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Towards Sustainable Development: Can Industrial Intelligence Promote Carbon Emission Reduction

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Abstract: The realization of intelligent transformation is an important path for the industry to move towards low-carbon development. Based on panel data from 30 provinces in China, this study utilizes the intermediate effect model and spatial econometric model to analyze the influence of industrial intelligence on carbon emissions. The research reveals that industrial intelligence helps with carbon reduction, and the result is still valid after undergoing various tests. Industrial intelligence relies on green technological innovation, industrial structure upgrading, and energy intensity to realize carbon reduction. There is a spatial spillover role of industrial intelligence on carbon emissions, which has a positive influence on carbon reduction in local and adjoining regions. The influence of industrial intelligence on carbon emissions exhibits heterogeneity in the regional dimension, time dimension, and industrial intelligence level dimension. The research provides empirical evidence and implications for using artificial intelligence to achieve carbon reduction.

Keywords: industrial intelligence; carbon emissions; energy intensity; mediating effect; spillover effect

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1. Introduction

With the increasing human activities, greenhouse gas emissions have caused extreme issues such as glacier ablation [1], sea level rise [2], and ecosystem destruction [3]. It is urgent to decrease greenhouse gas emissions and mitigate global warming. In order to better cope with climate warming caused by increasing carbon dioxide concentration, countries need to transition from a high-carbon emission economic development model that relies mainly on fossil fuels to a low-carbon emission economic development model. By 2022, 136 countries have set carbon-neutral targets. The European Union has set a vision to realize zero emissions by 2050 through the European Climate Act.

Currently, China's economic development is facing enormous pressure for low-carbon transition. Its carbon emissions have been the world's highest since 2005 [4]. In 2022, carbon emissions were 11.48 billion tons, an increase of about 459 times compared with 25 million tons in 2010. In view of this, China made a commitment to realize the "dual carbon" target of carbon peaking and carbon neutrality [5]. Although China has made great efforts, the task remains daunting [6]. The Chinese government emphasizes that carbon reduction is a systemic change, and driving carbon reduction is the vital path to realizing green growth.

With the continuous breakthrough of deep learning algorithms, the social utilization of artificial intelligence (AI) technology has become a trend, industrial intelligence (INT) has emerged, and intelligent development has become a crucial content of the 4th industrial revolution [7]. Among the leading countries in industrial intelligence, Germany presented the "Industry 4.0" strategy [8]. The United States launched an "Advanced Manufacturing Partnership" plan [9]. Japan initiated the "Intelligent Manufacturing" program [10], and China, following the "Made in China 2025," proposed to "promote the high-end, intelligent, and green manufacturing industry" [11]. Both carbon reduction and industrial intelligence have become the development targets of all countries. Low-carbon development is a dynamic process oriented by industrial low-carbon, and the extensive combination of AI technology and industry provides new momentum for economic transformation. China's industrial intelligence has been developing rapidly, and the scale of the intelligence industry is second only to the United States [12]. So, can INT effectively reduce carbon emissions? What are the mechanisms of action? Is there heterogeneity in impacts? Answers to these questions will be the core concern of this study. Exploring these queries will not only help enrich the relevant research on industrial intelligence but also provide targeted policy references for promoting low-carbon development.

Industry is a crucial part of the state economy and a main source of carbon emissions [13]. Therefore, reducing industrial emissions is an important task in combating climate warming. At present, although academic research on whether industrial intelligence can promote carbon reduction is still controversial, both governments and enterprises have more expectations for the role of industrial intelligence as a path to achieving carbon reduction. At the micro level, the existing research mainly studies the influencing factors and economic consequences of industrial intelligence [14] but lacks the exploration of the environmental consequences. At the macro level, although the environmental consequences of industrial intelligence have been examined, no unified conclusions have been drawn [15], especially the absence of a study on the mechanism for carbon reduction. What is the potential relation between INT and carbon emissions, and whether industrial intelligence can help carbon emission reduction, these issues are worth considering and exploring. In view of this, to expand the studies in related fields, this paper intends to explore whether industrial intelligence can drive carbon emission reduction.

The marginal contributions of this study are as follows: First, it extends the studies on the environmental consequences of industrial intelligence and the elements influencing carbon emissions, contributes to the implementation of the "dual carbon" goal, and provides a vital basis for other economies to realize carbon reduction through industrial intelligence. Second, it opens the theoretical black box of industrial intelligence influencing carbon reduction and structures a logical chain of the association of INT and carbon emissions from green technology innovation, industrial upgrading, and energy intensity, which builds paths for firms to implement carbon reduction. Third, this study proves the spillover effect of INT on carbon emissions, providing practical evidence for driving regional cooperation in reducing carbon emissions through intelligence technology.

