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Research Article

Carbon Emission Performance of Robot Application: Influencing Mechanisms and Heterogeneity Characteristics

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With the new round of technological revolution and industrial change, industrial robots have an important role to play in the fight against climate change and in achieving the goal of "carbon peaking and carbon neutrality." Based on the panel data of the application level of industrial robots in Shanghai and Shenzhen A-share listed companies from 2011 to 2019, this study examines the impact of industrial robots on carbon emission performance and discusses specific ways industrial robots can affect carbon emission performance. The results show that industrial robots can significantly improve carbon emission performance. Mechanism analysis shows that industrial robots can improve carbon emission performance through productivity and competition effects. Heterogeneity analysis shows that the application effect of industrial robots varies based on enterprise nature, regional location, and carbon emission intensity. The study can make potential contributions. First, this study systematically analyzes the impact of artificial intelligence technology on carbon emissions from the perspective of carbon emission performance, which can supplement the research on carbon emission performance. Second, this study calculates application levels of artificial intelligence technology at the enterprise level and uses panel and linear intermediary effect models to analyze the transmission mechanism between the application of artificial intelligence technology and carbon emission performance. Third, the heterogeneity analysis results can provide empirical support for formulating differentiated artificial intelligence carbon reduction strategies and be used as a reference to further promote the green development of artificial intelligence technology.

1. Introduction

With the rapid development of the global economy, the greenhouse effect is becoming increasingly severe and poses a serious threat to human development. Therefore, the ecological environment has become a global issue. How to effectively control carbon dioxide and other greenhouse gas emissions and slow down the global warming process has attracted great attention from countries worldwide. President Xi Jinping noted at the 75th Session of the United Nations General Assembly that China would adopt stronger policies and measures to reach its peak total carbon emissions by 2030 and achieve carbon neutrality by 2060. China's economic success in the past decades has been attributed to the dividends of industrialization; however, the crude and energy-consuming industrial development model has placed enormous pressure on the ecological environment and posed major challenges to achieving the "double carbon" target.

To this end, the 20th National Congress of the Communist Party of China proposed accelerating the green transformation of development and promoting green, low-carbon economic, and social development. In the digital economy era, AI technology innovation and major technological breakthroughs have given developing countries a different development path and connotation in the industrialization process. Moreover, China's 14th Five-Year Plan and outline of the 2035 Vision proposed to "promote the clean, low-carbon and safe, and efficient use of energy and deeply promote the low-carbon transformation in industry, construction, and transportation," while simultaneously requesting to "take the digital transformation as a whole to drive the production methods, the development of the economy, and the development of the society. Digital transformation as a whole drives changes in production, lifestyle, and governance." This indicates how to accelerate the deep integration of the digital and real economies, thereby promoting green and low-carbon industrial development. Therefore, in the context of achieving the "double carbon" goal and promoting high-quality economic development, exploring the impact mechanism of industrial intelligent robots on carbon emission performance is helpful for not only exploring an effective path for improving carbon emission performance from the perspective of AI technology innovation but also eliminating inefficient resource use and heavy environmental pollution in developing countries. This would also have great theoretical significance and practical value for accelerating the green transformation and upgrading of industrial structure; building a green, low-carbon, and cyclic economic system; and achieving the "double carbon" goal.

Achieving green, low-carbon transformational development through digital technology applications has become an inevitable choice for China to build new development patterns and adapt to new developmental stages. The carbon emission reduction effect of digital technology applications is not only highly valued by the state but has also received increasing attention from academia. Extant literature reflects two main representative views on the impact of digital technology applications on carbon emissions. One view is that digital technology applications have a positive impact on carbon emission reduction, and both traditional theoretical and empirical studies emphasize that technological progress is an important driving factor for enhancing carbon emission efficiency. In addition, the innovation spillover effect of digital technology applications will optimize industrial structure, promote the transformation of labor- and resource-intensive industries into technology-intensive industries, promote the leap of industrial structure, and realize an advanced industrial structure. An advanced industrial structure will also promote production factor reallocation among sectors, leading to the flow of production factors from low-productivity to high-productivity sectors and resulting in an advanced industrial structure and "structural dividend," thereby optimizing the energy consumption structure, improving the efficiency of factors and resources, and ultimately improving carbon emission efficiency.

Li et al. [1] used spatial panel data from Chinese provinces and cities and found that increasing the degree of digitization plays a positive role in reducing carbon emissions. Another view is that technological advances not only improve energy efficiency and save energy but also reduce the cost and price of unit products, promote economic growth, stimulate product market demand, and bring more energy consumption [2]. When the energy savings generated by applying digital technology exceed energy demand, an "energy rebound effect" with occur, resulting in increased energy consumption and reduced carbon emission efficiency. Gu et al. [3] found three mechanisms of technological progress in carbon emissions: the direct, rebound, and technological effects. Although technological progress is regarded as an important power source for solving the profound internal contradiction between economic growth and carbon emission reduction, it has been agreed by academic circles [4]. However, previous research has usually deconstructed the role of technological progress in carbon emissions from the perspective of nonembodied technological progress, such as green innovation and green total factor productivity, while in reality, technological progress is often manifested as embodied technological progress. Nonembodied technological progress cannot suitably reflect the actual effects of technological progress on carbon emissions. Capital-embodied technological progress combines capital accumulation with technological progress and changes the original factor structure, which is regarded as the key driving force for improving energy efficiency and reducing carbon emissions [5]. Therefore, whether digital technology can improve enterprises' carbon emission performance is an ambiguous issue in theory that requires more detailed and comprehensive empirical testing.

In practice, issues related to digital technology and carbon emissions are particularly significant. As a developing country, China has gained latecomer advantages in the digital technology field. If digital technology can improve enterprises' carbon emission performance and promote the "double carbon" goal, then China is expected to embark on a new development path different from that of developed countries through digital technology, and this valuable experience will become an important part of the "governance of China," spread to more developing countries, and significantly contribute to global green development.

Therefore, this study examines the impact of digital technology on corporate carbon emission performance at the firm level. Using data on Chinese A-share listed companies from 2011 to 2019, we compile industrial robot usage data at the enterprise level and adopt econometric methods to draw the following conclusions. First, improving the level of robot use will significantly promote manufacturing enterprises' carbon emission performance, thereby accelerating the manufacturing enterprises' low-carbon transformation. These findings are further strengthened by the results of a series of robustness tests based on the method of tool variables. Second, a mechanism analysis shows that the application of industrial intelligent robots has productivity and competition effects, which will encourage manufacturing enterprises to improve their carbon emission performance through equipment upgrades. Third, a heterogeneity analysis shows that improving robot use will promote manufacturing enterprises' carbon emission performance in the two types of regions through productivity and competition effects. Improving robot use levels plays a significant role in promoting the carbon emission performance of state-owned enterprises, but the effect is not significant in nonstate-owned enterprises. The productivity and competition effects of robot use are more significant in state-owned enterprises and form the mechanism through which state-owned enterprises improve their carbon emission performance. Compared with low-carbon emission industries, the promotion effect of improved robot use levels on manufacturing enterprises' carbon emission performance and the productivity effect of robot use are more significant in high-carbon emission industries. The competition effect is significant for both types of enterprises.

Recently, scholars have increased their focus on the impact of digital technology automation on carbon emissions. Felipe [6] creatively divided technological progress into capital manifestation and nonembodiment, and combined the role of technology and its proportion in great-leap-forward development to propose an interpretation framework of capital-based technological progress, providing an analytical benchmark for examining the impact of artificial intelligence technology on carbon emissions. Along this framework, some scholars have discussed the impact of digital technology on industrial transformation and upgrading and low-carbon development [5, 7–10].

Compared with the existing literature, the contributions of this study are mainly reflected in three aspects.

