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Carbon emission reduction effects of industrial robot applications: Heterogeneity characteristics and influencing mechanisms

Yaya Li [a], Yuru Zhang [a], An Pan [b,*], Minchun Han [c], Eleonora Veglianti [d]

[a] School of Finance and Economics, Jiangsu University, Zhenjiang, Jiangsu, China
[b] School of Economics, Zhongnan University of Economics and Law, Wuhan, China
[c] School of Economics, Huazhong University of Science and Technology, Wuhan, China
[d] Faculty of Management, Economy and Sciences, University Catholic of Lille, Lille, France

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ABSTRACT

Industrial robots are a key enabling technology of Industry 4.0 and the artificial intelligence revolution, which is of great significance in sustainable development. Existing research has focused on the economic effects of industrial robot application, but research on the environmental effects remains insufficient. Based on the environmental Kuznets curve (EKC) model and using sample data from 35 countries from 1993 to 2017, this paper empirically examines the carbon emission reduction effects of industrial robot application. Three key findings emerged. First, the application of industrial robots significantly reduces carbon intensity. The application of industrial robots leads to increased productivity, the optimisation of factor structures, and technological innovation in production, which improve energy efficiency and reduce carbon intensity. Second, there is a two-dimensional heterogeneity in the carbon intensity reduction effects of industrial robot application in terms of the application fields and possible countries for application. Compared to other fields, the application of industrial robots in manufacturing, agriculture, and electricity, gas, and water supply fields significantly promotes carbon intensity reduction. Furthermore, industrial robots in developed countries have better emission reduction effects than in developing countries. Third, the application of industrial robots has a dual-channel mediating mechanism for carbon intensity reduction: first, there is a mediating role of green total factor productivity and energy intensity; second, absorptive capacity plays a moderating role. On the one hand, high absorptive capacity brings about a better innovation environment and enhances the effects of carbon emission reduction; on the other hand, the application of industrial robots promotes carbon intensity reduction by positively influencing the improvement of green total factor productivity and energy intensity. Finally, policy recommendations are provided based on the results.

1. Introduction

Global warming is mainly caused by excessive carbon dioxide emissions and has brought about a series of catastrophic effects, such as melting glaciers, floods, and abnormal weather. Mitigating climate change and reducing carbon emissions have become the most pressing issues in the world. The global carbon emission reduction goals proposed by the United Nations include the reduction of global greenhouse gas emissions by 45%, compared to 2010 levels, by 2030, and achieving net zero emissions by 2050. However, on October 25, 2021, a report released by the World Meteorological Organization (WMO) showed that the globally averaged CO_2 mole fraction in 2020 was 413.2 ± 0.2 ppm. The annual increase was higher than the average growth rate over the past decade, despite the approximately 5.6% drop in fossil-fuel CO_2 emissions in 2020 due to restrictions related to the COVID-19 pandemic [1]. The wide application of Industry 4.0 and artificial intelligence (AI) technology in economic and social activities has become a great source of hope and a key factor in achieving global sustainable development goals [2–5]. Industrial robots are a key enabling technology for Industry 4.0 and the AI revolution, particularly in terms of the smart and low-carbon transformation of traditional industries. The wide application of industrial robots in manufacturing and other fields can reduce the waste of resources in production, shorten production times, and reduce energy consumption via automation, which are of great significance in

* Corresponding author.
E-mail addresses: yizhi19881107@126.com (Y. Li), zyr_281528@163.com (Y. Zhang), panan0819@zuel.edu.cn (A. Pan), minchunhust@163.com (M. Han), eleonora.veglianti@univ-catholille.fr (E. Veglianti).

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sustainable development [6–8]. The decline of carbon intensity indicates the existence of a carbon emission reduction effect [9]. As shown in Fig. 1, the trend of the application intensity of industrial robots has increased year on year since 1993, reaching its peak in 2017. In addition, the carbon intensity in this period showed a downward trend, and the global average carbon intensity in 2017 was only half of that in 1993, which means that a carbon emission reduction effect exists.

Grossman and Krueger [10] first proposed the environmental Kuznets curve (EKC) hypothesis in order to mitigate climate change and achieve sustainable development. Scholars have focused on the factors affecting carbon dioxide emissions, such as economic growth and technological progress, population size, industrial structure, urbanisation, environmental regulations, digital economy, etc. [11–17]. For example, Du et al. [18] found that green technology innovation, per capita GDP, urbanisation level, industrial structure, trade openness, and energy consumption structure significantly affect carbon dioxide emissions. In recent years, the environmental effects of key enabling technologies have become research hotspots, such as the impact of information and communication technologies (ICT), autonomous vehicles, digital technologies, AI, and other environmental technologies [19–25]. Using data from China's industrial sector, Liu et al. [26] verified that AI technology has significantly reduced carbon intensity. However, relevant studies have not provided consistent conclusions. For example, on the one hand, ICT technology has been shown to promote the optimisation of energy and industrial structures and to reduce carbon emission intensity [27]; on the other hand, the stimulating effects of technology on economic growth have also been shown to increase carbon emissions, resulting in a rebound effect [20].

According to the definition of the International Federation of Robotics (IFR), an industrial robot is a reprogrammable multi-purpose automatic control-operated machine used in industrial automation. Industrial robots are an enabling technology for Industry 4.0 and the AI revolution that differ from early automation and traditional information and communication technologies [28,29]. Existing research has focused on the impact of industrial robots on economic activities, including productivity, employment, technological innovation, and crisis management [30–32]. For example, Acemoglu and Restrepo [33] found that the increase in the application of industrial robots reduced employment and wage levels. Graetz and Michaels [28] confirmed that the application of industrial robots increased labour productivity and total factor productivity, while also reducing low-skilled workers' employment share. Liu et al. [34] explained that the application of industrial robots has improved technological innovation in the manufacturing industry by increasing knowledge creation and technology spill-over. In contrast, research regarding the environmental effects of industrial robots is insufficient. Only a few scholars have discussed the potential effects of industrial robot technology on pollution reduction, both from theoretical and qualitative perspectives [6,7]. However, there remains a lack of quantitative analyses that have empirically investigated the effects of carbon emission reduction, heterogeneity characteristics, and possible mechanisms influenced by industrial robot application.

Therefore, this topic is worthy of further study to understand the actual effects of industrial robot application in reducing carbon dioxide emissions. Based on the existing research, we propose three basic problems that need to be addressed. First, does the application of industrial robots effectively reduce carbon intensity? Second, are there heterogeneous characteristics in the impact of industrial robot application on carbon intensity in different regions and different fields? Third, what is the possible mechanism for the application of industrial robots to promote carbon intensity reduction?