2. Literature Review

The studies on carbon emissions mainly analyze spatio-temporal features and influential factors on the basis of measuring carbon emissions. For the measurement of carbon emissions, most studies have adopted the DEA model, but because this measurement method ignores factors such as undesirable output and policy uncertainty, the final carbon emission efficiency will be distorted [16]. Thus, some scholars began to choose the SBM model with unexpected outputs for measurement and showed that the regional differences in carbon emissions are large and have significant regional agglomeration characteristics, which are closely related to external influencing factors [17]. In terms of time dimension, with the advancement of industrialization, the total global carbon emissions show a continuous upward trend until some developed countries' emissions peak and slowly decline due to factors such as industrial transformation in recent years [18]. In the short term, there are seasonal fluctuations in carbon emissions, such as increased energy consumption in winter due to increased heating demand, which increases carbon emissions [19]. From the spatial distribution, developed countries account for a relatively large share of historical cumulative carbon emissions, but in recent years, the carbon emissions of emerging economies have grown faster [20]. At the regional level, urban areas tend to be carbon-intensive areas, especially industrially developed cities and densely populated metropolises, while rural areas are relatively low [21]. The carbon emission intensity of industrial land and transportation land is higher than that of agricultural land and forest [22–24]. Many studies have used carbon intensity to measure carbon emissions, and they have shown that industrial transformation [25], economic growth [26], urbanization [27], energy consumption [28], green innovation [29], and environmental regulation [30] exist in varying degrees of effect on carbon emissions. Other scholars have evaluated the carbon reduction effect of smart cities [31] and low-carbon pilot policies [32].

Artificial intelligence-related research is developing rapidly and is fruitful. It started from simulating human logic in the early days and now takes deep learning and other technologies as the core, covering machine learning, multimodal, computer vision, image and video processing, natural language processing, human–computer interaction, and other fields. It is widely used in many fields, such as industrial development [33], financial risk assessment [34], and intelligent scheduling in the manufacturing industry [35]. With the boom in AI technology and its wide operation in the industrial sector, some literature began to focus on the link between INT and carbon emission. From the macro level, existing researches mainly focus on the city and province levels. Mao et al. [36] tested the impact of INT on carbon intensity using urban panel data and concluded that INT exhibited a restrictive role in it. Chen et al. [37] suggested that the carbon reduction in INT is more obvious in big cities but not in small cities. Tao et al. [38] investigated the impact of INT on carbon emissions using provincial data and concluded that it has a spillover effect. Research showed that artificial intelligence technology significantly reduced carbon emission intensity, indirectly confirming that industrial intelligence may exhibit inhibitory action on carbon emission [39]. From the micro level, Chen and Jin et al. [40] found that the intelligent application can obviously reduce carbon intensity through micro-enterprise data. Zhang and Shen [41] used data from listed companies to find that INT can raise carbon efficiency through process optimization and competitive effect. Huang et al. [42] argued that INT significantly reduced the carbon intensity of small companies.

3. Theoretical Analysis and Research Hypothesis

3.1. Direct Impact of Industrial Intelligence on Carbon Emissions

The impact of industrial intelligence on carbon emissions is manifested in a multiplicity of aspects. First, industrial intelligence significantly promotes the reasonable allocation of elements and optimizes production links [43]. Through the effective utilization of advanced new information technology systems, industrial intelligence possesses the capability to monitor the transaction and usage of energy elements in real time with remarkable precision. It can then judiciously and accurately allocate energy elements to the specific production links and enterprises that genuinely have an urgent need for them. This meticulous process not only leads to a notable increase in energy efficiency but also brings about a substantial decrease in carbon emissions.

Second, industrial intelligence plays a crucial role in accelerating knowledge creation. The utilization of industrial robots is highly dependent on highly skilled workers, who tend to exhibit a heightened environmental consciousness [44]. Simultaneously, these highly skilled workers showcase higher work efficiency. With the continuous increase in the number of highly skilled laborers and the progressive construction of the industrial internet, it provides substantial assistance in strengthening the learning effect. This, in turn, enables the achievement of carbon reduction by enhancing production efficiency through more refined and efficient processes.

Third, industrial intelligence serves as a powerful driver for promoting the green development of the value chain. For the core enterprises within the value network, industrial intelligence actively promotes a substantial boost of output efficiency and expansion of production scale, facilitating the realization of green growth [45]. In order to enhance the competitiveness of enterprises in the market, other enterprises within the industry chain will also resort to the utilization of robots. This is conducted to increase production quality, achieve green and efficient development, and consequently reduce carbon emissions. As a result of these comprehensive influences and interrelated factors, the following assumption is proposed:

H1. *Industrial intelligence can reduce carbon emissions.*

3.2. The Influence Mechanism of Industrial Intelligence on Carbon Emissions

The core essence of industrial intelligence resides in propelling an intelligent technology revolution. On the one hand, the attributes of industrial intelligent automation tools offer significant assistance to enterprises in attaining low-cost and highly efficient innovation capabilities [46]. Enterprises embrace the intelligent production mode characterized by independent reasoning and decision-making. This approach not only enables them to curtail innovation costs but also fortifies green transaction management and drives green technological innovation [47]. Firm green innovation plays a crucial role in reducing carbon intensity by optimizing production links. This optimization process involves meticulous reengineering and refinement of various production stages, leading to a more streamlined and energy-efficient operational framework. On the other hand, leveraging the advantage of automation, robots have the capacity to liberate a portion of the human workforce from arduous and repetitive mechanical labor. This liberation grants individuals more leisure time to engage in knowledge acquisition, learning, and experience exchange. Such engagement is instrumental in fostering the creation of novel knowledge [48]. As a versatile and all-encompassing technology, industrial intelligent technology bestows the impetus for the green transformation of companies through seamless integration with other technologies. It spurs enterprises to adopt a green innovation mode, facilitating the elevation of the technical level. The green technology innovation sparked by industrial intelligence leads to a decreased reliance on fossil energy. This reduction in utilization subsequently and effectively curbs carbon emissions [49], contributing to a more sustainable and environmentally friendly industrial landscape. Accordingly, we propose the following hypothesis:

H2a. *Industrial intelligence can limit carbon emissions by driving green technology innovation.*

Intelligence has revolutionized the traditional crude production mode by seamlessly incorporating AI, big data, cloud computing, and other intelligent elements into the production process. This integration not only boosts efficiency but also transforms machines into a novel type of human capital, thereby facilitating an upgrade of the industrial structure driven by technology [50]. The introduction of the intelligent manufacturing system precisely caters to people's demands. Moreover, with the continuous and escalating increase in personalized needs, it exerts a compelling force that spurs the growth of new technology. This dynamic interaction gradually eliminates the backward industries in a benign and progressive manner [51]. The traditional industry sector that is primarily based on energy happens to be one of the sectors that exhibit the highest degree of intelligent integration. The automation tool attribute of industrial intelligence holds the key to optimizing energy utilization. It propels the gradual evolution of traditional industries towards an advanced direction and effectively achieves carbon reduction through meticulous adjustments and improvements in energy consumption patterns and production processes [52]. Industrial intelligence serves as a powerful driver for the rapid growth of emerging leading industries, which boast higher productivity and more advanced technical levels. Simultaneously, it guides traditional industries to undergo a transformation into clean industries, ultimately leading to a significant reduction in carbon emissions [53]. Accordingly, the following assumption is proposed:

H2b. *Industrial intelligence can reduce carbon emissions by driving industrial structure upgrading.*

Industrial intelligence technology finds extensive application in the resource management system by leveraging digital infrastructure to construct energy control platforms. This enables full-cycle, all-round temporal and spatial monitoring, as well as the precise identification of energy waste and inefficiency [54]. Industrial enterprises are empowered to obtain production-related data through intelligent technology. Such an approach is highly conducive to the realization of dynamic adjustment of energy supply. It ensures that energy consumption and economic output are in harmonious alignment, thereby effectively curbing energy intensity and achieving a reduction in carbon emissions [55]. In addition, industrial enterprises have the capacity to establish energy consumption analysis models based on energy data. This enables the digital transformation of existing manufacturing equipment and processes. By optimizing process parameters and upgrading equipment, they can effectively achieve the purpose of curbing energy intensity and consequently realize carbon reduction. This process involves in-depth analysis and fine-tuning of various operational aspects to ensure maximum energy efficiency and minimal waste [56]. At the level of optimizing the resource system, enhancing energy efficiency holds significant implications. It implies reducing the demand for fossil fuels to achieve the same or even greater energy services with a reduced amount of energy. This not only leads to the application of a greater proportion of renewable energy but also reduces the overall energy need. It promotes a seamless energy transition, facilitates the attainment of a clean energy supply, and thereby contributes to a substantial reduction in carbon emissions [57]. Accordingly, the following assumption is proposed:

H2c. *Industrial intelligence can reduce carbon emissions by reducing energy intensity.*

Based on the above theoretical analysis, the mechanism of industrial intelligence driving carbon emission reduction is shown in Figure 1.

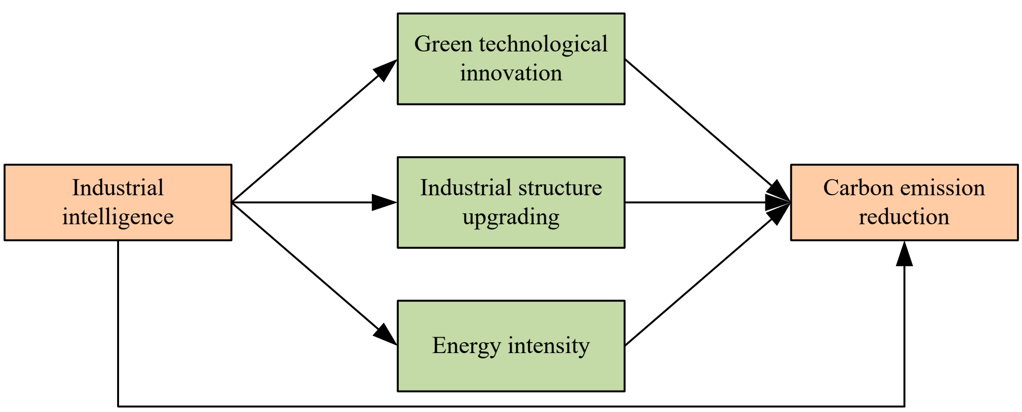

Figure 1. The mechanism of industrial intelligence driving carbon emission reduction.