First, from the perspective of carbon emission performance, this study systematically analyzes the impact of artificial intelligence technology on carbon emissions. The existing literature mostly focuses on the relationship between digital technology and carbon emissions, and artificial intelligence is the core of digital technology. The analysis of artificial intelligence and carbon emission performance, as represented by industrial intelligent robots, is still in its infancy. Thus, this study can provide a useful supplement to the existing literature. Second, by calculating the application level of artificial intelligence technology at the enterprise level and using panel semiparametric and linear intermediary effect models to analyze the transmission mechanism between artificial intelligence technology application and carbon emission performance, this study reveals the indirect mechanism through which artificial intelligence technology can promote improved carbon emission performance. Third, based on the impact of artificial intelligence technology on carbon emission performance, this study analyzes the heterogeneity from the aspects of geographical location, ownership structure, and industry carbon emission degree, and the conclusions can provide empirical support in formulating differentiated artificial intelligence carbon emission reduction strategies.

The remainder of this paper is arranged as follows: the second part is theoretical analysis and hypothesis formulation, the third part describes the data sources and research design, the fourth part presents the benchmark empirical results and robustness test, the fifth part is impact mechanism identification and heterogeneity analysis, and the sixth part provides discussion, theoretical and practical implications and limitations for research, the seventh part provides the research conclusions.

2. Theoretical Analysis and Hypothesis Formulation

2.1. Analysis of the Factors Influencing Carbon Emission Performance. Ang [11] noted that effectively promoting clean technology innovation and improving carbon emission performance are particularly crucial for Chinese industries to achieve low-carbon development to better fulfill their carbon emission reduction responsibilities. Through a review of the relevant literature, we find that previous research has mainly explored the factors influencing carbon emissions from five perspectives: economic development, industrial policy, population, external shocks, and technological innovation.

In terms of economic development, researchers have thoroughly explored the relationship between carbon emissions and economic development factors, such as economic growth [12, 13], financial development [14], international trade [15–17], and fixed-asset investment [18]. In terms of economic growth, Nasir et al. [14] found a significant long-term relationship between financial and economic development and environmental degradation. However, two competing perspectives exist on FDI and trade: the pollution refuge and pollution halo hypotheses. The argument in favor of the pollution refuge hypothesis is that FDI leads to environmental degradation because of the host country's desire to attract FDI by relaxing environmental regulations. However, studies supporting the pollution halo hypothesis argue that FDI and trade bring about advanced technology and good management practices that help reduce carbon emissions. Much academic research has been conducted along these two lines; however, no consistent findings have been obtained. Although the shift in the energy mix from nonrenewable to renewable energy and the reduction of solid fuels have contributed to reduced air pollution [19–21], increases in total energy use have led to higher emissions [22] and energy intensity has played a similar role [23, 24]. Regarding infrastructure investment, Wang et al. [18] showed that it leads to increased air pollution. Wang et al. [25] found the digital financial inclusion positively impacts CO_2 emissions of local cities, but negatively impacts neighboring cities, and breadth of coverage and depth of use significantly correlates with CO_2 emissions.

Regarding industrial policies, Chien et al. [19] found that environmental taxes play a positive role in reducing carbon emissions. Neves et al. [26] and Khan et al. [27] found that environmental regulations are effective in reducing carbon dioxide emissions. Based on an analysis of the spatial aggregation characteristics of regional carbon emission intensity, Liu et al. [28] found that the influence channel of environmental regulations on carbon emission reduction is nonlinear under the influence of spatial spillover effects, and this nonlinearity is insignificant or even negative in the immediate period, but significantly positive in the long term. Wang et al. [25] found that diverse environmental regulations are needed to promote sustainable green development and to further expand the theoretical and practical exploration of political connections on firm pollution. In another paper, Wang et al. [29] found that firm political connections have a promoting effect on carbon emissions of industrial enterprises. The moderating mechanism analysis demonstrates that the mitigation effect is better in the command-and-control environmental regulation (CCI) than that in the market-based environmental regulation (MBI).

Among population studies, Cole and Neumayer [30] found an inverted U-shaped relationship between population growth and pollutant emissions, with no significant effects of urbanization and housing area per capita on carbon emissions. They also found that the relationship between population agglomeration and per capita carbon emissions has an inverted N-shaped curve; per capita carbon emissions, population agglomeration, and economic development have spatial spillover effects; and an increase in per capita carbon emissions in neighboring provinces will aggravate increases in local emissions. The spatial diffusion effect of population concentration and economic development is conducive to improving development efficiency and promoting global emission reduction.

Regarding external shocks, researchers have mainly examined the dimensions of financial crises and public health emergencies (e.g., novel coronavirus outbreak). Liu and Song [31] compared the differences in firms' carbon emission intensity before and after the financial crisis, reporting an overall increase in carbon emissions after the crisis, and then compared the effects of different epidemic prevention policies in China, the U.S., India, and the EU in response to the novel coronavirus epidemic on national carbon emissions. Han et al. [32] studied the impact of the novel coronavirus epidemic on carbon intensity reduction in China based on a dynamic economic-energy-environmental CGE model. The results indicated that the larger the epidemic shock is in the short term, the less favorable it is to carbon intensity reduction. The impact of the epidemic on the marginal abatement cost of carbon was more significant in the short term when achieving a set carbon intensity reduction target; however, the marginal abatement cost of carbon was found to converge across scenarios in the long term. Thus, the epidemic did not significantly affect the carbon peak time point in China but will significantly reduce the carbon peak. Cheng et al. [33] indicated that local government and energy users to mitigate the negative impacts from the expected or unexpected fluctuations in the oil and the neighboring natural gas markets, which will enact appropriate state-level price discovery and energy policy and investment decision makings.

In terms of technological innovation, Ehrlich and Holdren [34] and Grossman and Krueger [35] were among the first to develop a theoretical framework to analyze the relationship between technological progress and carbon emissions, arguing that technological progress is a solution to the problem of environmental pollution caused by population growth. Afonso et al. [36] noted that technological development is a sufficient condition for reducing carbon emissions; however, Vinuesa et al. [2] argued that technological development cannot completely solve the carbon emission problem. Researchers cannot reach a consensus on the relationship between technological progress and carbon emissions for two reasons. First, they cannot clearly identify the mechanism underlying the effect of technological progress on carbon emissions, and second, the effect of technological progress on carbon emissions is influenced by other factors. By analyzing macro-level data, such as data from provinces and cities, Chinese scholars have found that technological progress can significantly reduce enterprises' carbon emissions and contribute to transforming and upgrading industrial structure as well as the green transformation of national economic development [37–40]. Sun et al. [41] found that the development of information and communication technology could alleviate carbon emissions on a global scale.

In summary, previous researchers have conducted several theoretical and practical explorations of the influencing factors of carbon emissions and obtained research results, providing a reference for accurately understanding the relationship between artificial intelligence and carbon emissions. However, it cannot be ignored that previous studies have mostly focused on the relationship between technology and carbon emissions, and the analysis of industrial robots and carbon emissions performance from a microlevel is still in its infancy. Compared with existing research, this study can expand the current literature on three points.

First, artificial intelligence, as represented by industrial intelligent robots, is a relatively new concept. Currently, research on the relationship between artificial intelligence and carbon emissions has mainly focused on regions and industries at the meso level. Few scholars have determined the application level of industrial intelligent robots at the microlevel and analyzed the impact on carbon emission performance. Second, although industrial intelligent robots can affect corporate carbon emission performance through various channels, no researchers have yet conducted a systematic analysis of the impact mechanism of industrial robots on carbon emission performance. Based on an analysis of existing literature, we identify the two potential mechanisms of productivity and competition effects and tested them using a mesomeric effect model. Third, most studies have not effectively addressed the issue of mutual causality. Based on the effective control of endogeneity problems caused by mutual causality through a propensity score matching (PSM)-triple difference (DDD) model, this study verifies the impact of industrial robot application on corporate carbon emissions.