This article aims to conduct an in-depth empirical study of the problems outlined above using data on industrial robot application from 35 countries from 1993 to 2017. The contributions of this article are mainly related to the following three aspects. First, unlike the existing literature that has focused on the economic effects of industrial robot application, this article explores the relationship between industrial robot application and carbon emission reduction. For the first time in the field, our study empirically examines the carbon emission reduction effects of industrial robot application. This not only addresses a gap in the research on the environmental effects of industrial robot application, but also provides a new perspective for the realisation of energy saving measures, emission reduction, and green development initiatives. Second, regarding the study framework, we consider that high absorptive capacity is conducive to the spill-over and absorption of industrial robot technology; we also examine how this may amplify the carbon emission reduction effects of industrial robot application. Thus, for the first time in the field, absorptive capacity is included as a moderating variable; moreover, we examine the application of industrial robots to promote carbon emission reduction through the improvement of green total factor productivity and reducing energy intensity. This paper uses green total factor productivity and energy intensity as the mediating variables to study the path of industrial robot application affecting carbon emission reduction. Third, in terms of research design, we consider the heterogeneity of industrial robot application in various countries and fields of application, including an empirical examination of the heterogeneity effects of carbon emission reduction, thus expanding the depth and breadth of the overall field of research.

The remainder of this paper is organised as follows. Section 2 describes the study's theoretical basis and research hypotheses. Section 3 provided details of the research methods and data. Section 4 presents and discusses the empirical test results. Finally, Section 5 provides conclusions and related policy implications.

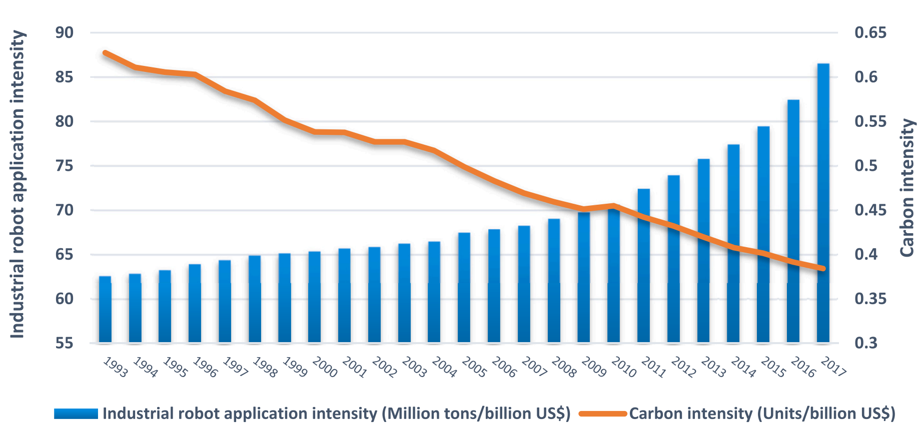

Fig. 1. Industrial robot application intensity and carbon intensity from 1993 to 2017.

2. Theoretical basis and hypotheses

2.1. Industrial robot application and carbon intensity

Industrial robots are an important enabling technology in Industry 4.0. The reliability of their automation enables manufacturers to reduce total waste in the manufacturing chain [6,35]. The application of industrial robots provides many economic benefits, such as manufacturing agility, operation cost savings, labour productivity, and total factor productivity improvement [28,36]. Although the application of industrial robots does not necessarily prioritise environmental sustainability, the introduction of industrial robots has unintentionally led to a positive impact on the environment by reducing waste, improving energy efficiency, and enabling cleaner production [6,7,37]. In particular, the application of industrial robots promotes the technological innovation of enterprises through knowledge creation, knowledge spill-over, learning ability improvement, R&D, and talent investment [34]. It has also been shown that industrial robot technology simplifies green process innovation [7] and that green innovation further reduces carbon intensity [18,38]. The decline in carbon intensity indicates the existence of a carbon emission reduction effect, showing that economic growth and environmental development are gradually achieving a win–win situation [9]. In addition, the widespread use of industrial robots in production and operation has also led to the optimisation of production factors in various enterprises, promoting the reconfiguration of production resources and factors and optimising the production process, thus improving energy efficiency and reducing carbon intensity [37,39]. The application of industrial robots has also improved labour productivity, expanded output with equal input, reduced resource and energy consumption, and reduced carbon intensity [28]. Finally, the intelligent transformation of enterprises entailed by the application of industrial robots has further promoted social sustainability by improving working conditions, creating new job opportunities, and enhancing customer experiences, which in turn promote carbon intensity reduction [40]. Therefore, four hypotheses are proposed in this paper, beginning with the following:

H1. Industrial robot application can promote carbon intensity reduction.

2.2. Heterogeneity of industrial robot application in reducing carbon intensity

The application of industrial robots has different characteristics in different regions and fields. This begs the question as to whether there is heterogeneity in the carbon reduction effects of industrial robot application. Previous studies have noted that the impact of AI technology on the environment has industry heterogeneity, and compared to capital-intensive industries, the environmental effects are greater in labour-intensive and technology-intensive industries [26]. From the perspective of different fields of industrial robot application, 85% of industrial robot applications are in manufacturing sector, with far fewer applications found in agriculture, mining, construction, education, water and electricity supply, and other fields. According to IFR data, in the manufacturing sector, 72% of the application of industrial robots is in the automotive and electronic fields, while 12.9% is in the metal industry [6]. Different application intensities may lead to different characteristics of their impact on carbon emission reduction in various fields. In addition, in terms of different regions, the application levels of industrial robots in developed countries account for about 65.5% of global applications, while developing countries account for only 35.5%. On the one hand, different countries or regions have significant differences in technology and R&D levels, which leads to different spill-over and absorption capacities of industrial robot technology. Thus, the carbon intensity reduction brought about by technological innovations and structural upgrading may be heterogeneous. On the other hand, differences in industrial structures among countries will also lead to differences in the application of industrial robots, which will further impact the effects of carbon emission reduction. Therefore, the following hypothesis is proposed:

H2. The carbon intensity reduction effects of industrial robot application have heterogeneity in fields of application and different countries.

2.3. The mechanisms of industrial robot application affecting carbon intensity

The carbon emission reduction effects of industrial robot application have regional heterogeneity, which may be affected by regional absorptive capacity. Absorptive capacity refers to the ability of enterprises or regions to identify, absorb, and apply external knowledge by using previous relevant knowledge, as well as convert it into business value [41]. Absorptive capacity is widely measured by R&D intensity in the literature [42,43]; regions with high absorptive capacity can better identify and utilise external knowledge sources [44]. Industrial robots are a complex technology, and thus for some application enterprises or regions, industrial robot application brings challenges regarding technology absorption and integration [34]. High absorptive capacity means that enterprises can quickly adapt to the changes in innovation environments and technologies, better digest and utilise industrial robot technologies, and enhance competitive advantages. Therefore, the interactions between absorptive capacity and industrial robot application may become a catalyst for carbon intensity reduction, strengthening the carbon emission reduction effects of industrial robot application. Specifically, when the regional absorptive capacity is high, the stronger the positive impact of industrial robot application is on carbon intensity reduction. In contrast, areas with low absorptive capacity have been shown to have difficulty absorbing and applying industrial robot technology and knowledge. Taken together, this may then hinder the carbon intensity reduction role of industrial robot application. Therefore, we assume the following:

H3. Absorptive capacity positively moderates the relationship between industrial robot application and carbon intensity reduction.