3.3. Spatial Spillover Effect of Industrial Intelligence on Carbon Emissions

The high permeability and strong diffusion characteristics of industrial intelligence technology offer exceptionally favorable external conditions for the fluidity of knowledge and talent. Industrial intelligence is highly dependent on data, and the attributes of data elements, such as their remarkable efficiency, cleanliness, reproducibility, and the possibility of massive access, ensure that their circulation is liberated from the constraints of space. The cross-regional flow of carbon emission data not only breaks down geographical barriers but also holds the potential to significantly enhance management efficiency and actively promote carbon reduction in neighboring regions [58]. This data flow enables a more comprehensive and coordinated approach to addressing carbon emissions, facilitating the sharing of best practices and strategies. Furthermore, extensive studies have firmly confirmed that carbon dioxide possesses highly significant mobility characteristics [59]. There exist intimate economic connections between neighboring areas. Intelligence, in this context, can further fortify the space linkage and exponentially multiply the accessibility of knowledge and information. It enables the realization of the spillover of intelligent technology, subsequently exerting a pronounced spillover role on the low-carbon development of surrounding regions. This spillover effect can lead to the dissemination of innovative low-carbon technologies and management practices, fostering a collective effort towards sustainable development across a wider geographical area [60]. In view of this, the hypothesis is proposed as follows:

H3. *There is a spatial spillover effect of the impact of industrial intelligence on carbon emissions.*

4. Methods and Data

4.1. Methods

4.1.1. Baseline Regression Model

An ordinary model is first established to discuss the influence of INT on carbon emissions, as shown in Equation (1):

$$Carbon_{it} = \alpha_0 + \alpha_1 INT_{it} + \alpha_2 \sum Control_{it} + \varepsilon_{it} \tag{1}$$

where $Carbon_{it}$ is the industrial carbon emission intensity, INT_{it} is industrial intelligence, $Control_{it}$ are control variables, α is a coefficient, and ε_{it} is an error term.

$$INT_{it} = \sum_{j=1}^{J} \frac{employ_{i,j,t=2006}}{employ_{i,t=2006}} \times \frac{Robot_{jt}}{employ_{j,t=2006}} \tag{2}$$

where INT_{it} denotes the industrial robot penetration rate of region i in year t, $employ_{i,j,t=2006}$ is the employment number of industry j in region i in 2006, $employ_{i,t=2006}$ is the number of employed people in region i in 2006, $Robot_{jt}$ is the installed volume of industrial robots in the industry j in the year t provided by the Global Industrial Robot Report, and $employ_{j,t=2006}$ is the number of people employed in industry j in 2006.

4.1.2. Intermediate Effect Model

The baseline regression does not answer the question of what factors might be the route of industrial intelligence. Adopting the intermediate effect method to further analyze the possible path of the INT on carbon emissions [61].

$$M_{it} = \eta_0 + \eta_1 INT_{it} + \eta_2 \sum Control_{it} + \nu_{it} \tag{3}$$

$$Carbon_{it} = \beta_0 + \beta_1 INT_{it} + \beta_2 M_{it} + \beta_3 \sum Control_{it} + \xi_{it} \tag{4}$$

where M denotes the mediating variables, INT_{it} is industrial intelligence, $Carbon_{it}$ is the industrial carbon emission intensity, $Control_{it}$ are control variables, η and β represent coefficients, and ν_{it} and ξ_{it} are random disturbance terms.

4.1.3. Spatial Econometric Model

There may be spatial links between INT and carbon emissions. A spatial measurement model needs to be established for further analysis:

$$\begin{aligned} Carbon_{it} = \alpha_0 + \rho W Carbon_{it} + \alpha_1 INT_{it} + \gamma_1 W INT_{it} + \\ \alpha_2 \sum Control_{it} + \gamma_2 W \sum Control_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \mu_{it} \tag{6}$$

where $Carbon_{it}$ is the industrial carbon emission intensity, INT_{it} denotes the industrial robot penetration rate of region i in year t, ρ represents the spatial autoregressive coefficient of the dependent variable, and W is the spatial weight matrix. α and γ represent coefficients; ε_{it} is the spatial error autocorrelation term; λ represents the spatial autocorrelation coefficient, and μ_{it} is a random disturbance term.

4.2. Variables

4.2.1. Dependent Variable

Carbon emissions are accounted for using the conversion coefficient of standard coal for industrial consumption of coal, crude oil, and natural gas, and the total industrial carbon emissions of each province are obtained by adding up the accounting results. Carbon intensity is measured using the logarithm of the ratio of total industrial carbon emissions to industrial output in each province. The industrial added value of each province is adjusted according to the constant price of 2006.

4.2.2. Independent Variable

Industrial intelligence (INT) is represented by the penetration rate of industrial robots. Referring to Huang et al. [62], based on the International Federation of Robotics (IFR) database, the industrial intelligence index was constructed by estimating the penetration rate of industrial robots in each province. See Equation (2) for the measurement method.

4.2.3. Intermediate Variables

Green technology innovation (GTE). Because of the time lag between patent application and patent authorization, patents may be used in production during the application process. The former can reflect the regional innovation capacity well in the current period. Therefore, the number of green patent applications is selected to represent green technological innovation and is treated logarithmically.

Industrial structure upgrading (IND). The transformation of the industry to the advanced level makes the backward industry gradually eliminated by the emerging industry. In this paper, the upgrading of industrial structure is expressed by the ratio of the added value of the tertiary industry and the secondary industry.

Energy intensity (EI). As a vital index to measure energy efficiency, energy intensity reflects the output benefit of energy consumption. We use the ratio of industrial energy consumption to total industrial output to express it.

4.2.4. Control Variables

Economic development (PGDP): Wang et al. [63] believed that economic level is the vital element influencing carbon emissions. Drawing on this study, per capita GDP is chosen to express the economic level and converted to comparable prices using the

GDP index. Urbanization (Urb): Urbanization increases energy utilization and has an influence on carbon emissions. The ratio of urban population to total population is used to characterize the urbanization. Foreign direct investment (Fdi): It can not only promote domestic technical innovation through the technical spillover of foreign enterprises but also make the country become a "pollution paradise" [64]. We use the ratio of actual utilization of foreign capital to GDP to represent foreign direct investment. Environmental regulation (Er): Scholars generally agreed that stronger environmental governance would force firms to reduce carbon emissions [65]. We use the logarithm of industrial pollution control investment to measure environmental regulation.