2.2. Robot Application and Carbon Emission Performance. Industrial robots are a key enabling technology for Industry 4.0 and the artificial intelligence revolution, particularly in terms of the smart, low-carbon transformation of traditional industries. Scientific and technological progress is the key to energy conservation and emission reduction [42], core driver of long-term stable economic growth, and fundamental way to promote the transformation of the economic growth mode [43]. Energy consumption has long shown an upward trend, which has placed substantial pressure on environmental protection and carbon emission control [44]. Although energy use efficiency has increased substantially in recent years, it remains at a relatively backward level, and the gap is obvious compared with developed countries. The direct result of low energy usage is reduced efficiency, which is hindered by energy cleaning and high pollution emissions [45, 46]. China's natural resource reserves are characterized as "rich in coal, poor in oil, and low in gas," and the pollution from coal combustion is the most serious among all resources. Although China has recently adopted fiscal policies to guide enterprises' production and residents' lifestyles toward clean energy consumption (e.g., wind, nuclear, and solar), transforming new energy sources into convenient energy for production and living generally requires specialized technologies.

The large-scale application of robots can improve industrial technology levels. The application of robots will lead to a shift toward "cleaner production," and the increased automation will reduce the factor input per unit of output and decrease the optimal carbon emission intensity of enterprises, thereby reducing the total level of carbon emissions and improving enterprises' carbon emission performance. Furthermore, according to the Porter hypothesis, technological progress can stimulate the "innovation compensation" effect, and production technology progress can increase economic output while maintaining carbon emissions or reduce carbon emissions without changing economic output, thereby achieving carbon emission efficiency. In this study, this mechanism channel is referred to as the "productivity effect."

In addition, the green transformation of enterprises is itself a process of reallocating resources in the direction of "greening," and the market mechanism plays an important role in guiding enterprises to actively engage in green and low-carbon transformation. The market mechanism of elimination of the fittest can not only force inefficient enterprises out of the market but also attract high-efficiency and new enterprises to enter the market, effectively guiding the flow of green production resources from low-environmental efficiency enterprises to high-environmental efficiency enterprises, achieving optimal resource allocation among enterprises by accelerating their turnover to improve social production efficiency [42]. Using industrial intelligent robots can significantly reduce enterprises' labor costs, and enterprises can compete in the market through cost leadership strategy, squeezing out enterprises with low productivity and green competitiveness, thus promoting improved carbon emission performance. In this study, this mechanism channel is referred to as the "competition effect." Based on the above analysis, the following hypothesis is proposed:

H1: The application of robots will significantly improve the carbon emission efficiency of enterprises in the manufacturing industry.

3. Data Sources and Study Design

3.1. Data Sources and Sample Selection. Drawing from existing research practices, this study uses two main data sources. The first is the Global Robot Database, published by the International Federation of Robotics (IFR), which provides data on robots in 17 broad categories of industries in more than 70 countries and regions worldwide, and is currently the most authoritative database on robot application that has been widely used in related research [47]. The second is the China Energy Statistical Yearbook, published by the National Bureau of Statistics, which reports the annual consumption of different types of fossil fuels, such as coal, oil, and diesel, in each province of China and provides a database for estimating the carbon performance of Chinese industries and enterprises. Additionally, data on control variables, return on net assets, firm size, and firm nature were obtained from the CSMAR database. This study's sample includes 9,244 observations of Chinese manufacturing companies listed on Shanghai and Shenzhen A-shares, from 2011 to 2019, used to estimate and test the econometric model.

3.2. Measurement Model Setting. Most researchers have used panel models to explore the economic consequences of industrial robots [1, 47]. For the core question of this study, examining the direct effects of industrial robot use on carbon emission performance and the productivity, and competition effects, we construct an econometric model as follows:

$$\text{carbon}_{i,t} = \alpha_0 + \alpha_1 \text{exposure}_{i,t} + \alpha_2 X_{i,t} + \lambda_{i,t} + \varphi_{i,t} + \epsilon, \tag{1}$$

where i represents the firm and t represents the year. The explanatory variable carbon denotes a firm's carbon performance and the explanatory variable exposure denotes the level of robot application in manufacturing firms. To avoid bias from omitting explanatory variable, a set of firm-level control variables is included in X. To avoid the problem of missing explanatory variables caused by unobservable factors, this study also controls for industry and year fixed effects; ξ is a random disturbance term. The main concern of this study is the estimated coefficient of the core explanatory variable exposure α_2; if the estimated value of α_2 is significantly positive, it indicates that robot application in manufacturing firms helps improve firms' carbon performance.

Furthermore, the mediation effect analysis of Baron and Kenny [48] is used to test whether the productivity and competition effects are the mediation mechanism of robot application promoting carbon emission performance. To verify this mediation mechanism, we construct the following models:

$$\begin{aligned} M_{i,t} = {} & \alpha_0 + \alpha_1 \text{exposure}_{i,t} + \alpha_2 X_{i,t} \\ & + \lambda_{i,t} + \varphi_{i,t} + \epsilon, \end{aligned} \tag{2}$$

$$\begin{aligned} \text{carbon}_{i,t} = {} & \alpha_0 + \alpha_1 \text{exposure}_{i,t} + \alpha_2 M_{i,t} + \alpha_3 X_{i,t} \\ & + \lambda_{i,t} + \varphi_{i,t} + \epsilon. \end{aligned} \tag{3}$$

3.3. Variable Setting

3.3.1. Manufacturing Carbon Performance. The existing literature on carbon performance is relatively scattered. Mielnik et al. [49] first proposed using carbon emissions per unit of energy consumption as an evaluation criterion to measure climate change. Clarkson et al. [50] used the inverse of total carbon emissions per million dollars of net sales as a proxy variable for carbon performance. Domestic and international studies on carbon emissions are more often conducted at the macro level, such as national, industrial, and regional studies, and less research has been conducted at the microlevel. Considering the availability of microlevel data, this study draws on Busch et al. [51] who used revenue per unit of carbon emissions as an indicator of corporate carbon performance, with larger values indicating better carbon performance. Because the carbon emission data in the China Energy Statistical Yearbook are at the industry level, we estimate enterprises' carbon emissions by industry carbon emissions with the help of enterprise operating costs. Thus, carbon performance is estimated as follows:

$$\text{carbon emission performance} = \frac{\text{enterprise operating income}}{(\text{industry carbon emissions}/\text{industry main business costs} + 1) \times \text{enterprise operating costs}}. \tag{4}$$

3.3.2. Robot Application Levels in Enterprises. Identifying and measuring firm-level robot application is difficult. This study draws on industry-level robot data in China and microdata of Chinese listed manufacturing companies to construct a robot application based on the "Bartik instrumental variable" [47, 52, 53]. A robot application was constructed at the enterprise level in China to measure the enterprises' actual artificial intelligence technology application levels.

Industrial robot import information is obtained from enterprise product trade data provided by the China Customs Trade Database of General Administration of Customs of China. This database contains product-level information for each trading enterprise, including trade prices, quantities, and amounts. Moreover, this database provides HS eight-digit code information for products, which provides the conditions for identifying enterprises' imports of industrial robots. The enterprise-level data are mainly obtained from the Chinese National Bureau of Statistics' Database of Chinese Industrial Enterprises. This database covers all state-owned enterprises and some nonstate-owned enterprises (with a main business revenue of 5 million and above). The survey process of this database has a problem with distorted sample information caused by errors in some enterprises' reports; therefore, this study draws on existing research practices to screen the initial sample using the following process. First, financial and insurance firms are removed, due to different regulatory environments. Second, enterprises with less than eight employees are excluded. Third, given that the national industry classification standard used in the database was changed in 2002 and 2011, in this study, the industry classification code is unified to the 2002 national industry classification standard for all years. Fourth, based on the existing international GAAP, enterprises with current assets larger than total assets, fixed assets larger than total assets, net fixed assets larger than total assets, missing enterprise codes, and unreasonable establishment times are deleted from the sample.