In addition, we seek to determine whether green total factor productivity is an intermediary mechanism in the impact of industrial robot application on carbon intensity. Studies have found that the increase in the application of industrial robots contributes about 0.36% points to the growth of annual labour productivity, while also improving total factor productivity [28]. Further, high-tech innovations, including AI, industrial robots, and other technological innovations, are regarded as the fundamental driving forces of green total factor productivity growth, which is crucial to sustainable economic development [45]. The improvement of total factor productivity is known to be an important mechanism for reducing carbon intensity. Green total factor productivity considers the impact of the environment on the basis of total factor productivity and is more likely to become an important channel for climate-change mitigation and carbon emission reduction [46]. Therefore, the application of industrial robots not only improves total factor productivity through efficient and intelligent production arrangements, but also improves the energy utilisation efficiency of products and processes through technological innovation spill-over effects and factor structure optimisation effects, leading to an increase in green total factor productivity and further promoting carbon intensity reduction. Therefore, this article posits the following hypothesis:

H4a. The application of industrial robots promotes carbon intensity reduction by positively affecting green total factor productivity.

Further, we aim to determine whether energy intensity is an intermediary mechanism in the impact of industrial robot application on carbon intensity. Studies have shown that there is a positive relationship between energy intensity and carbon intensity, i.e. a reduction in energy intensity leads to a reduction in carbon intensity [47,48]. At the same time, some scholars have pointed out that the application of industrial robots has promoted the reduction of energy intensity in the manufacturing sector. On the one hand, the application of industrial robots can the promote technological innovation of enterprises, improving energy efficiency and reducing energy intensity, thereby effectively controlling carbon emission intensity [34,39]; on the other hand, industrial robots replace low-skilled labour and improve productivity, thereby reducing energy intensity and reducing carbon emissions per unit of output [28,39]. Therefore, the application of industrial robots improves energy efficiency and reduces energy intensity through technological innovation effects and productivity improvement effects, thereby reducing carbon intensity. Based on the above discussions, this paper proposes the following hypothesis:

H4b. The application of industrial robots promotes carbon intensity reduction by negatively affecting energy intensity.

The present study's theoretical model is presented in Fig. 2.

3. Methodology and data

3.1. Model specification

Most scholars have used the extended EKC model to explore the influencing factors of carbon emissions [49]. The traditional EKC model reveals the relationship between income level and carbon emission, and an inverted U-shaped relationship between the two has been found. Subsequently, scholars have investigated the impact of trade, urbanisation, climate aid, and other factors on carbon emissions and extended the classical EKC model [50,51]. This paper focuses on the carbon emission reduction effects of industrial robot application. The extended model is based on the classical EKC model, with industrial robot application and other variables added. The extended model is as follows:

$$\ln CI_{it} = \alpha_0 + \alpha_1 \ln robot_{it} + \beta_1 \ln pgdp_{it} + \beta_2 (\ln pgdp_{it})^2 + \beta control_{it} + \varepsilon_{it} \tag{1}$$

Model (1) is used to test H1 and H2; if α_1 is less than 0 and the p-value is less than 0.1, this indicates that industrial robot application could promote carbon emission reduction. In the model, α_0 is a constant term, and *CI* indicates carbon intensity. The variable *robot* represents the operational stock of industrial robots per unit of GDP; and *pgdp* is the real GDP per capita; *control* represents other control variables, mainly population size (*pop*), energy consumption per capita (*enuse*), urbanisation rate (*urban*), industrial structure (*indus*), trade openness (*trade*), and country fixed effect (μ_i). The variable ε represents the random disturbance term, while α_1 and β are coefficients of each variable. The variable i represents country, t represents year, and ln represents the logarithmic form to eliminate heteroscedasticity.

To test H3, this paper uses Baron and Kenny's [52] and Yuan and Zhang's [53] moderating effect analysis method to test whether regional absorptive capacity plays a moderating role in the path of industrial robot application affecting carbon emission reduction; absorptive capacity and the interaction term between absorptive capacity and industrial robot application are introduced into the model. If the coefficient of the interaction term is significant, this proves that absorptive capacity has a significant moderating effect. The specific model is set as follows:

$$\ln CI_{it} = \alpha_0 + \alpha_1 \ln robot_{it} + \beta_1 \ln pgdp_{it} + \beta_2 (\ln pgdp_{it})^2 + \beta control_{it} + \varphi ac_{it} + \lambda \ln robot_{it} \times ac_{it} + \varepsilon_{it} \tag{2}$$

where: *ac* is the moderating variable, namely absorptive capacity, and is represented by the proportion of R&D expenditure in relation to the GDP of each country; φ is the moderating variable coefficient; and λ is the interaction coefficient. If λ is less than 0 and its p-value is less than 0.1, this indicates that absorptive capacity positively regulates the relationship between industrial robot application and carbon emission reduction.

Further, to verify *H4*, the mediation effect analysis of Baron and Kenny [52] and Pei et al. [17] is used to test whether green total factor productivity and energy intensity are the mediation mechanism of industrial robot application promoting carbon emission reduction. To verify this mediation mechanism, we construct the following models:

$$M_{it} = \alpha_0 + \alpha_2 \ln robot_{it} + \beta_1 \ln pgdp_{it} + \beta_2 (\ln pgdp_{it})^2 + \beta control_{it} + \varepsilon_{it} \tag{3}$$

$$\ln CI_{it} = \alpha_0 + \alpha_3 \ln robot_{it} + \gamma M_{it} + \beta_1 \ln pgdp_{it} + \beta_2 (\ln pgdp_{it})^2 + \beta control_{it} + \varepsilon_{it} \tag{4}$$

where *M* represents the mediating variables, namely green total factor productivity (*gtfp*) and energy intensity (*ei*). *gtfp* is one intermediary variable, which is expressed by the cumulative value of the global Malmquist–Luenberger (GML) productivity index. The other intermediary variable is *ei*. First, the significance of α_2 and γ are analysed. If both are significant, the mediating effect is shown to exist. The significance of α_3 is further analysed. If α_3 is significant, a partial mediating effect is indicated.

