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Industrial Intelligence, Low-Carbon Transition and Implications for Offshore Renewable Energy: Evidence from Chinese Provinces

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ABSTRACT: In the context of global climate change, increasing energy security challenges, and marine ecological degradation, advancing the intelligent transformation of industrial systems and accelerating the development of marine renewable energy have become crucial pathways to achieving low-carbon growth and building a sustainable blue economy. Industrial intelligence plays a key role in supporting marine energy development through intelligent manufacturing and smart operation and maintenance technologies. Drawing on data from 30 provinces in China between 2011 and 2022, this study employs a structural equation model to systematically examine the impact mechanism of industrial intelligence on carbon emissions. The findings indicate that industrial intelligence significantly reduces carbon emissions. Furthermore, industrial structure upgrading serves as a mediating factor in this relationship, while green technological innovation positively moderates the emission-reduction effect of industrial intelligence. Multi-group analysis reveals notable regional disparities in the effectiveness of industrial intelligence in curbing emissions. These findings not only clarify the carbon reduction mechanisms of industrial intelligence within traditional industrial systems, but also offer valuable insights for enhancing the intelligence level of marine energy equipment manufacturing and reducing the development costs of marine renewable energy sources, such as offshore wind power.

KEYWORDS: Industrial intelligence; carbon emission reduction; industrial structure upgrading; green technology innovation; blue economy; marine renewable energy

1 Introduction and Literature Review

1.1 Introduction

Amidst escalating global climate change and ecological crises, green and low-carbon development has become a broad consensus within the international community. As a major carbon-emitting country, China has been steadfastly advancing high-quality development and green transformation under the guidance of its “dual-carbon” strategy. With profound adjustments underway in the global energy structure, marine renewable energy is increasingly recognized as a critical growth area for achieving low-carbon transition and ensuring energy security, accounting for approximately 80% of the world’s renewable energy potential. Meanwhile, the strategic role of the blue economy in ecological protection, energy transition, and industrial upgrading is becoming increasingly prominent, placing higher demands on technological innovation, equipment manufacturing capabilities, and the greening of energy systems. However, marine energy development still faces significant challenges, including high costs, complex deployment, insufficient grid integration, and inadequate cross-sectoral coordination. Consequently, promoting industrial intelligence centered on artificial intelligence, big data, and smart manufacturing not only facilitates the green upgrading

of traditional industrial systems [1], but also provides essential technological support for the production of marine energy equipment, intelligent operations and maintenance, and the construction of offshore energy networks, thereby advancing the high-quality development of the blue economy.

As the core product of the Fourth Industrial Revolution, industrial intelligence is accelerating the reconstruction of the industrial system through the integration of advanced technologies such as artificial intelligence, Internet of Things, industrial robots, and big data. Studies have pointed out that offshore wind power, tidal energy, and wave energy have significant potential in reducing regional dependence on fossil energy, improving energy security, and promoting the greening of marine industries. The dependence of marine energy development on high-end equipment manufacturing, intelligent operation and maintenance systems, environmental monitoring technology and digital management platforms has been increasing, making the technology application of industrial intelligence in the field of marine energy more and more extensive. Based on this, industrial intelligence is not only the driving force of the green transformation of the terrestrial industrial system, but also an important technical foundation for marine energy technology innovation, equipment upgrading and sustainable development of the blue economy.

Against this background, this study aims to systematically examine whether and how industrial intelligence contributes to carbon emission reduction. Using panel data from 30 provincial-level administrative regions in China over the period 2011–2022, this paper employs a partial least squares structural equation modeling approach to analyze the direct effect of industrial intelligence on carbon emissions, the mediating role of industrial structure upgrading, the moderating role of green technological innovation, and regional heterogeneity in these relationships.

The marginal contribution of this paper is as follows: First, there is no unified measurement index of industrial intelligence in the existing relevant research, and most scholars use the number of industrial robots to represent the level of industrial intelligence. Second, the existing research mainly discusses the direct effects of industrial intelligence and carbon dioxide emissions, and few literatures introduce the variables of industrial structure upgrading and green technology innovation, and explore the synergistic effects of the three. Third, there is little literature on the heterogeneity analysis of industrial intelligence, and this paper uses geographical location as the basis to study the differences in the impact mechanism of industrial intelligence on carbon emission reduction in different regions, so as to provide a regional reference for the green development strategy of land-sea coordination.

1.2 Literature Review

Previous studies have explored the potential role of industrial intelligence on carbon emissions and green development from different perspectives. Some studies have shown that industrial intelligence may reduce carbon emissions at the macro level by promoting high-end manufacturing, optimizing industrial structure, and enhancing technological innovation capabilities [2–4]. Specifically, the application of industrial intelligence can improve enterprise R&D investment, optimize production processes, and have a positive impact on carbon emission reduction in energy-intensive industries [5–7]. In addition, some studies have pointed out that the impact of advanced technologies such as artificial intelligence on carbon emissions is non-linear, that is, the carbon reduction effect can only be fully manifested when technological development reaches a certain level and green innovation capabilities are improved [8]. Recent international studies have further emphasized the conditional nature of technological emission reduction, which points out that renewable energy technologies will have different environmental impacts in different fields, and these results show that the carbon emission reduction effect of industrial intelligence is influenced by structural and institutional factors rather than the inevitable result of technology adoption [9]. Despite the increasing literature on industrial intelligence and green development, several shortcomings remain.