Then, this study adopts the "two-step method" to match variables such as robot imports calculated from the China Industrial Enterprise Database and China Customs Trade Database, referring to Yu [54]. Specifically, enterprise name and year are first matched one-to-one, and then, using the enterprise location postal code and last seven digits of the phone number, the samples that were not successfully merged according to enterprise name are merged again. To ensure accurate merging, the second merging is filtered according to the following conditions: (1) missing postal code or phone number, (2) unreasonable postal code, and (3) unreasonable phone number. Finally, a comprehensive database containing enterprises' basic information, financial operation information, and import/export trade information is obtained.

3.3.3. Control Variables. This study refers to Acemoglu and Restrepo [47], Li et al. [1], and Shao et al. [4] to select control variables at the firm microlevel. These variables include two positions in one (*separation*, whether firms' chairperson and general manager are the same individual); the shareholding ratio of the first largest shareholder (*large*, the number of shares held by the first largest shareholder divided by the number of outstanding shares); Tobin's q (to measure firm growth), book-to-market ratio (MB, the book value of the firm divided by the market value); net cash flow from operating activities (*Pc*, divided by the number of outstanding shares); net cash flow from operating activities (*Pcf*, the cash flow from operating activities divided by the total assets of the firm); firm size (*size*, the natural logarithm of the firms' total assets); firm nature (state-owned versus nonstate-owned enterprises); and analysts (Anaattention, the natural logarithm of the number of analysts following the company).

4. Baseline Empirical Results and Robustness Tests

4.1. Baseline Regression Results. According to the setting of econometric (1), this study estimates the impact of robot application on carbon performance in the manufacturing industry, by using regressions without and with control variables included. Meanwhile, to avoid possible omitted variables, heteroscedasticity, and serial correlation problems in the estimation, year and industry fixed effects are included in the estimation process, and robust standard deviations are used to ensure the robustness of the estimation. The specific estimation results are shown in Table 1. The results in column (1) of Table 1, which only includes robot application without controlling for year and industry fixed effects, show that the impact of robot application on manufacturing firms' carbon performance is significantly positive at the 1% level, which is consistent with the research hypothesis. The results show that the application of robots significantly promotes carbon performance; thus, H1 is supported. In Table 1, the estimates in column (2) remain robust after including industry and year fixed effects, column (3) after including control variables and not controlling for year and industry fixed effects, and column (4) after including control variables and controlling for both year and industry fixed effects.

From the perspective of economic significance, for every standard deviation increase in the application level of industrial intelligent robots, enterprises' carbon emission performance increases by 0.147 percentage points, equivalent to 2.73% of the average carbon emission performance. This supports the hypothesis that the application of industrial intelligent robots significantly improves enterprises' carbon emission performance. Notably, some foreign literature at the national and industrial levels posits that the application of industrial intelligent robots will reduce carbon emission performance. This study provides different evidence based on conclusions at the enterprise level, which may reflect the phased laws of China's artificial intelligence technology development and the particularity of enterprise carbon emission performance.

Regarding the control variables, a significant positive relationship is observed between the net cash flow from operating activities (Pcf) and carbon emission performance. In China, manufacturing enterprises face a large financing constraint dilemma, and the net cash flow from operating activities reflects the profitability and capital adequacy of enterprises from the side. The procurement of industrial robots requires high costs, and enterprises without sufficient capital will not invest in technology; thus, the more abundant their capital, the more likely enterprises are to upgrade their equipment by introducing new technologies Therefore, more capital-rich enterprises are likely to upgrade their equipment by introducing new technologies, which will promote industrial upgrading and transformation, and generally help improve the carbon performance of enterprises and related industries. The larger the size of an enterprise, the higher the likelihood it will use more robotic equipment when it upgrades its technology for low-carbon transformation, and the scale effect of the application of robots will improve the efficiency of enterprise resource utilization, thereby reducing enterprises' carbon performance.

4.2. Robustness Test

4.2.1. Controlling Endogeneity Problems. Effective control of potential endogeneity problems is key to accurately identifying the causal relationship between robot application and manufacturing firms' carbon emission performance. Bidirectional causality is the most important cause of the endogeneity problem in identifying the causal relationship between robot application and carbon performance. As the level of environmental regulation in China increases, regions with more carbon emissions from manufacturing industries will face stronger pressure to reduce carbon emissions, prompting local governments to use financial subsidies and tax incentives to encourage enterprises to introduce robot equipment to save energy and reduce emissions in manufacturing production processes. Therefore, the level of carbon emissions from regional manufacturing industries will also affect the local level of robot application, resulting in a reverse causal relationship between robot application and carbon emission performance. Based on this, and drawing on Du and Lin [55], this study uses the density of robot installation in the Czech Republic, which is most similar to the density of robot installation in the manufacturing industry in China during the same period, as an instrumental variable for regression analysis.

As Table 2 shows, the F-test values of the first-stage regression equations are all greater than 10 and pass the 1% significance test, indicating that the instrumental variables satisfy the correlation requirements. However, the effect of the instrumental variables on the carbon emission performance of the manufacturing industry is not significant, indicating that the instrumental variables do not directly firms' carbon emission performance. Thus, the exogeneity requirement of the instrumental variables is satisfied. Furthermore, the LM test results also imply that the instrumental variable is not underidentified and is reasonably valid. The regression coefficient of artificial intelligence penetration remains significantly negative after adopting this instrumental variable to effectively control for the endogeneity problem, indicating that the promotional effect of an increase in robot application level on carbon emission performance in manufacturing enterprises is robust.

In addition, considering that changes in any economic factor are inherently consistent and the results of the previous period usually have an impact on the results of the later period [1], there may be a lagged effect on the changes in manufacturing firms' carbon emission performance after the application of robots. Therefore, this study uses the generalized method of moments to estimate a dynamic panel data model for robustness analysis of potential endogeneity issues. The regression results in column (1) of Table 3 indicate that this study's findings remain robust.

4.2.2. Replace Key Metrics. To further verify the reliability of the model and avoid one-sidedness in the research findings due to over-reliance on a single metric, this study uses the total carbon emission data from the high-resolution global carbon dioxide emission database released by the team of academician Tao Shu of Peking University in the process of measuring carbon emission performance, resubstitutes it into the formula for calculating carbon emission performance, and records it as *carbon_new1*. The results are shown in column (1) of Table 4. The direction and significance of each coefficient are consistent with the benchmark regression results; therefore, the model is shown to be robust. Drawing on the practice of Li et al. [1] who used the ratio of total factor productivity growth to GDP growth in each city per calendar year as a proxy indicator for the degree of regional low-carbon transition development, we rerun the regression analysis of the ratio of total factor productivity

Table 1: Regression results of robots application and carbon performance.

Variables	(1) Carbon	(2) Carbon	(3) Carbon	(4) Carbon
Exposure	0.005*** (0.000)	0.004*** (0.000)	0.003*** (0.000)	0.002*** (0.000)
Separation			−0.004* (0.002)	−0.002 (0.002)
Large			−0.006*** (0.001)	−0.006*** (0.001)
TobinQ			−0.015 (0.014)	−0.014 (0.014)
MB			−0.102 (0.078)	0.065 (0.078)
SOE			−0.397*** (0.058)	−0.254*** (0.089)
Pcf			0.288* (0.152)	0.469*** (0.151)
Size			0.250*** (0.017)	0.364*** (0.019)
Anaattention			0.001 (0.001)	0.000 (0.001)
Constant	4.911*** (0.035)	4.927*** (0.009)	−0.161 (0.378)	−2.815*** (0.437)
Ind/year	No	Yes	No	Yes
Observations	9,244	9,244	9,244	9,244
R-squared	0.081	0.070	0.124	0.137
Number of stkcd	1,122	1,122	1,095	1,095

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

Table 2: Robust tests for the benchmark regression.

Dependent variable	Carbon	
Independent variable	(1)	(2)
IV	0.017 (0.024)	
Exposure		0.346*** (0.117)
Sample size	8523	8523
Underidentification test		
LM test value	—	17.223
(p)	—	$p \leq 0.001$
Weak instrumental variable test		
First stage F-test value	—	17.341
(p)	—	$p \leq 0.001$

Note. ***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively; robustness tests were performed controlling for relevant control variables, time fixed effects, and industry fixed effects.