3.2. Definition of variables

3.2.1. Dependent variable: carbon intensity (CI)

The decline of carbon intensity indicates the existence of a carbon emission reduction effect [9]. Following Xuan et al. [9] and Pan et al.

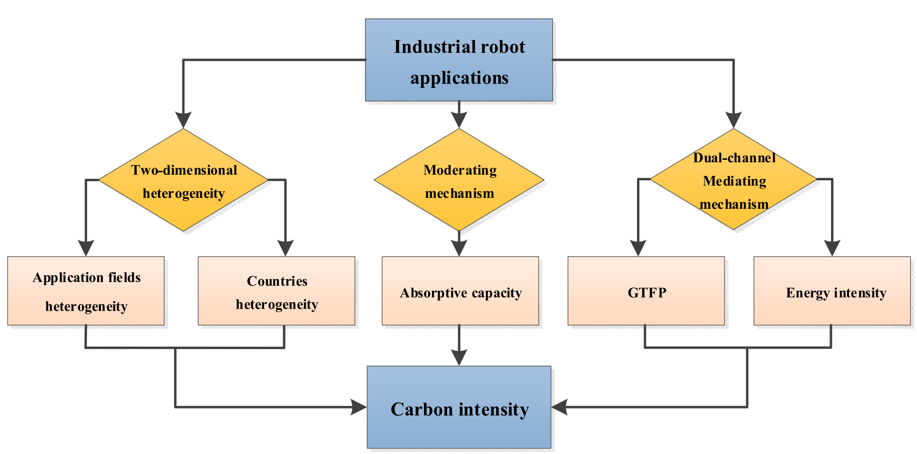

Fig. 2. Theoretical model.

[54], carbon intensity (carbon emissions in relation to GDP) is used to represent the carbon emission index in this paper. The data on carbon intensity were obtained from the International Energy Agency (IEA).

3.2.2. Independent variable: industrial robot application intensity (robot)

The IFR released the application data for industrial robots at the level of “country-industry-time”. In this paper, the installed stock of industrial robots per unit GDP is used to represent the application intensity of industrial robots. Specifically, the industrial robot data were obtained from the industrial robots’ report issued by the IFR. To avoid the impact of exchange rate and inflation, the GDP used is the real GDP measured in 2010 in US dollars.

3.2.3. Control variables

Per capita GDP (pgdp). The EKC model emphasises the nonlinear relationship between income and carbon emissions. To test the EKC hypothesis, this paper uses per capita GDP to represent income levels.

*Population size (*pop*)*. The impact of population size on carbon emissions is mainly reflected in two aspects: the expansion of population size increasing energy consumption in terms of production activities and daily life, which puts significant pressure on the ecological environment [55]; and the expansion of population size enriching human capital, which improves technology and innovation, and negatively impacts carbon emissions [56]. Population size is expressed by the total population of each country at the end of each calendar year.

Energy consumption per capita *(*enuse*)*. For nearly a century, human beings have used a significant amount of energy, such as coal and oil, causing the emission of large quantities of carbon dioxide and other greenhouse gases, and in turn leading to global warming [57]. In this study, energy use per capita of oil equivalent is used to represent energy consumption.

*Urbanisation rate (*urban*)*. The development of urbanisation has meant that cities have become the main gathering places for energy consumption and carbon dioxide emissions. In the process of urbanisation, energy consumption increases, leading to an increase in carbon dioxide emissions [58]. However, a reasonable level of urbanisation can also improve environmental conditions and significantly improve energy-use efficiency, which ultimately reduces carbon emissions [59]. Therefore, urbanisation may have different impacts on carbon emissions at different stages. The present study uses the ratio of urban population to total population as an indicator of the urbanisation rate.

*Industrial structure (*indus*)*. The change of industrial structures impacts carbon intensity, and the development of energy-saving, green, and high-tech industries will no doubt further promote the reduction of carbon emissions [60]. Referring to the research of Lin and Zhu [49], this paper uses the proportion of added value of the secondary industry in terms of GDP to represent the industrial structure.

*Trade openness (*trade*)*. Trade liberalisation reduces friction, which can further expand production scale and thus promote carbon emissions [61]. In addition, through trade links, advanced technologies can be transferred from technologically advanced economies to technologically backward economies, so that technology-importing countries can improve energy-use efficiency and thus reduce carbon emissions [10]. In this paper, we use the sum of merchandise exports and imports per unit of GDP to represent trade openness.

3.2.4. Moderator variable: absorptive capacity (ac)

Absorptive capacity refers to the ability of enterprises or regions to identify, absorb, and apply external knowledge by using previous relevant knowledge, as well as to convert it into business value [41]. Following Lu et al. [43], the present study uses the ratio of nominal R&D expenditure to nominal GDP, namely regional R&D intensity, to measure the absorptive capacity.

3.2.5. Mediator variables:green total factor productivity (gtfp) and energy intensity (ei)

The measurement of green total factor productivity can be estimated by a variety of measures [62,63]. In this article, we follow the research of Oh [64] and Liu and Xin [65] to estimate the green total factor productivity of various countries, using labour, capital stock, and energy consumption as inputs, real GDP as expected output, and carbon dioxide emissions as undesired output to measure the green total factor productivity of each country included. Specifically, this is calculated based on the GML productivity index. Further, energy intensity is defined as the energy use per $1000 GDP [constant 2011 purchasing power parity (PPP)]; a low ratio indicates a high energy efficiency.

The present study is based on data from the IFR, IEA, and the World Bank’s World Development Indicators (WDIs). The IFR database contains the annual installation volume and operational stock of industrial robots by industry from 1993 to 2017 for 50 countries. Accounting for the need to match with other variable data and to ensure the representativeness of the selected sample countries, we ultimately selected 35 countries (see the Appendix for details). These sample countries account for more than 99% of the world’s industrial robot operational stock. As shown in Fig. 3, the countries with the greatest application intensity of industrial robots are Japan, South Korea, and Germany, and their operational stocks and annual installations are ranked among the highest in the world. The statistical descriptions of all variables are shown in Table 1. Table 2 lists the correlation coefficients and the variance inflation factor (VIF) of the variables. As we found the VIF value to be far less than 10, and no serious collinearity between the variables was determined.

4. Results and discussion

4.1. Baseline regression

We applied the *F*-test, Lagrange multiplier (LM) test, and Hausman test to determine the best statistical method. The results strongly support that the fixed-effects model is the best method to serve as the basis for our empirical analysis.

Table 3 shows the estimated results of the benchmark regression (Eq. (1)), adding the control variables in turn, as shown in columns 1–4. Through stepwise regression, after controlling relevant variables, column 5 shows that the impact of industrial robot application on carbon intensity is negative at the 1% significant level, which is consistent with the research hypothesis. The results show that the application of industrial robots significantly promotes carbon intensity reduction, and thus H1 is verified. The wide application of industrial robots promotes the reduction of production waste, as well as the improvement of energy efficiency and cleaner production, which positively impacts the environment.