4.3. Data Sources

Since the complete data of robot inventory of sub-industries of IFR in China started to be recorded in 2006 and updated in 2019, to ensure the integrity and continuity of variables, the relevant data of 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2006 to 2019 are taken as study samples. In the calculation of industrial intelligence indicators, according to the employment data provided by the China Labor Statistics Yearbook, the industry classification standard in China's statistical system is compared with the data industrial robots provided by IFR and classified. Fossil fuel consumption is based on the China Energy Statistical Yearbook. The green patent data are from the National Intellectual Property Information Service Platform and is found using WIPO's Green List of International Patent Classifications as a standard. The data of control variables are mainly from the China Statistical Yearbook. The descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics.

Variables	Sample	Mean	St	Min	Max
Carbon emission intensity (Carbon)	420	1.4632	0.5383	0.1761	3.6285
Industrial intelligence (INT)	420	6.2874	1.7925	2.6072	11.3865
Green technology innovation (GTE)	420	2.1471	1.5632	1.629	4.6427
Upgrading of industrial structure (IND)	420	1.0126	0.5328	0.4971	3.1136
Energy intensity (EI)	420	0.9432	0.5728	0.2065	3.6347
Economic level (PGDP)	420	4.4185	2.2431	0.6145	16.4735
Urbanization (Urb)	420	0.6043	0.7562	0.2746	0.8832
Foreign direct investment (Fdi)	420	0.0227	0.0201	0.0005	0.1026
Environmental regulation (Er)	420	2.6943	0.9735	−0.7436	4.1724

5. Results

5.1. Baseline Regression Results

According to the Hausman test results, the fixed effect model is suitable for the research, and the results are shown in Table 2. Columns (1)–(3) show that the industrial intelligence coefficients are significantly negative. Furthermore, control variables are included in column (4); the industrial intelligence coefficient is also negative, manifesting that it has an obvious inhibiting role on carbon emissions, verifying H1.

Table 2. Baseline regression results.

Variables	(1)	(2)	(3)	(4)
INT	−0.088 *** (−4.47)	−0.081 *** (−3.25)	−0.075 *** (−3.84)	−0.072 *** (−4.21)
PGDP				0.083 *** (8.17)
Urb				0.064 *** (5.42)
Fdi				−0.008 ** (−2.28)
Er				−0.012 *** (−6.38)
Constant	0.542 ***	0.538 ***	0.476 ***	0.459 ***
Time fixed effect	Yes	No	Yes	Yes
Provincial fixed effect	No	Yes	Yes	Yes
R^2	0.264	0.353	0.397	0.482

Note: ***, **, and * are significant at 1%, 5%, and 10% levels, respectively, and the t value is in parentheses, the same below.

5.2. Robustness Test

5.2.1. Replace the Explained Variable

In addition to carbon intensity, the explained variable can also be expressed by carbon emissions per capita (CE). Columns (1) and (2) in Table 3 exhibit that the coefficients of industrial intelligence are still sensibly negative, indicating that industrial intelligence helps to curb carbon emissions, confirming that the results are robust.

Table 3. Results of the robustness test and endogeneity test.

Variables	Replace the Explained Variable		Adjust the Sample Size		Instrumental Variable Method	
	(1) CE	(2) CE	(3) Carbon	(4) Carbon	(5) INT	(6) Carbon
INT	−0.072 *** (−3.41)	−0.053 *** (−3.68)	−0.062 (−3.38)	−0.058 *** (−3.25)		
AIU					0.126 ** (2.31)	
INT_IV						0.087 *** (6.29)
PGDP		0.087 *** (4.96)		0.071 *** (5.74)	0.084 *** (3.53)	0.076 *** (6.24)
Urb		0.064 *** (6.29)		0.056 *** (3.25)	0.049 *** (4.14)	0.032 *** (3.72)
Fdi		−0.013 ** (−2.15)		−0.021 ** (−2.24)	−0.009 *** (−2.92)	−0.015 *** (−3.46)
Er		−0.027 *** (−5.52)		−0.032 *** (−3.48)	−0.024 *** (−4.53)	−0.031 *** (−5.23)
Constant	0.493 *** (7.85)	0.764 *** (6.72)	0.637 *** (5.91)	0.582 *** (4.37)	0.862 *** (6.41)	0.522 *** (4.85)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.482	0.497	0.315	0.356	0.468	0.372

Note: ***, **, and * are significant at 1%, 5%, and 10% levels, respectively, and the t value is in parentheses.

5.2.2. Adjust the Sample Size

After removing municipalities, the results are displayed in columns (3) and (4). The industrial intelligence coefficients are basically consistent with the above and prominently negative, indicating that the findings remain robust after adjusting the sample size.

5.2.3. Endogeneity Test

Refer to existing research [66], according to the convergence of the utilization scale of industrial robots in different countries, and consider the manufacturing similarities and the actual installation of industrial robots. We use the penetration rate of industrial robots in the US as the instrumental variable (AIU); see Table 3. In column (5), the AIU is positively correlated with industrial intelligence. In column (6), the influence coefficient of the fitting value of the industrial intelligence tool variable (INT_IV) on carbon emission intensity is significantly negative, proving the robustness of the conclusions.