Table 3: The results of SYS-GMM analysis.

Variables	(1) Sys-gmm Carbon
Exposure	0.002***(0.000)
L. carbon	0.784*** (0.008)
Separation	−0.003** (0.001)
Large	−0.001 (0.001)
Tobinq	−0.033** (0.015)
MB	−0.633*** (0.083)
SOE	−0.071*** (0.024)
Pcf	−0.192 (0.166)
Size	0.065*** (0.012)
Anaattention	−0.003** (0.001)
Constant	0.183 (0.258)
Ind/year	Yes
R-squared	0.1126
Observations	8,870
Number of stkcd	1,095

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

Table 4: Robustness checks of baseline regression.

Variables	(1) Carbon_new1	(2) Carbon_new2
Exposure	0.0001** (0.000)	0.001*** (0.000)
Separation	0.000 (0.002)	−0.001** (0.000)
Large	−0.001 (0.001)	−0.001*** (0.000)
Tobinq	0.021 (0.014)	−0.004 (0.003)
MB	0.046 (0.078)	−0.043** (0.018)
SOE	0.263*** (0.060)	−0.074*** (0.012)
Pcf	0.073 (0.151)	0.044 (0.036)
Size	0.040** (0.017)	0.040*** (0.004)
Anaattention	−0.000 (0.001)	0.000 (0.000)
Constant	6.976*** (0.381)	0.965*** (0.083)
Ind/year	Yes	Yes
R-squared	0.2313	0.1982
Observations	6,997	6,997
Number of stkcd	1,095	1,095

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

growth to main business income growth (*carbon_new2*) of manufacturing enterprises as a proxy indicator for enterprises' carbon emission performance. The results are shown in column (2) of Table 4 and again indicate that the application of robots will promote manufacturing enterprises' carbon emission performance.

4.2.3. PSM-DDD Analysis. To mitigate the problem of missing variables and reverse causality, we use regional digitization policy shocks as a natural experiment for PSM-DDD estimation. To promote digital transformation, in December 2015, the Ministry of Industry and Information Technology identified 25 National Smart Development Model Cities that should accelerate information infrastructure upgrades and technological innovation, promote the transformation and upgrading of the information industry, and increase the level of public service networking.

We believe this policy can promote the application of artificial intelligence technology in local enterprises. Therefore, we use these cities as a treatment group and the other cities as a control group.

First, to overcome the bias caused by differences in the initial conditions of enterprises in the treatment and control group cities, we use PSM to perform one-to-one intracaliper nearest neighbor matching for enterprises in the treatment and control group cities. All matched covariates are control variables in the baseline regression. Then, from the perspective of building smart demonstration cities to promote digital transformation, which may improve enterprises' carbon emission performance, we constructed a DDD model containing the three dimensions of city, industry, and year to identify the causal relationship between digital transformation and corporate labor income share. Specifically, based on a comparison of the dual differences between the treatment and control group cities before and after the policy, a third difference is added by introducing industry attributes. The method of introducing industry factors into the third difference has been widely applied in recent research. Compared to the double difference method, which can only control for the fixed effects of two dimensions (enterprise and year), the DDD method can control for cities × fixed year effect, industry × the fixed effect of the year, excluding the influence of omitted variables that change over time at the city and industry levels. This helps to eliminate the interference of other policy shocks implemented for cities or industries [40]. The model is set as follows:

$$\begin{aligned}\text{Carbon}_{\text{ijpt}} = \beta_1 \text{Treatcity}_p * \text{Post} * \text{Digi}_j + \gamma X_{\text{ipjt}} \\ + \varepsilon_i + \varepsilon_{\text{jt}} + \varepsilon_{\text{pt}} + \delta_{\text{ipjt}},\end{aligned} \tag{5}$$

where the subscript i represents the enterprise, j represents the industry, p represents the city, and t represents the year. The explained variables $\text{Carbon}_{\text{ijpt}}$ represent the carbon emission performance at the enterprise level. The key explanatory variable is $\text{Treatcity}_p * \text{Post} * \text{Digi}_j$; among them, Treatcity_p is the smart city dummy variable, which takes a value of 1 when the enterprise is in a smart city, and 0 otherwise; *Post* is the policy year dummy variable, which takes a value of 1 when the current year is after 2015, and 0 otherwise; and Digi is the digital industry dummy variable, which takes the value of 1 when the enterprise is in an industry for which the average digitization degree exceeds the average of all industries, and 0 otherwise. The coefficient β_1 is a DDD estimator, indicating the impact of smart city demonstration construction on the carbon emission performance of the digital industry. The regression also controls for interaction Treatcity_p with Digi_j, city × year fixed effect ε_{pt}, and industry × year fixed effect ε_{jt}. Under the cross-fixation effect, the individual terms of Treatcity_p, Digi_j, and Post, and the interaction terms Treatcity_p and Digi_j with Post will be absorbed by the fixed effect and do not need to be controlled. In addition, the robust standard error of clustering at the urban level is used in the regression.

Table 5 reports the regression results of the PSM-DDD estimation. Column (1) shows the basic regression results, and the DDD estimation coefficient is significantly positive at the 1% level, indicating that the construction of smart demonstration cities improved the carbon emission performance of the digital industry. This indicates the role of digital construction in improving carbon emission performance. Column (2) lists the results of robustness tests, in which we removed the sample in the pilot city list but not in the final established demonstration city, and the estimation result remained stable.

Table 5: The results of PSM-DDD model.

	(1) Carbon	(2) Carbon
Treatcity * post * digital industry	1.635*** (0.774)	2.064*** (0.759)
Treatcity * industry	Yes	Yes
Firm-level fixed effect	Yes	Yes
Treatcity * year	Yes	Yes
Year * industry	Yes	Yes
Exclude the previous pilot cities	No	Yes
Observations	9147	7532
Adj-R^2	0.057	0.054

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

5. Influence Mechanism Identification and Heterogeneity Analysis

5.1. Impact Mechanism Identification. This section discusses the mechanisms through which industrial intelligent robots improve enterprise production methods and enhance carbon emissions performance. We conduct an in-depth analysis from two aspects: productivity and competition effects.

To further verify the possible mediation mechanism of robot application affecting carbon emission performance, according to equations (2) and (3), the effect of M as an intermediary channel is tested using a three-step method. We use the change in the productivity of green firms as a proxy for the productivity effect (ppe) and the Herfindahl index as a proxy for the degree of competition in the market (HHI), and regress them as explanatory variables. The Herfindahl index is an inverse indicator; the larger its value, the higher the degree of monopoly in the market, and conversely, the higher the degree of competition in the market with a larger number of firms of comparable size. The regression results in Table 6 show that the influence of M is an intermediary mechanism for robot application in promoting carbon emission performance.

First, robot application in column (1) is significantly positive at the 10% level, and ppe in column (2) is also significant at the 10% level, indicating that the productivity effect is a potential path through which robot application can affect carbon performance. Second, robot application in column (3) is significantly positive at the 1% level, and HHI in column (4) is significant at the 10% level, indicating that the competition effect is another potential path through which robot application can affect carbon performance.

Table 6: The results of the mechanism test.