In addition, the regression results for the control variables show that, first, the coefficient of the per capita GDP is positive, and the coefficient of the square term of the per capita GDP is negative. The variables are significant at 5% and 1%, respectively, which indicates that there is an inverted U-shaped relationship between income and carbon emissions. This is in line with the EKC hypothesis and is consistent with the research results of Du et al. [18] and Lin and Zhu [49]. Second, the population size and energy consumption per capita are significantly positive, which shows that an increase in population and energy consumption per capita can negatively impact ecological efficiency and lead to an increase in carbon intensity. Increases in population requiring the significant consumption of raw materials directly promote energy consumption and increased carbon intensity. This is consistent with the research results of Pan et al. [54]. Third, the regression coefficient of industrial structures is positive at the 1% significance level, indicating that the growth of the proportion of secondary industry can increase carbon intensity. This is also consistent with the research results of Pan et al. [54]. Given the rapid development of secondary industries, such as

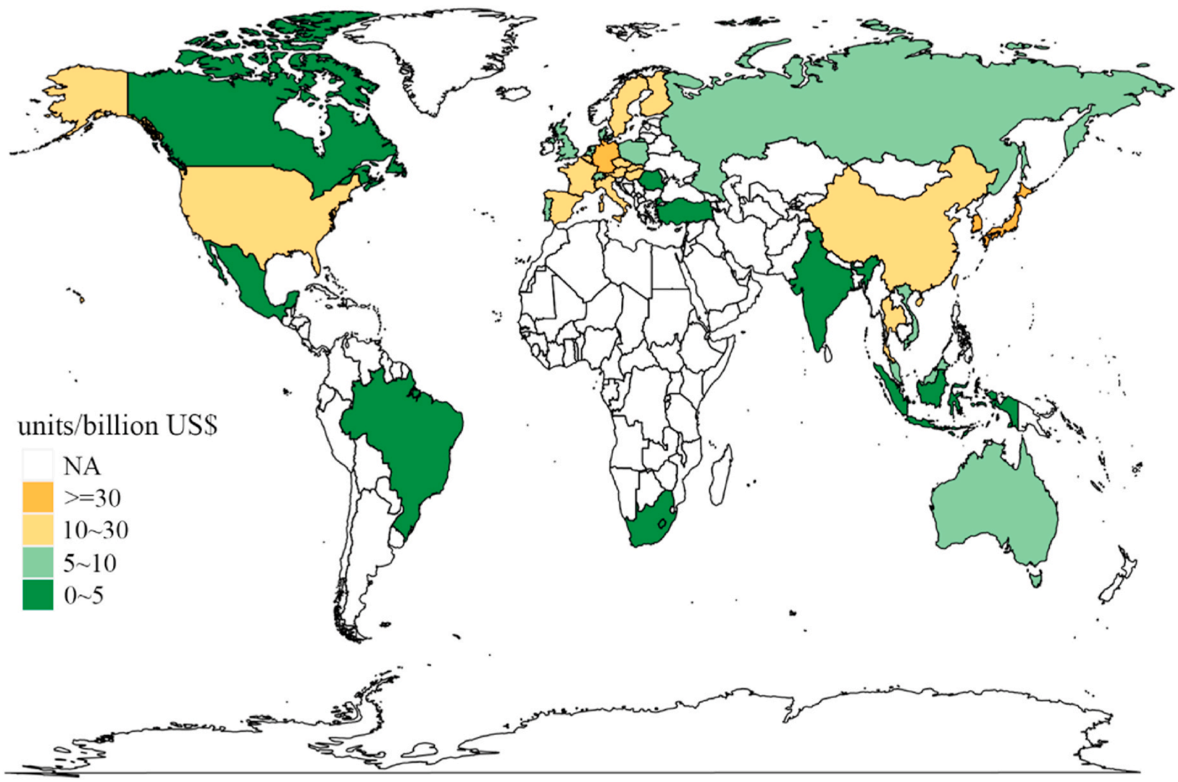

Fig. 3. The country distribution of average application intensity of industrial robots from 1993 to 2017.

Table 1
The statistical description of the variables.

Variable	Definition	Unit	Obs.	Mean	Std. dev.	Min	Max
ln *CI*	CO_2 emissions intensity	Million tons/billion US$	875	−0.955	0.729	−2.957	0.778
ln *robot*	Industrial robot application intensity	Units/billion US$	875	2.120	1.310	−5.098	5.313
ln *pgdp*	Per capita GDP	US$/person	875	9.721	1.141	6.228	11.26
ln *pop*	Population size	Million people	875	3.643	1.439	1.198	7.234
ln *enuse*	Energy consumption per capita	kg of oil equivalent/person	793	7.935	0.712	5.630	9.043
urban	Urbanisation rate	%	875	69.48	17.60	21.39	100
indus	Industrial structure	%	853	28.83	6.872	17.24	48.53
trade	Trade openness	%	873	84.65	62.25	15.64	437.3
ac	Absorptive capacity	%	745	1.575	0.977	0.0476	4.553
ln *gtfp*	Green total factor productivity	/	875	−0.063	0.423	−3.413	0.967
ln *ei*	Energy intensity	kg of oil equivalent/thousand US$	789	4.746	0.392	3.773	6.002

Table 2
Correlation analysis and VIF test.

	VIF	ln *CI*	ln *robot*	ln *pgdp*	ln *pop*	ln *enuse*	*urban*	*indus*	*trade*	*ac*	ln *gtfp*	ln *ei*
ln *CI*		1										
ln *robot*	1.810	−0.340	1									
ln *pgdp*	1.640	−0.747	0.437	1								
ln *pop*	1.270	0.422	−0.199	−0.558	1							
ln *enuse*	1.310	−0.371	0.477	0.868	−0.512	1						
urban	1.010	−0.547	0.350	0.830	−0.423	0.788	1					
indus	1.780	0.619	−0.059	−0.629	0.310	−0.425	−0.520	1				
trade	1.780	−0.107	0.257	0.098	−0.523	0.154	0.178	0.102	1			
ac	1.800	−0.623	0.529	0.736	−0.276	0.684	0.620	−0.396	0.005	1		
ln *gtfp*	1.670	0.108	−0.120	−0.110	0.231	−0.113	−0.144	−0.048	−0.449	−0.074	1	
ln *ei*	1.460	0.748	−0.162	−0.409	0.282	0.0506	−0.229	0.437	−0.151	−0.127	0.040	1

manufacturing industries, their energy consumption intensity is relatively high, which has an obvious facilitating effect on carbon intensity. Finally, the regression coefficient of trade openness and urbanisation is negative at the 1% significance level, showing that through trade linkages, technology transfer improves the energy efficiency of technology-importing countries, thus reducing carbon intensity. With the improvement of urbanisation, carbon intensity gradually decreases, indicating that with the promotion of green urbanisation, the ecological value of innovation receives more attention in the process of urbanisation, which leads to the reduction of carbon intensity. This is consistent

Table 3
Results of the baseline regression.