5.3. Mechanism Analysis

In Table 4, columns (1) and (2) show that the influence of INT on green technology innovation is significantly positive. When industrial intelligence and green technology innovation jointly affect carbon emissions, their coefficients are significantly negative, indicating that industrial intelligence promotes carbon reduction by green technology innovation, which verifies H2a. Column (3) reveals that INT significantly promotes industrial structure upgrading, and column (4) indicates that the coefficients of INT and industrial structure upgrading are negative. It shows that industrial intelligence would limit carbon emissions by upgrading industrial structure and verifying H2b. Column (5) shows that industrial intelligence negatively affects energy intensity, and column (6) shows that the industrial intelligence coefficient is negative and energy intensity is positive, indicating that industrial intelligence inhibits carbon emissions through decreasing energy intensity, verifying H2c.

Table 4. Mediating effect test.

Variables	**Green Technology Innovation**		**Upgrading of Industrial Structure**		**Energy Intensity**	
	(1) GTE	**(2) Carbon**	**(3) IND**	**(4) Carbon**	**(5) EI**	**(6) Carbon**
INT	0.075 *** (6.25)	−0.062 *** (−3.56)	0.104 *** (4.27)	−0.057 *** (−4.74)	−0.131 ** (−2.18)	−0.054 *** (−4.31)
GTE		−0.132 *** (−8.45)				
IND				−0.144 *** (−5.39)		
EI						0.137 *** (7.62)
PGDP	0.224 *** (6.53)	0.087 *** (3.46)	0.153 *** (3.22)	0.074 *** (4.28)	−0.027 *** (−4.41)	0.081 *** (5.13)
Urb	0.164 *** (2.89)	0.043 *** (4.72)	0.128 *** (2.96)	0.022 *** (3.41)	0.016 *** (3.77)	0.037 *** (2.96)
Fdi	0.051 *** (4.48)	−0.011 ** (−2.37)	0.142 *** (3.54)	−0.018 *** (−4.46)	−0.038 ** (2.39)	−0.024 *** (−3.25)
Er	0.153 ** (3.37)	−0.055 *** (−3.21)	0.024 ** (5.38)	−0.047 *** (−4.63)	−0.105 ** (4.17)	−0.032 *** (−5.27)

Table 4. *Cont.*

Variables	Green Technology Innovation		Upgrading of Industrial Structure		Energy Intensity	
	(1) GTE	**(2) Carbon**	**(3) IND**	**(4) Carbon**	**(5) EI**	**(6) Carbon**
Constant	4.823 ***	0.834 ***	3.217 ***	0.767 ***	4.436 ***	0.341 ***
	(3.52)	(3.58)	(4.39)	(4.32)	(7.42)	(3.68)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.637	0.484	0.571	0.493	0.535	0.378

Note: ***, **, and * are significant at 1%, 5%, and 10% levels, respectively, and the t value is in parentheses.

5.4. Spillover Effect Analysis

Examining if there exists a spatial correlation among variables, the first step is to utilize Moran's I index to test if there are spatial links between INT and carbon emissions. As shown in Figure 2, both Moran's I indices are significantly positive, manifesting that there is a spatial positive correlation between variables. Thus, it is rational to utilize the spatial measurement model to discuss the relation between INT and carbon emissions.

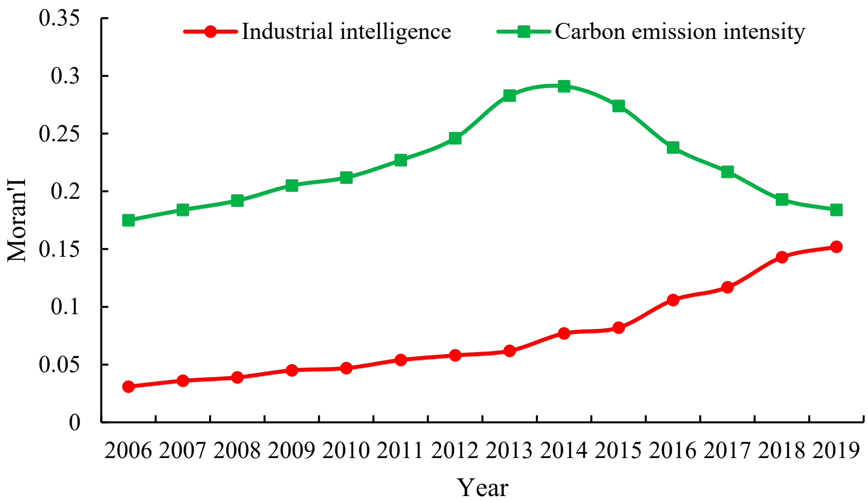

Figure 2. Moran's I index of industrial intelligence and carbon emission intensity.

