	0.959	0.929

v.heterogeneity analysis

High-carbon emitting industries. The criterion for distinguishing high-carbon-emitting industries from low-carbon-emitting ones is the overall carbon emissions total. Table 7 demonstrates that introducing industrial robots tends to dampen carbon emissions in both heavily and lightly polluting sectors, as evidenced by models 2 and 4. With carbon emission intensity as the dependent variable, the respective p-values are 1% and 10%. These statistics reveal significant disparities in the impact of industrial robots on carbon emission intensity across different sectors, particularly showing a more pronounced effect in industries that generate greater emissions. This primarily suggests that industries with lower carbon emissions have intrinsic characteristics that are less correlated with industrial intelligence.

Table 7 Industry Heterogeneity Test (High Carbon Emitting Industries/Low Carbon Emitting Industries)

variant	High-carbon emitting industries (1) lntce	 (2) cei	Low-carbon emission industries (3) lntce	 (4) cei
lnrob	-0.1365** (-2.4724)	-0.0336*** (-3.8388)	-0.1603** (-2.5995)	-0.0040* (-1.7628)
control variable	be	be	be	be
Year/industry effect	be	be	be	be

r²	0.9252	0.9053	0.6421	0.6432
sample size	126	126	126	126

High technology-intensity industries. The study categorizes sectors as either high or low robot-operated inventory-dependent industries. In Table 8, the data is crystal clear: regarding carbon emissions totals or intensity, the effect of industrial robots differs greatly across technology-intensive industry. Notably, the suppression effect is more pronounced in industries that heavily utilize industrial robots. This is mainly related to the fact that the mature technology relied on by industries with high technology intensity cannot completely replace high-carbon emission production methods, while their energy use efficiency and the degree of low-carbon transformation do not significantly exceed that of industries with low technology intensity.

Table 8 Industry Heterogeneity Test (High Technology Intensive Industries/Low Technology Intensive Industries)

	High technology-intensive industries		Low technology-intensive industries	
variant	(1)	(2)	(3)	(4)
	lntce	cei	lntce	cei
lnrob	-0.0961*	-0.0023	-0.2261***	-0.0380***
	(-1.8594)	(-1.5975)	(-2.8941)	(-4.3040)
control variable	Yes	Yes	Yes	Yes
Year/industry effect	Yes	Yes	Yes	Yes
R^2	0.5960	0.5997	0.9299	0.9084
Observations	126	126	126	126

High-scale industries. Due to the differences in infrastructure, raw material demand as well as manpower demand, and capital demand of each industry, there are differences in scale between different industries, and the industry scale indicators in this paper are the main business income and the number of enterprise units in each industry. The variations in industry size are categorized into large-scale and small-scale sectors for the difference test in the aforementioned experiment. The discrepancy between the overall carbon emissions and the emission rate is substantial, highlighting the varying suppression effects of industrial robots on carbon emissions in industries of different magnitudes. Notably, the influence of industrial robots on cutting down emissions is more evident in smaller-scale operations.

Whether we look at total carbon emissions or the intensity of those emissions, the extent of the suppressive effect of industrial robots varies significantly among industries of different sizes, with smaller industries experiencing a more noticeable impact. This is primarily attributed to the fact that larger-scale industries, due to their substantial carbon emissions and the complexities associated with transformation challenges, exhibit less significant emission reduction effects compared to smaller-scale industries. Although individual enterprises in smaller-scale industries may have lower carbon emissions, their collective impact could be substantial, given their sheer numbers, and thus they may significantly contribute to the overall mitigation of carbon emissions.

Table 9 Industry Heterogeneity Test (High-Scale Industries/Low-Scale Industries)

	High-scale industries		Low-scale industries	
variable	(1)	(2)	(3)	(4)
	lntce	cei	lntce	cei
lnrob	-0.0787	-0.0184*	-0.2225***	-0.0165***
	(-1.3080)	(-1.8521)	(-3.1743)	(-3.9154)

control variable	Yes	Yes	Yes	Yes
Year/industry effect	Yes	Yes	Yes	Yes
R^2	0.9387	0.9305	0.9018	0.7823
Observations	126	126	126	126

CONCLUSION

Focusing on the industry frontier, this study meticulously divides the research object into 18 sectors, and deeply analyzes the impact mechanism of industrial robot integration on the scale and extent of carbon emissions. Empirical research based on industry panel data from 2006 to 2019 reveals the following key findings:(1) The application of industrial robots plays a significant role in the reduction of the total amount and intensity of industrial carbon emissions, and in particular, it shows a more excellent effect on the control of carbon emission intensity. This finding has been subjected to a rigorous robustness test, which fully confirms its scientific validity and reliability; (2) the intermediate test finds that industrial robots effectively curb industrial carbon emissions by optimizing the human-robot collaboration mode and improving the efficiency of energy use; (3) it is noteworthy that industrial robots show obvious industry differences in promoting the process of carbon emission reduction, and this emission reduction effect is found in the high-carbon emission, low-technology-intensive, and small-scale industries. technology-intensive and small-scale industries, reflecting the significant differences in the absorption and application capabilities of robotics in different industries.

Policy Implications

The objective of achieving "carbon peak and carbon neutrality" spurs industrial transformation and upgrading. This approach aims to enhance energy efficiency, reduce emissions, and foster high-quality economic development. Based on empirical findings and research outcomes, this paper proposes the following recommendations:

Firstly, it is crucial to vigorously advocate for the integration of industrial robots within the manufacturing workflows of Chinese companies. On one side, there needs to be a boost in funding for smart industrial technologies, including artificial intelligence, automation, robotics, the Internet of Things (IoT), and cloud computing, to address the shortcomings in the intelligent transformation of the production supply chain. Conversely, utilizing data gathered from robots for analysis can refine production processes and significantly improve overall efficiency. By monitoring and analyzing key performance indicator data in real time, manufacturers can identify bottlenecks and make data-driven decisions. Ensure the efficiency and quality of industrial robot applications and drive the industry towards greater efficiency and intelligence.

Secondly, key industries with greater room for emission reduction should be supported to reach the peak first, and detailed carbon peak programs for industries should be formulated. Amid the pressing challenges posed by global climate change, fostering green innovation has emerged as a strategic imperative, particularly for technology-driven industries and small to medium-sized enterprises (SMEs). Encouraging these sectors to prioritize sustainable investments is not just a choice but a necessity in today’s rapidly evolving environmental landscape. On the other side, support localities and key industries that have the conditions to take the lead in achieving the "carbon peak" goal, focusing on industrial industries with a high level of technology and scale (automobile and other transport manufacturing industries, and computer, communications and other electronic equipment manufacturing industries), and actively upgrading the level of intelligent production in these industries, and transforming and upgrading them to green, low-carbon and high-efficiency production.

Thirdly, the advancement and utilization of clean energy and eco-friendly technologies have emerged as the essential choice of the era. On one side, it is imperative to implement strategies that include advocating for clean energy, enhancing energy efficiency, and bolstering resource recycling, all aimed at facilitating the early attainment of peak emissions within pivotal industries. For example, in mining and manufacturing industries, carbon emission intensity can be reduced through measures such as rationally controlling production capacity, promoting green and low-carbon technologies, and building a circular economy industry chain; Conversely, it’s essential to elevate companies’ understanding of clean energy and green technologies, while also steering investments and talent toward the green and low-carbon sectors through initiatives like training and subsidies. The government should increase clean energy publicity, popularise relevant low-carbon knowledge, and encourage the application of green technology. This will foster sustainable economic and social progress and assist in reaching the "carbon peaking and carbon neutrality" goal promptly.

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