Variable	(1)	(2)	(3)	(4)	(5)
ln *robot*	−0.101***	−0.005	−0.010***	−0.012***	−0.009***
	(–12.24)	(–0.90)	(–3.31)	(–3.79)	(–2.59)
ln *pgdp*		3.129***	0.333***	0.426***	0.325**
		(18.69)	(2.90)	(3.35)	(2.54)
$(\ln pgdp)^2$		−0.216***	−0.084***	−0.087***	−0.079***
		(–23.53)	(–13.63)	(–12.85)	(–11.20)
ln *pop*			0.210***	0.241***	0.190***
			(3.85)	(3.98)	(3.09)
ln *enuse*			1.167***	1.135***	1.092***
			(43.02)	(38.19)	(35.05)
urban				−0.045***	−0.039***
				(–3.33)	(–2.94)
indus				0.004***	0.005***
				(2.89)	(3.65)
trade					−0.001***
					(–4.12)
_cons	−0.794***	−10.566***	−6.103***	−6.633***	−5.928***
	(–42.14)	(–13.80)	(–11.78)	(–11.70)	(–10.13)
N	770	770	688	655	655
Adjusted R^2	0.130	0.716	0.923	0.915	0.918
F	149.798	657.661	1652.685	1017.088	915.269

Notes: *t*-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with the research results of Wang and Wang [66] and Yuan et al. [59].

4.2. Robustness test of baseline regression

To further verify the reliability of the model, this paper tested the robustness of the benchmark regression. First, we replaced the independent variable. We used the installed stock of industrial robots per capita in place of the installed stock of industrial robots per unit GDP. The amount of industrial robot applications per capita was expressed as the installed stock of industrial robots per million employees. The results are shown in column 1 of Table 4. The direction and significance of each coefficient are consistent with the benchmark regression results, and the model is therefore shown to be robust. Second, outliers were eliminated. In the present study, all explanatory variables were winsorised at the 1% and 99% significance levels. The regression results are shown in column 2 of Table 4. We found that the influence coefficient of industrial robot application on carbon intensity is still significantly negative, and there is no difference in the coefficient direction and significance of the other variables. Therefore, we consider the model to be robust. Third, considering the endogeneity problem, the regression results of the fixed-effects model may have been biased due to the two-way causality between the dependent variable and the independent variable. Based on this, we used a lag term of industrial robot application as a tool variable for instrumental variables-generalised method of moments (IV-GMM) estimation to mitigate the potential endogeneity problem. The results are shown in column 3 of Table 4. Comparing the regression results of the IV-GMM model with the fixed-effects estimation results, we found the coefficient of the industrial robot application to still be negative, which again shows that industrial robot application can effectively improve carbon intensity; therefore, the model is considered to be robust. The regression results of the control variables, such as per capita GDP, population size, and urbanisation rate, are consistent with the results of the fixed-effects model, which will not be repeated here.

Table 4
Robustness checks of baseline regression.

Variable	(1)	(2)	(3)
	ln *CI*	Winsorisd	IV-GMM
ln *robot*	−0.009***	−0.021***	−0.030***
	(–2.80)	(–5.42)	(–27.69)
Control variables	YES	YES	YES
N	655	671	644
Adjusted R^2	0.918	0.911	/
F	917.067	864.931	/

Notes: *t*-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3. Heterogeneity analysis

4.3.1. Heterogeneity in different application fields

According to the data from the *2018 World Robot Report: Industrial Robots* released by the IFR, industrial robots are mainly used in the following six fields: agriculture, forestry, and fishing; mining and quarrying; manufacturing; electricity, gas, and water supply; construction; and education and R&D. There are differences in the application intensity of industrial robots in different fields, raising the question as to whether there is any significant difference in their impact on carbon intensity. To answer this question, we examined the carbon emission reduction effects of industrial robots in different fields. The sub-sample results are shown in Table 5, columns 1–6. From the estimation results, it can be seen that the application of industrial robots in agriculture, forestry, fishing, electricity, gas, and water supply fields reduce the carbon intensity at the 1% significance level, and their application in the manufacturing field significantly reduces carbon intensity at the 5% significance level, showing that industrial robot application in the fields of manufacturing, agriculture, forestry, fishing, electricity, gas, and water supply can promote carbon intensity reduction. In addition, the application of industrial robots in mining and quarrying field increase carbon intensity at the 10% significance level.

Industrial robots are most widely used in the manufacturing industry, used not only to improve manufacturing efficiency, but also to reduce energy consumption and waste in production processes, which ultimately reduces carbon intensity [6]. The electricity, gas, and water supply industry mainly relies on fossil fuels and is a high carbon emission industry [67,68]. Through the life-cycle management of industrial robots in the fields of electricity, gas, and water supply, relying on internet big data, intelligent control, operation, and maintenance can be achieved, and the use efficiency of fossil fuels can be improved, leading to reduced carbon intensity [69]. Agriculture is one of the largest anthropogenic sources of greenhouse gas emissions [70]. The main causes of agricultural pollution are the excessive use of chemical fertilisers in agricultural production processes and the low utilisation rate of chemical fertilisers [71,72]. The application of industrial robots in the agriculture, forestry, and fishing field can improve the scientific

Table 5
The results of heterogeneity analysis.

Variable	Dimension I: application field heterogeneity						Dimension II: country heterogeneity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agriculture, forestry, fishing	Mining and quarrying	Manufacturing	Electricity, gas, and water supply	Construction	Education and R&D	Developed countries	Developing countries
ln *robot*	−0.016**	0.013*	−0.027***	−0.032***	−0.000	−0.008	−0.041***	−0.000
	(–2.32)	(1.94)	(–4.40)	(–5.01)	(–0.07)	(–1.28)	(–5.37)	(–0.02)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
N	318	247	547	251	435	483	479	176
Adjusted R^2	0.691	0.640	0.698	0.817	0.642	0.666	0.926	0.926
F	106.226	66.944	185.817	164.527	117.033	143.394	747.733	276.897

Notes: *t*-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

utilisation of chemical fertilisers. At the same time, the promotion of agricultural mechanisation and agricultural robot technology can effectively reduce carbon intensity [73].