The spatial analysis needs to establish the space matrix first, and we constructed a 0–1 adjacency weight matrix (W1), a geographical distance space weight matrix (W2), and an economic distance space weight matrix (W3) in turn. Combined with the Ansenlin judgment criteria, the SDM model was chosen for further analysis through comparison between corrected R^2 and Log-likelihood results. The results in Table 5 show that under different matrices, the negative effect of INT on carbon emissions exists as a spillover effect. From the point of view of direct and indirect effects, INT inhibits local carbon emissions and is also conducive to reducing emissions in surrounding regions, which verifies H3. Analyzing the reasons, the government's support for industrial intelligence has, to some extent, affected its development and emission reduction effectiveness. For example, the introduction of relevant industrial support policies, providing financial subsidies and tax incentives for enterprises to upgrade and transform towards intelligence, can effectively promote the process of industrial intelligence, thereby enhancing its inhibitory effect on carbon emissions. Strict environmental policies and carbon emission supervision systems can encourage enterprises to increase investment in intelligent emission reduction and improve the application effect and emission reduction efficiency of industrial intelligent technology. Meanwhile, policy coordination and cooperation between regions are crucial for leveraging the emission reduction spillover effects of industrial intelligence. By establishing cross-regional policy coordination mechanisms and promoting optimized resource allocation and technology exchange and sharing, the positive role of industrial intelligence in reducing carbon emissions can be further amplified.

Table 5. Regression results of the SDM model.

Variables	(1) W1	(2) W2	(3) W3
INT	−0.086 *** (−3.93)	−0.079 *** (−2.81)	−0.082 (−3.34)
W×INT	−0.025 ** (−2.24)	−0.018 ** (−2.31)	−0.016 * (−1.69)
Controls	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes
R^2	0.642	0.617	0.658
Direct effect	−0.047 *** (−4.53)	−0.053 *** (−3.46)	−0.042 *** (−2.84)
Indirect effect	−0.018 ** (−2.27)	−0.015 ** (−2.14)	−0.017 ** (−2.06)
Total effect	−0.065 *** (−3.58)	−0.068 *** (−2.96)	−0.059 *** (−3.05)

Note: ***, **, and * are significant at 1%, 5%, and 10% levels, respectively, and the t value is in parentheses.

5.5. Heterogeneity Analysis

The above studies primarily examined the effect mechanism of INT on carbon emissions but did not reveal the difference of intelligent techniques on carbon emissions, and it is impossible to judge whether its influence changes with the development of industrial intelligence. In view of this, we will investigate the heterogeneity of intelligent development from the regional dimension, time dimension, and industrial intelligence level dimension; see Table 6.

(1) In the regional dimension. Dividing China into three regions: east, middle, and west. Refer to the study of Li and Zhou [67] for the specific division of regions. The results show that industrial intelligence exhibits positive carbon reduction in both eastern and middle regions, and the reduction role for the former is significantly greater than that for the latter. However, industrial intelligence has no obvious influence on carbon emissions in the western area, which is caused by the backward industrial intelligence foundation and weak intelligence application in the western region.

(2) In the time dimension. Considering the gradual improvement of INT, we select the middle year of the research interval for the division of the research interval, which is divided into two phases, 2006–2012 and 2013–2019, and try to test if the dynamic influence of INT on carbon emissions has heterogeneity in different time periods. The results manifest that the emission reduction in INT is evidently enhanced as the study interval is drawn closer. Obviously, this is mainly due to the gradual maturity of the INT development system.

(3) In the intelligent level dimension. Based on the average value of the intelligence level, the research samples are divided into high INT and low INT areas. The results evidence that both high industrial intelligence and low industrial intelligence significantly inhibit carbon emissions, and it is found that the carbon reduction role in high-level areas is more obvious than that in low-level areas.

Table 6. Results of heterogeneity analysis.

Variables	Regional Heterogeneity			Time Heterogeneity		Level Heterogeneity	
	(1) East	**(2) Middle**	**(3) West**	**(4) 2006–2012**	**(5) 2013–2019**	**(6) High level**	**(7) Low level**
INT	−0.124 *** (−5.28)	−0.098 *** (−3.16)	−0.014 (−1.07)	−0.023 ** (−2.28)	−0.104 *** (−3.49)	−0.107 *** (−4.56)	−0.039 ** (−2.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.634	0.565	0.286	0.442	0.617	0.523	0.468

Note: ***, **, and * are significant at 1%, 5%, and 10% levels, respectively, and the t value is in parentheses.

6. Discussion

This study clarifies the impact mechanism of INT on carbon emissions. Next, we will discuss the findings. First, the research reveals the positive influence of INT on carbon reduction, a finding that is consistent with previous literature [68]. The integration of new technologies represented by AI into the production link will bring about productivity improvement and promote production methods that meet the requirements of low-carbon development, thereby reducing carbon emissions. Intelligent technology advances will drive companies to smart transformation, form a networked collaborative production mode, improve the allocation of resources, and thus decrease carbon intensity. The existing studies have explored the environmental consequences of INT and believe that it reduces pollution emissions. However, most researchers have discussed the effect of enterprise intelligence on carbon emissions at the microscopic level. Wang et al. [69] believed that INT effectively reduced enterprise emissions. We discussed the positive influence of INT on carbon reduction from the macro level and enriched the existing research conclusions.