	(1) Ppe	(2) Carbon	(3) Hhi	(4) Carbon
Exposure	−0.0001* (−1.75)	0.003*** (12.24)	−0.0001*** (−2.90)	0.003*** (14.41)
Separation	−0.001** (−2.25)	−0.004 (−1.51)	0.000*** (4.48)	−0.004* (−1.77)
Large	−0.000* (−1.65)	−0.006*** (−4.35)	0.000*** (6.84)	−0.005*** (−4.13)
Tobinq	−0.011** (−2.46)	−0.003 (−0.18)	−0.001 (−1.53)	−0.015 (−1.06)
MB	−0.085*** (−3.28)	−0.174** (−1.98)	0.008** (2.22)	−0.104 (−1.32)
SOE	−0.055*** (−5.72)	−0.430*** (−6.83)	0.008*** (2.65)	−0.393*** (−6.80)
Pcf	0.030 (0.57)	0.454** (2.53)	−0.001 (−0.08)	0.280* (1.83)
Size	0.013*** (3.01)	0.319*** (15.73)	−0.014*** (−16.94)	0.241*** (14.07)
Anaattention	0.004*** (9.67)	−0.003** (−2.07)	0.000* (1.64)	0.001 (0.59)
Ppe		−0.028* (−1.68)		
Hhi				−0.471* (−1.95)
_cons	−0.125 (−1.35)	−1.623*** (−3.60)	0.374*** (20.22)	0.084 (0.22)
Ind/year	Yes	Yes	Yes	Yes
N	5870	5870	6997	6997
Adj. R^2	0.16	0.19	0.23	0.17

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

5.2. Heterogeneity Analysis. Differences in geographic location, ownership structure, and degree of industrial carbon emissions may lead the corresponding regions to choose different paths and approaches to promote low-carbon transformation according to their own development [1], which in turn may lead to different degrees of heterogeneity in the effects of robot application on the carbon emission performance of different types of manufacturing enterprises. This study examines these heterogeneous effects and their mechanisms from the perspectives of location, ownership structure, and industry dimension differences.

5.2.1. Location Differences. In this study, according to the registered location of the listed companies, we first divide the sample of manufacturing enterprises into eastern, central, and western regions for regression analysis. The corresponding parameter estimation results are shown in columns (1) and (2) of Table 7. The results show that robot application makes a higher contribution to the carbon emission performance of manufacturing enterprises in the eastern region compared with those in the central and western regions. To further investigate the reasons behind the regional differences in the impact of robot application on firms' carbon performance, this study tests the two potential mechanism channels proposed in the previous study in groups based on different regional samples. The results are shown in columns (3)–(10) of Table 7. For both the eastern and the central and western regions, robot application will promote carbon emission performance of manufacturing enterprises in both types of regions through the two channels of the productivity effect and competition effect, thereby accelerating the low-carbon transformation of enterprises.

5.2.2. Ownership Structure Differences. Considering the differences in the corporate nature of the sample, this study divides the sample into two subsample groups for separate regression analyzes: state-owned enterprises and nonstate-owned enterprises. Columns (1) and (2) of Table 8 show the corresponding parameter estimation results. Robot application contributes significantly to carbon emission performance in the sample of state-owned enterprises; however, this effect is not significant for nonstate-owned enterprises. This indicates that the productivity and competition effects from robot application are more significant in state-owned enterprises, compared with nonstate-owned enterprises. A possible reason for this is that local governments tend to maintain and strengthen the market position of state-owned enterprises through biased policies, such as tax incentives, government subsidies, and enhanced market monopolies, which provide a "breeding ground" for state-owned enterprises to introduce and use robots in production, while also providing a mechanism for most manufacturing industries with state-owned enterprises to induce productivity and competition effects. This provides the basis for the productivity and competition effects of most state-owned enterprises. Therefore, the productivity and competition effects of robot application are more pronounced in state-owned rather than nonstate-owned enterprises.

5.2.3. Industry Dimensional Differences. According to data from the 2018 World Robot Report: Industrial Robots released by the IFR, 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 research and development. The application intensity of robots varies across fields, raising the question of whether the impact on carbon emission performance shows any significant differences [1]. This study examines the differences in the effects of robot application on enterprises' carbon emission performance by classifying the metal smelting, plastic chemical, and nonmetallic mineral industries as high-carbon emission industries and the remaining industries as low-carbon emission industries. Columns (1) and (2) of Table 9 show that the promotion

Table 7: The results of heterogeneity analysis: location differences.

	(1) Eastern Carbon	(2) Western Carbon	(3) Eastern Ppe	(4) Eastern Carbon	(5) Western Ppe	(6) Western Carbon	(7) Eastern Hhi	(8) Eastern Carbon	(9) Western Hhi	(10) Western Carbon
Exposure	0.003*** (2.82)	0.002*** (14.26)	−0.000* (−1.67)	0.003** (2.29)	−0.000* (−1.79)	0.003*** (12.41)	−0.000* (−1.79)	0.003*** (2.77)	−0.000** (−2.31)	0.003*** (14.48)
Separation	−0.022 (−1.08)	−0.004* (−1.73)	−0.003 (−1.52)	−0.019 (−0.88)	−0.001** (−2.16)	−0.003 (−1.41)	0.001 (0.86)	−0.022 (−1.04)	0.000*** (4.28)	−0.004* (−1.67)
Large	−0.010 (−0.81)	−0.005*** (−4.14)	0.002 (1.34)	−0.012 (−0.84)	−0.001* (−1.74)	−0.006*** (−4.06)	0.003*** (3.02)	−0.008 (−0.61)	0.000*** (6.47)	−0.005*** (−3.92)
Tobinq	0.059 (0.41)	−0.016 (−1.12)	−0.011 (−0.42)	0.084 (0.53)	−0.012** (−2.51)	−0.004 (−0.27)	−0.004 (−0.48)	0.053 (0.37)	−0.001* (−1.67)	−0.016 (−1.14)
MB	0.241 (0.35)	−0.112 (−1.42)	−0.051 (−0.43)	0.338 (0.44)	−0.088*** (−3.30)	−0.186** (−2.10)	0.003 (0.07)	0.242 (0.35)	0.008** (2.19)	−0.115 (−1.45)
SOE	−0.125 (−0.35)	−0.386*** (−6.56)	−0.050 (−1.40)	−0.213 (−0.55)	−0.057*** (−5.74)	−0.416*** (−6.54)	0.010 (0.40)	−0.127 (−0.35)	0.008** (2.54)	−0.383*** (−6.56)
Pcf	−1.599 (−0.87)	0.285* (1.87)	0.433 (1.54)	−1.303 (−0.63)	0.018 (0.34)	0.445** (2.47)	−0.108 (−1.08)	−1.566 (−0.85)	0.001 (0.16)	0.278* (1.82)
Size	0.087 (0.60)	0.250*** (14.63)	−0.006 (−0.43)	0.117 (0.74)	0.015*** (3.21)	0.321*** (15.56)	−0.007 (−0.67)	0.088 (0.60)	−0.014*** (−17.22)	0.241*** (13.87)
Anaattention	0.001 (0.13)	0.001 (0.54)	0.001 (0.56)	−0.002 (−0.17)	0.004*** (9.76)	−0.003** (−2.09)	−0.001 (−1.55)	0.000 (0.02)	0.000** (2.06)	0.001 (0.60)
Ppe				0.062* (1.63)		−0.031* (−1.74)				
Hhi								−0.967* (−1.75)		−0.426* (−1.73)
_cons	3.202 (0.96)	−0.165 (−0.43)	0.214 (0.68)	2.433 (0.68)	−0.154 (−1.60)	−1.671*** (−3.65)	0.188 (0.82)	3.232 (0.96)	0.380*** (20.52)	0.065 (0.17)
N	176	6821	155	155	5715	5715	176	176	6821	6821
Adj. R^2	0.06	0.12	0.03	0.04	0.03	0.13	0.18	0.06	0.11	0.12

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

Table 8: The results of heterogeneity analysis: ownership structure differences.