In contrast, the regression results for the carbon emission reduction effect of industrial robots in mining and quarrying reveal increased carbon intensity, but in construction, education, and R&D they are not significant. The possible reason for this is that the application of industrial robots in the mining and quarrying industry has greatly promoted production efficiency, further causing the production process to emit more carbon dioxide [74]. The carbon intensity of the construction industry mainly comes from raw building materials [75]. The field of education and R&D belongs to the service sector, and its carbon intensity are low. Therefore, H2 is considered to be verified. The carbon emission reduction effects of industrial robot application are shown to have heterogeneous characteristics in various fields of application.

4.3.2. *Heterogeneity in different countries*

Considering the differences in economic development levels of the sample countries, according to the classification standards of the United Nations and the OECD, we comprehensively considered the human development index (HDI) and per capita GDP to classify developed and developing countries. If a country's HDI is not less than 0.9 and GDP per capita is not less than 45% of the per capita GDP of the United States in 2017, it is considered to be a developed country; otherwise, it is considered to be a developing country. Based on this, we divided the sample countries into 23 developed countries and 12 developing countries. Columns 7 and 8 of Table 5 report the regression results for developed and developing countries, respectively. The explanatory variable in column 7 is positive at the 1% significance level, with a coefficient of −0.041, but the coefficient of column 8 is not significant, indicating that the application of industrial robots in developed countries can significantly reduce carbon intensity. However, the effects of carbon emission reduction in developing countries are not obvious. Compared to developing countries, the application of industrial robots in developed countries has better emission reduction effects. A possible reason for this is that developed countries have better innovation environments than developing countries and have stronger absorption capacities for emerging technologies. Thus, in developed countries, the environmental effects of the technologies could be better brought into play. Thus, H2 is verified. The carbon intensity reduction effects of industrial robot application are shown to have regional heterogeneity. In Section 4.4, explain the reasons for the regional differences from the perspective of the influence mechanism.

4.4. *Test of moderating mechanism*

To further understand why there is regional heterogeneity in the carbon emission reduction effects of industrial robots, we used the moderating effect model (Eq. (2)) to verify the moderating role of absorptive capacity. According to the test path in Eq. (2), absorptive capacity and the interaction terms of industrial robot application and absorptive capacity were gradually introduced. The regression results are shown in column 3 of Table 6. The regression coefficients of the independent variable ln *robot* and the interaction term ln *robot* × *ac* are both negative at the 1% significance level, indicating the existence of a moderating mechanism, i.e. high absorptive capacity is seen to positively increase the impact of industrial robot application on carbon intensity. Therefore, H3 is verified. This mechanism explains why industrial robot application in developed countries have better carbon reduction effects. Developed countries have a high absorptive capacity, which enables quicker adaptation to the changes brought about by the environment of innovation and technological advances. Therefore, the technology spill-over and absorption capacity of industrial robots in developed countries are stronger, allowing industrial robots to play a significant role in emission intensity reduction in developed countries. On the contrary, the R&D environment in developing countries is shown to be poor, and it is thus difficult for industries there to absorb and apply industrial robot technology and knowledge. This further limits the emission reduction effects, and thus the emission reduction effects in developing countries are shown to be relatively weak. Therefore, absorptive capacity plays a positive moderating role in the impact of industrial robot application on carbon intensity reduction.

4.5. *Test of the mediating mechanism*

To further verify the possible mediation mechanism of industrial robot application affecting carbon emission reduction, according to Eqs (3) and (4), the effect of *M* as an intermediary channel was tested using a three-step method. The regression results in Table 7 show that the influence of *M* is the intermediary mechanism of industrial robot application in promoting carbon emission reduction.

First, column 1 shows the results of the benchmark regression, and columns 2 and 3 provide the results of the mediation mechanism model. The estimation results in column 1 show that ln *robot* is negative at the 1% significance level, i.e. industrial robot application promotes carbon intensity reduction. Second, ln *robot* in column 2 is positive at the 1%

Table 6
The results of the moderating mechanism test.

Variable	(1)	(2)	(3)
ln *robot*	−0.009***	−0.008**	−0.023***
	(–2.59)	(–2.30)	(–4.25)
ac		−0.009	0.021
		(–0.90)	(1.58)
ln *robot* × *ac*			−0.016***
			(–3.60)
Control variables	YES	YES	YES
N	655	605	605
Adjusted R^2	0.918	0.910	0.912
F	915.269	681.696	627.889

Notes: *t*-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7
The results of the mediating mechanism test.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	ln *CI*	ln *gtfp*	ln *CI*	ln *CI*	ln *ei*	ln *CI*
ln *robot*	−0.009***	0.096***	−0.007**	−0.021***	−0.005***	−0.018***
	(−2.59)	(5.57)	(−2.12)	(−5.42)	(−5.63)	(−4.59)
M			−0.015*			0.569***
			(−1.93)			(3.38)
Control variables	YES	YES	YES	YES	YES	YES
N	655	654	654	671	671	671
Adjusted R^2	0.918	0.124	0.918	0.911	0.992	0.913
F	915.269	16.804	814.445	864.931	1.0e+04	782.852

Notes: t-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

significance level, while ln *gtfp* in column 3 is negative at the 10% significance level, indicating the existence of a mediating mechanism. Meanwhile, ln *robot* in column 3 is negative at the 5% significance level, indicating that the mediation effect of green total factor productivity is significant and that this mediation is partial. Therefore, as an intermediary variable, green total factor productivity is shown to play a partial intermediary role; the application of industrial robots indirectly reduces carbon intensity by promoting the improvement of green total factor productivity. Thus, *H4a* is verified, i.e. the application of industrial robots significantly reduces carbon intensity by promoting green total factor productivity.

Second, column 4 shows the results of the benchmark regression, and columns 5 and 6 provide the results of the mediation mechanism model. First, the estimation results in column 4 show that lnrobot is negative at the 1% significance level, i.e. industrial robot application promotes carbon intensity reduction. Second, lnrobot in column 5 is negative at the 1% significance level, while ln *ei* in column 6 is positive at the 1% significance level, indicating the existence of the mediating mechanism. Meanwhile, lnrobot in column 6 is negative at the 1% significance level, indicating that the mediation effect of energy intensity is significant and that this mediation is partial. Therefore, as an intermediary variable, energy intensity is shown to play a partial intermediary role; the application of industrial robots indirectly reduces carbon intensity by reducing energy intensity. Thus, *H4b* is verified, i.e. the application of industrial robots significantly reduces carbon intensity by reducing energy intensity.

4.6. Robustness tests of the influencing mechanism

Robustness tests for the influencing mechanisms were carried out. First, to test the robustness of the moderating mechanism, the moderating variable was replaced by the number of R&D personnel per million people (ln *researcher*). Regression results are shown in column 3 of Table 8. The estimated coefficients of the variables only changed slightly, and their coefficient symbols did not change, indicating that the model of the moderating mechanism in this paper is robust. Second, a robustness test for the mediating mechanism was carried out. The installed stock of industrial robots per capita was used to replace the installed stock of industrial robots per unit GDP, and the results are shown in Table 9. We found that the estimated coefficients of the main variables only changed slightly in numerical value, and the coefficient signs did not change substantially. The above analysis shows that the empirical results of the influencing mechanisms are robust.