Second, scholars tend to focus on the mechanism of INT on carbon reduction. We incorporate green technology innovation, industrial structure upgrading, and energy intensity into the analysis framework of the relation between INT and carbon reduction to analyze the mediating mechanism. The mediating role of green technology innovation has been proven. Intelligent technology provides support for enterprise innovation, has a spillover radiation effect on technologies of related enterprises, and promotes the innovation capability of firms. Technological innovation can bring technological dividends and strengthen the end management of carbon emissions. Intelligence drives the process, information, and automated production of enterprises and then prompts the industrial structure to advance. The industry has reduced carbon emissions in the process of adjusting to high-tech industries. Industrial intelligence is integrated into the industry, promoting the reallocation of factors and helping to decrease carbon intensity. Policies are important means to promote green technology innovation, industrial structure transformation, and reduce energy intensity. A sound policy system can increase support for enterprises in green technology innovation, such as providing special research and development funds and establishing innovation reward mechanisms. Guiding policies for industrial restructuring promote the transformation and upgrading of traditional industries towards green and low-carbon directions, creating a more favorable policy environment for industrial intelligence to promote carbon reduction. Mandatory environmental regulation policies can effectively reduce energy intensity.

Third, the impact of INT on carbon emissions has a spillover role. It was confirmed by Tu et al. [70]. The utilization of industrial intelligence techniques in this region will induce the absorption, imitation, and learning of surrounding areas and promote the popularization of intelligent techniques in other regions to accelerate industrial intelligence transformation through technology diffusion, thus reducing carbon emissions. The development of AI, such as robots, has created a close relationship between the upstream and downstream industries in the region and the nearby regions. INT can improve output efficiency, optimize supply chain management, and stimulate technological innovation of upstream and downstream industries in the neighboring regions, effectively propelling the improvement of regional competitiveness and regional carbon reduction. Therefore, INT can curb carbon emissions in local and surrounding regions, showing spatial spillover effects. It is necessary to develop a unified industrial intelligence development plan and carbon emission standards, which will help promote cross-regional sharing and exchange of technology. Provide financial support to regions that actively participate in regional technology cooperation and industrial collaborative transformation so as to give full play to the spatial spillover effect of industrial intelligence and achieve broader carbon reduction targets.

Fourth, heterogeneity analysis results show that different regions, time periods, and intelligence levels are different in carbon emissions. Most existing studies have explored the relation between them in terms of regional heterogeneity. The eastern region, with its superior economic foundation, abundant talent resources, and advanced research environment, is able to introduce and promote cutting-edge industrial intelligence technologies more quickly. These technologies not only improve production efficiency but also achieve innovative breakthroughs in energy management, resource optimization, and other areas, thereby more effectively reducing carbon emissions. In terms of policies, the eastern region often introduces and implements preferential policies to support the development of industrial intelligence earlier, such as fiscal subsidies, tax reductions, etc., to encourage enterprises to increase investment in the field of industrial intelligence and accelerate the process of carbon reduction. The policy support for the central and western regions is also increasing, but there may be room for improvement in the precision and targeting of policies. Time period research shows that with the development of time, the carbon reduction role of INT becomes more and more obvious. This is due to the gradual increase in industrial intelligence, which has significantly reduced carbon emissions. We also found that areas with high levels of industrial intelligence have greater carbon emission reduction effects than areas with low levels. This finding enriches the conclusions of existing studies.

7. Conclusions and Implications

7.1. Conclusions

This study selected sample data at the provincial level to investigate the influence of industrial intelligence on carbon emissions. It implied that INT can sensibly decrease carbon emissions. Green technology innovation, industrial structure upgrading, and energy intensity are the transmission paths of industrial intelligence and play an intermediary role in carbon emissions. The carbon reduction effect of industrial intelligence exists in typical spillover features in the spatial dimension, which promotes local carbon reduction and helps to limit emissions in peripheral localities. The impact of industrial intelligence on carbon emissions is heterogeneous in regional dimension, time dimension, and intelligence level dimension.

7.2. Implications

We obtain the following enlightenments. First, the government should increase intelligent policy support and improve the complete industrial chain of China's intelligent technologies from project initiation to achievement transformation. It is necessary to take green and low-carbon as the guidance, realize the extensive interaction of intelligent technique and industry, and orderly promote industrial transformation and green development. Second, carbon emission reduction can be facilitated by driving green technological innovation, upgrading industrial structures, and diminishing energy intensity. Enterprises need to adhere to green innovation, continue to increase intelligent investment, and help carbon emission reduction with intelligent transformation. Firms should actively transform extensive industries and constantly move toward the development of high-end industries. Efforts are focused on renewable energy and gradually decreasing the intensity of traditional energy to realize carbon reduction targets. Third, local governments should establish industrial intelligence links in the region and encourage inter-regional exchange in technologies and production elements. Highly intelligent regions drive the utilization and popularization of intelligent techniques in the surrounding areas, prompt the interaction of intelligent technology and traditional industry, and expand the spatial spillover effect of intelligent technology on carbon reduction.

7.3. Limitations

This article still has some limitations. First, we analyze the relationship between INT and carbon emissions at the provincial level. There are areas not covered in the study that will have an impact on the overall research. In the future, the study scale can be extended to the city to increase the sample coverage rate and further discuss the relationship between the two. Second, we take China as the study object, and whether the conclusions are applicable to other economies remains to be verified. The intelligence level and carbon emissions vary greatly in different countries. We can collect data from multiple countries and continue to discuss the influence of INT on carbon emissions. Third, carbon emissions are influenced by multiple factors. This article only focuses on the mediating effects of industrial intelligence on carbon emissions reduction through green technology innovation, industrial structure transformation, and energy intensity. Further exploration is needed to determine whether there are other mediating variables involved. In the future, we can continue to explore and enrich the theoretical research in this field.

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