	(1) NonSOE Carbon	(2) SOE Carbon	(3) NonSOE Ppe	(4) NonSOE Carbon	(5) SOE Ppe	(6) SOE Carbon	(7) NonSOE Hhi	(8) NonSOE Carbon	(9) SOE Hhi	(10) SOE Carbon
Exposure	0.003 (1.14)	0.001*** (1.09)	−0.000 (−1.15)	0.003*** (8.34)	−0.002* (−1.75)	0.003*** (9.01)	0.000 (1.57)	0.003*** (10.18)	−0.000*** (−4.51)	0.003*** (10.17)
Separation	−0.005 (−1.24)	−0.005* (−1.78)	0.001 (0.52)	−0.005 (−1.32)	−0.002*** (−3.60)	−0.004 (−1.27)	0.001*** (2.96)	−0.005 (−1.38)	0.000*** (3.24)	−0.005 (−1.63)
Large	−0.005** (−2.15)	−0.004*** (−2.74)	−0.001 (−1.48)	−0.006** (−2.30)	−0.000 (−0.53)	−0.005** (−2.45)	0.000*** (2.79)	−0.005** (−2.27)	0.000*** (5.29)	−0.004** (−2.35)
Tobinq	0.029 (0.94)	−0.012 (−0.76)	0.006 (0.57)	0.043 (1.32)	−0.016*** (−3.32)	−0.001 (−0.07)	−0.001 (−0.59)	0.029 (0.94)	−0.001 (−1.55)	−0.013 (−0.80)
MB	−0.210 (−1.37)	−0.004 (−0.05)	0.057 (1.06)	−0.240 (−1.43)	−0.138*** (−4.65)	−0.085 (−0.81)	−0.010 (−1.21)	−0.212 (−1.38)	0.010** (2.51)	0.006 (0.07)
SOE	0.659 (0.90)	0.000 (.)	0.000 (.)	−0.497 (−0.58)	0.000 (.)	0.000 (.)	0.207*** (5.05)	0.000 (.)	0.000 (.)	0.000 (.)
Pcf	0.296 (1.09)	0.241 (1.31)	0.232** (2.23)	0.418 (1.34)	−0.062 (−1.04)	0.415* (1.89)	−0.008 (−0.57)	0.294 (1.08)	0.004 (0.51)	0.242 (1.31)
Size	0.192*** (5.78)	0.286*** (13.83)	0.003 (0.29)	0.245*** (6.29)	0.017*** (3.36)	0.362*** (14.41)	−0.005*** (−2.85)	0.193*** (5.81)	−0.016*** (−17.03)	0.263*** (12.46)
Anaattention	0.003 (1.32)	−0.000 (−0.22)	0.004*** (5.28)	0.001 (0.40)	0.004*** (8.14)	−0.005*** (−2.68)	−0.000 (−0.35)	0.003 (1.33)	0.000* (1.77)	−0.000 (−0.14)
Ppe				−0.052 (−0.77)		−0.007** (−2.14)				
Hhi								0.745* (1.92)		−1.238*** (−4.03)
_cons	0.000 (0.8)	−0.988** (−2.10)	−0.069 (−0.36)	0.000 (1.02.)	−0.169 (−1.55)	−2.616*** (−4.63)	0.000 (1.07.)	0.583 (0.80)	0.415*** (19.56)	−0.410 (−0.85)
N	2158	4839	1832	1832	4038	4038	2158	2158	4839	4839
Adj. R^2	0.09	0.13	0.03	0.08	0.03	0.15	0.02	0.09	0.16	0.13

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

Table 9: The results of heterogeneity analysis: industry dimensional differences.

	(1) High Carbon	(2) Low Carbon	(3) High Ppe	(4) High Carbon	(5) Low Ppe	(6) Low Carbon	(7) High Hhi	(8) High Carbon	(9) Low Hhi	(10) Low Carbon
Exposure	0.003*** (10.14)	0.002*** (10.09)	−0.000* (−1.66)	0.003*** (8.34)	−0.000* (−1.85)	0.003*** (9.01)	0.000* (1.77)	0.003*** (10.18)	−0.000*** (−4.51)	0.003*** (10.17)
Separation	−0.005 (−1.24)	−0.005* (−1.78)	0.001 (0.52)	−0.005 (−1.32)	−0.002*** (−3.60)	−0.004 (−1.27)	0.001*** (2.96)	−0.005 (−1.38)	0.000*** (3.24)	−0.005 (−1.63)
Large	−0.005** (−2.15)	−0.004*** (−2.74)	−0.001 (−1.48)	−0.006** (−2.30)	−0.000 (−0.53)	−0.005** (−2.45)	0.000*** (2.79)	−0.005** (−2.27)	0.000*** (5.29)	−0.004** (−2.35)
Tobinq	0.029 (0.94)	−0.012 (−0.76)	0.006 (0.57)	0.043 (1.32)	−0.016*** (−3.32)	−0.001 (−0.07)	−0.001 (−0.59)	0.029 (0.94)	−0.001 (−1.55)	−0.013 (−0.80)
MB	−0.210 (−1.37)	−0.004 (−0.05)	0.057 (1.06)	−0.240 (−1.43)	−0.138*** (−4.65)	−0.085 (−0.81)	−0.010 (−1.21)	−0.212 (−1.38)	0.010** (2.51)	0.006 (0.07)
SOE	0.659 (0.90)	0.000 (.)	0.000 (.)	−0.497 (−0.58)	0.000 (.)	0.000 (.)	0.207*** (5.05)	0.000 (.)	0.000 (.)	0.000 (.)
Pcf	0.296 (1.09)	0.241 (1.31)	0.232** (2.23)	0.418 (1.34)	−0.062 (−1.04)	0.415* (1.89)	−0.008 (−0.57)	0.294 (1.08)	0.004 (0.51)	0.242 (1.31)
Size	0.192*** (5.78)	0.286*** (13.83)	0.003 (0.29)	0.245*** (6.29)	0.017*** (3.36)	0.362*** (14.41)	−0.005*** (−2.85)	0.193*** (5.81)	−0.016*** (−17.03)	0.263*** (12.46)
Anaattention	0.003 (1.32)	−0.000 (−0.22)	0.004*** (5.28)	0.001 (0.40)	0.004*** (8.14)	−0.005*** (−2.68)	−0.000 (−0.35)	0.003 (1.33)	0.000* (1.77)	−0.000 (−0.14)
Ppe				−0.052* (−1.77)		−0.007** (−2.14)				
Hhi								0.745* (1.92)		−1.238*** (−4.03)
_cons	0.000 (1.07)	−0.988** (−2.10)	−0.069 (−0.36)	0.000 (1.06)	−0.169 (−1.55)	−2.616*** (−4.63)	0.000 (1.19)	0.583 (0.80)	0.415*** (19.56)	−0.410 (−0.85)
N	2158	4839	1832	1832	4038	4038	2158	2158	4839	4839
Adj. R^2	0.09	0.12	0.13	0.07	0.03	0.13	0.08	0.09	0.11	0.11

***, **, and * denote rejection of the test at 1%, 5%, and 10% level, respectively.

effect of robot application on manufacturing firms' carbon emission performance is more significant in the high-carbon emission industries than in the low-carbon emission industries. Similarly, this study tests the two potential mechanism channels proposed in the previous paper in groups based on the two subsample groups mentioned above to explore whether differences exist in the impact mechanisms between the two sample types. The corresponding parameter estimation results are reported in columns (3)–(10) of Table 8. This study finds that the productivity and competition effects arising from robot application are significant in both sample types.

6. Discussion

This study empirically investigates the relationship between industrial robot application and carbon emission efficiency. The findings extend the economic literature on both artificial intelligence and carbon emissions and contribute to several theoretical implications. First, the findings provide scholars with new insights by identifying firm-level industrial robot application levels and their effects on carbon emission efficiency. Categorizing the mechanism into two areas (production and competition effects) can provide a comprehensive understanding of how artificial intelligence influences carbon emissions. Moreover, Felipe [6] divided technological progress into capital manifestation and nonembodiment, and prior research has mainly focused on capital nonembodiment. However, artificial intelligence is a type of capital manifestation of technological progress, and our findings can improve the current understanding in these two nascent research areas.

The purpose of this paper was to examine the direct effects of robot application on carbon emission performance. The mediating effect of productivity and competition on the application of industrial robots/carbon emission performance link were also studied. Furthermore, China is a vast country with unbalanced development among regions and large differences in industrial structure, which will bring regional heterogeneity to the application of artificial intelligence and regional carbon reduction and emission reduction (Li et al., 2019) [56]. We also conducted heterogeneity analysis from the three dimensions of ownership type, region, and industry.