Table 8
Robustness test I: moderating mechanism.

Variable	(1)	(2)	(3)
ln *robot*	−0.009***	−0.008*	−0.013***
	(−2.59)	(−1.91)	(−2.68)
ln *researcher*		−0.040***	−0.034**
		(−2.59)	(−2.18)
ln *robot* × ln *researcher*			−0.007**
			(−2.20)
Control variables	YES	YES	YES
N	655	519	519
Adjusted R^2	0.918	0.917	0.918
F	915.269	642.349	583.263

Notes: t-statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5. Conclusions, policy implications, and limitations

5.1. Conclusions

Existing research has focused more attention on the economic effects of industrial robot application, but research on the environmental effects remains insufficient. Based on the EKC model and using sample data from 35 countries from 1993 to 2017, this paper empirically tested the carbon emission reduction effects of industrial robot application and the attendant heterogeneity characteristics. Furthermore, the internal mechanism of industrial robot application affecting carbon intensity was explored using moderating and mediating mechanism tests. The conclusions reached were as follows. First, the application of industrial robots was found to significantly promote carbon intensity reduction. The application of industrial robots led to increased productivity, optimisation of factor structures, and technological innovations in production, which improved energy efficiency and reduced carbon intensity. Second, two-dimensional heterogeneity was found (in terms of application fields and countries) in the carbon emission reduction effects of industrial robot application. The application of industrial robots in manufacturing, agriculture, and electricity, gas, and water supply significantly promoted carbon intensity reduction, while the carbon emission reduction effects in the fields of construction, R&D, and education were not yet obvious. In addition, compared to developing countries, industrial robots had better emission reduction effects in developed countries. Third, a dual-channel mediating mechanism was found for the impact of industrial robot application on carbon emission reduction, where green total factor productivity and energy intensity played a mediating role; further, absorptive capacity played a moderating role. On the one hand, high absorptive capacity brought about a better environment for innovation and enhanced the effects of carbon emission reduction; on the other hand, the application of industrial robots promoted carbon emission reduction by positively influencing the improvement of green total factor productivity and energy intensity. The improvement of green total factor productivity was found to play a partially intermediary role in the carbon emission reduction effects of industrial robot application; the same was found for energy intensity.

5.2. Policy implications

Based on the above conclusions, we draw the following policy implications. First, to achieve the global carbon emission reduction target, countries should strive to promote the application of industrial robots in various fields and regions, improve the coverage of industrial robots, and give full play to the important role of industrial robots in carbon

Table 9
Robustness test II: mediating mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
	ln *CI*	ln *gtfp*	lnln*CI*	ln *CI*	ln *ei*	ln *CI*
ln *robot*	−0.009***	0.097***	−0.008**	−0.022***	−0.005***	−0.019***
	(–2.80)	(5.61)	(–2.33)	(–5.67)	(–5.39)	(–4.88)
M			−0.015*			0.567***
			(–1.88)			(3.38)
Control variables	YES	YES	YES	YES	YES	YES
N	655	654	654	671	671	671
Adjusted R^2	0.918	0.125	0.918	0.912	0.992	0.913
F	917.067	16.882	815.777	868.912	1.0e+04	786.446

Notes: t-statistics in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

emission reduction. Second, considering the two-dimensional heterogeneity of application fields and regions, the application of industrial robots in manufacturing, agriculture, electricity, gas, and water supply should be promoted first, and then extended to other fields. The application intensity of industrial robots varies greatly in different regions. Countries such as South Korea, Japan, and Germany should be taken as the benchmark for continuous improvement of the application intensity of industrial robots to better promote global carbon emission reduction. Third, considering the mechanism of industrial robot application affecting carbon emission reduction, efforts should be made to increase the absorptive capacity of various regions and industries, accelerate the spill-over and absorption of industrial robot technology, and provide a fruitful innovation environment for industrial robots to exert their carbon emission reduction effects. On the other hand, the improvement of green total factor productivity is the foundation of sustainable development. Countries should promote the improvement of green total factor productivity in various regions, give priority to the development of green low-carbon industries, transform traditional high energy-consuming industries, accelerate low-carbon industrial structures, and actively develop emerging industries with low-energy consumption and high added value that will not damage the environment while maintaining economic growth. Fourth, efforts should be made to use industrial robots as the carrier in order to promote the deep integration of emerging technologies with low-carbon industries, such as AI, big data, and fifth-generation mobile communication (5G).

5.3. Limitations

Despite the contributions of this article, there are some limitations. First, future research can decompose the carbon emission reduction effects of different types of industrial robots and compare the heterogeneous characteristics of the carbon emission reduction effects of different types of industrial robots. Second, this study only focused on the moderating effects of absorptive capacity; however, the carbon reduction effects of industrial robot application may also be affected by other variables, such as environmental regulation. Similarly, the improvement of green total factor productivity and energy intensity only play a partial mediating role, and other possible mediating mechanisms should be considered in future research. Finally, future research should not be limited to the national and regional level; it can be extended to the enterprise level to systematically describe the environmental effects and internal mechanisms of industrial robot application at various levels.

Author contribution

Yaya Li: Conceptualization, Methodology, Data curation, Writing – original draft. **Yuru Zhang**: Software, Data curation. **An Pan**: Conceptualization, Writing – review & editing. **Minchun Han**: Data curation, Writing – review & editing. **Eleonora Veglianti**: Data visualization.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data availability statement

Data is available from the authors upon request.

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Appendix

Table A1
Country list.

ISO3 code	Country name	ISO3 code	Country name
AUS	Australia	JPN	Japan
AUT	Austria	KOR	South Korea
BEL	Belgium	MEX	Mexico
BRA	Brazil	MYS	Malaysia
CAN	Canada	NLD	Netherlands
CHE	Switzerland	POL	Poland

(*continued on next page*)

Table A1 (*continued*)

ISO3 code	Country name	ISO3 code	Country name
CHN	China	PRT	Portugal
CZE	Czech Republic	ROU	Romania
DEU	Germany	RUS	Russia
DNK	Denmark	SGP	Singapore
ESP	Spain	SVK	Slovakia
FIN	Finland	SWE	Sweden
FRA	France	THA	Thailand
GBR	United Kingdom	TUR	Turkey
HUN	Hungary	USA	America
IDN	Indonesia	VNM	Vietnam
IND	India	ZAF	South Africa
ITA	Italy		

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