The findings of this study are in line with the extant literature exploring robots. For example, our result for AI reinforces the importance and contribution of robots to carbon emission performances (Ehrlich and Holdren [34] and Grossman and Krueger [35]). In this regard, similar to Li and Lin [5], Wamba [57], and Zhang et al. [58], our findings show that capital-embodied technological progress combines capital accumulation with technological progress and changes the original factor structure, which is regarded as the key driving force for improving energy efficiency and reducing carbon emissions. And also, the findings demonstrate the Porter effect of technological progress, consistent with the predictions of Afonso et al. [36].

Furthermore, our results regarding the mediation analysis corroborate findings from previous robot literature. We found that GTFP and HHI are mediating the relationship between robot application and carbon emission performance. This is consistent with previous literature highlighting the influence of technology and pressure on relationship between AI and firm performance [24, 59].

6.1. Theoretical Implications. This research has several theoretical implications for the emerging literature on industrial robots. This study extends the carbon reduction literature by providing a nomological network that links the application of industrial robots to carbon emission performance. For instance, it features among the first studies to draw on the capital-embodied technological progress view to assess the impact of robots application on carbon emission performance as well as the mediation effects of green total factor productivity and HHI on this relationship; this is a notable contribution to the emerging literature on robots, with empirical evidence on the importance of robots for improving firm performance. Future studies could build on our findings to integrate some critical external factors (e.g., Confucian culture) to account for the dynamic nature of the external environment (Fu et al., 2022).

This study also contributes to the research stream focusing on the capital-embodied technological progress view while enriching the emerging literature on the application of industrial robot. This goal is achieved through the identification of two important mediators of the relationships between robot and firm carbon emission performance. Another contribution is that it responds to the recent call by many scholars [1, 29, 60] to assess the actual impacts of industrial robots. In addition, this study drives important implications for the literature on robots and related technologies. The application of industrial robots represents a distinct and valuable capability that needs constant exploration by the emerging literature on carbon emissions [2, 56], especially for the digital transformation of the organizations.

6.2. Practical Implications. This study has several practical implications. First, governments should strengthen top-level designs and make overall plans for the industry layout of robotic inputs, thus fully releasing robots' energy-saving and emission-reducing potential. The study demonstrates the heterogeneity in the application of robots to improve the carbon performance of manufacturing enterprises in different geographical locations and with different ownership structures and industry dimensions. Thus, in promoting enterprises' low-carbon transformation, development strategies and policy ideas should be implemented to replace the surface with a point and focus, and accelerate the introduction of robots in China's central and western regions and nonstate-owned enterprises. Furthermore, the low degree of automation in high-carbon emission industries, such as plastics, chemicals, and nonmetallic minerals, should be considered. The root cause is that the production processes and procedures of such high-carbon emission industries are not fully compatible with the core uses of existing robots in China. Therefore, government departments should encourage and guide low-automation industries to optimize their own production processes and procedures, strengthen matching and integration with robot application in high-energy-consumption and high-pollution production links, enhance the end-governance effectiveness of industrial intelligent robots in energy conservation and emission reduction, and maximize the productivity and multiplier effects of industrial intelligent robots.

Second, we recommend making full use of the promotional role of government fiscal and monetary policies and the pulling role of financial intermediaries to actively build and improve the national green financial system and penetrate the channel of green financial services for low-carbon transformation development. The government should expand direct financial expenditures to support the development of green industries, such as establishing special financial projects, including “energy-saving and emission reduction incentive funds” and “renewable energy special development funds.” The government should also introduce relevant tax incentive and guidance policies for energy conservation and emission reduction to create a good institutional environment for the low-carbon transformation of manufacturing enterprises. However, we also recommend further strengthening the role of green credit in the allocation of financial resources, continuously promoting the optimization of the credit structure of banks and other financial intermediaries, raising the “green” threshold for loans to manufacturing enterprises, gradually increasing the proportion of green credit in the total amount of bank loans, and curbing the blind expansion of high-energy-consuming and high-polluting enterprises.

Third, consumers should be guided toward establishing a consumption concept and preferences for green and low-carbon products, while forcing the construction and improvement of market-oriented green technological innovation systems, and effectively bringing into play the positive role of technological innovation and market competition mechanisms on the low-carbon transformation of enterprises. The government can provide necessary technical support for China’s manufacturing enterprises to engage in energy conservation and emission reduction by setting up special research institutions and increasing support for low-carbon, zero-carbon, negative-carbon, and other cutting-edge technologies. In particular, state-owned enterprises should play a leading role in actively introducing new technologies and taking the initiative in carbon emission reduction tasks, to drive the transformation of industrial economic development to a green, low-carbon model. The government should also make scientific and reasonable use of environmental regulations and other policy instruments to exert external pressure for low-carbon transformation through the use of carbon emission rights and other market-oriented operation mechanisms, to enhance enterprises’ carbon emission performance.

6.3. Limitations and Future Research. As with any other research, this study has some limitations that should be acknowledged. First, this study mainly explores the impact of industrial intelligent robots on carbon emission performance based on econometric methods, which may not be able identify touch other potential impact mechanisms that cannot be quantified. In future research, we can evaluate the impact of industrial intelligent robots on carbon emissions based on exploratory case study and dynamic CGE models, and compare the findings with those of this study. Second, because of limited data availability, this study does not classify industrial intelligent robots; therefore, the conclusions may not be sufficiently accurate. With improved data availability, we can further compare and analyze the impact of different types of industrial intelligent robots and other digital technologies on carbon emission performance to provide empirical evidence for the government to apply when using digital technology to improve carbon emission performance.

7. Conclusions

As the economy with the highest CO_2 emissions worldwide, China plays a crucial role in the global carbon emission reduction and climate governance process, while also actively undertakes emission reduction obligations. The Chinese government has clearly stated that high-quality development is the primary task for building a modern socialist country in all aspects, and that the high-end, smart, and green development of the manufacturing industry should be vigorously promoted. However, academia has not provided the necessary attention to the link between robot application and manufacturing companies’ carbon emission performance, and consistent insights have not been provided on the potential impact channels involved. While recognizing the impact of artificial intelligence technology application on the labor market, it is important to further understand the environmental impact of robot application to promote manufacturing enterprises’ low-carbon transformation and thus contribute to high-quality economic development. In this context, this study uses the input-output model to measure the microlevel carbon emission performance of manufacturing enterprises based on the data of Chinese industrial enterprises, Chinese import and export data, and the “Bartik instrumental variable method,” to effectively measure the level of robot application in manufacturing enterprises. This study aims to identify the mechanism of the environmental impact of the application of robots and provide a basis for decision-making to accelerate the achievement of the “double carbon” goal in China’s manufacturing industry. The study led to the following conclusions:

(1) Increases in the level of robot application are found to significantly contribute to manufacturing firms’ carbon emission performance, thereby accelerating their low-carbon transformational development, and the results of several robustness tests based on the instrumental variables approach further strengthen this conclusion.

(2) The mechanism analysis results show productivity and competition effects on the application of

industrial intelligent robots, which encourage manufacturing enterprises to promote carbon emission performance through equipment upgrades.

(3) Heterogeneity analysis results show that an increase in the level of robot use promotes carbon emission performance of manufacturing enterprises in two types of regions through both productivity and competition effects. An increase in the level of robot use significantly promotes the carbon emission performance of state-owned enterprises; however, this effect is not significant for nonstate-owned enterprises. The productivity and competition effects generated by robot application are more significant for state-owned enterprises, as are the mechanism channels for these enterprises to improve their carbon emission performance. The promotion and productivity effects of robot application on manufacturing firms' carbon emission performance are more significant in high-carbon emission industries than in low-carbon emission industries; however, the competition effect is significantly present in all industries.

Data Availability

The data used in this study are available from the authors upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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