There is no consensus on how to comprehensively measure industrial intelligence, and many studies rely on single indicators, which may fail to capture its multidimensional characteristics. Furthermore, existing research primarily focuses on the direct relationship between industrial intelligence and carbon emissions, while the mediating roles of industrial restructuring and the moderating roles of green technology innovation have not received sufficient attention within a unified analytical framework. To address these shortcomings, this study constructs a multidimensional measurement framework for industrial intelligence, integrating industrial restructuring and green technology innovation into a comprehensive causal model, and conducting regional heterogeneity analysis based on geographical location. Through these studies, this paper aims to provide more detailed empirical evidence for the carbon reduction mechanism of industrial intelligence and to offer policy references for the coordinated green development of terrestrial industrial systems and marine energy sectors.

2 Theoretical Analysis and Research Hypotheses

2.1 *The Impact of Industrial Intelligence on CO₂ Emissions*

Industrial intelligence is an industrial upgrading process with advanced technologies such as artificial intelligence, industrial Internet, big data, Internet of Things and robots as the core, and is considered an important path to promote the green transformation of the manufacturing industry and achieve the “double carbon” goal. First, industrial intelligence relies on intelligent perception, real-time control, and algorithm optimization to carry out a high degree of integration and dynamic allocation of energy use processes [10], which can form the optimal allocation of resources in the production process, improve the marginal productivity of factors, help promote the withdrawal of high-energy-consuming and inefficient resources, and then release development space for energy-efficient and low-pollution resources, thereby significantly improving energy utilization efficiency and reducing carbon emissions per unit of output. At the same time, industrial intelligence has changed the path dependence of enterprise technology evolution, guiding technological progress to evolve in the direction of clean and intelligent. The introduction of new technologies not only shortens the iteration cycle of products and processes, but also accelerates the diffusion and transfer of green technologies among enterprises, resulting in stronger technology spillovers. In addition, intelligent means make the internal management and emission supervision systematized and digitized, further reduce ineffective production, reduce redundant energy consumption [11,12], improve the real-time perception, process feedback, and risk prediction ability of enterprises on environmental performance, and shift environmental governance behavior from “post-event response” to “forward-looking intervention”, thereby effectively avoiding excessive carbon emissions and resource redundancy. The following hypotheses are put forward in this paper:

Hypothesis 1: *Industrial intelligence has a significant effect on carbon emission reduction.*

2.2 *The Mediating Effect of Industrial Structure Upgrading*

In the process of promoting industrial intelligence, industrial structure upgrading is not only a direct result of technological change, but also an important transmission mechanism to achieve carbon emission reduction. Industrial structure determines the mode of resource allocation and energy use pattern, which is the core variable affecting the carbon emission intensity of a country or region. By improving the technical level and production efficiency, industrial intelligence provides a realistic foundation for the transformation of traditional industries and the expansion of emerging industries, and then promotes the evolution of industrial structure in the direction of high-end, service-oriented, and green [6,13]. First, intelligence promotes enterprises to reconstruct production processes and enhance product added value, thereby accelerating the intelligent upgrading and green transformation of traditional industries [3]. Secondly, the centralized

allocation of resource elements in high-tech industries and emerging formats promotes the redistribution of regional industrial gradients and drives the structural optimization of high-carbon regions. Industrial integration and technology spillover will help form a new synergistic relationship between the service industry and the manufacturing industry, and then realize the overall leap from manufacturing to intelligent manufacturing. In this process, the proportion of resource-dependent industries with high carbon density gradually decreases, while the proportion of technology-intensive industries with higher carbon efficiency increases, thereby reducing the carbon emission intensity of the overall economic system. The following hypotheses are put forward in this paper:

Hypothesis 2: *Industrial intelligence has a significant role in promoting industrial structure upgrading.*

Hypothesis 3: *Upgrading industrial structure has a significant effect on carbon emission reduction.*

Hypothesis 4: *The upgrading of industrial structure has a mediating effect on the impact of industrial intelligence on carbon emission reduction.*

2.3 The Moderating Effect of Green Technology Innovation

With the advancement of industrial intelligence, enterprises have deepened their dependence on green production processes, energy-saving and emission reduction equipment, and green product design, and green innovation has gradually become the core element connecting intelligent transformation and low-carbon development. On the one hand, green technology innovation has improved the “green absorption capacity” of intelligent production systems, that is, the ability of enterprises to deeply integrate intelligent technology with cleaner production processes. If enterprises lack green technology innovation capabilities, even if they achieve automation and intelligence, they may continue to expand on the path of high load and high energy consumption, forming a “reverse effect of technological progress”. Therefore, “intelligence” alone is not enough to automatically bring about “low-carbonization”, and green-oriented technological progress is a necessary condition for intelligent achievements to achieve carbon benefits [14]. On the other hand, green technology innovation also strengthens the ability of enterprises to cope with environmental regulations and market green demand, making the implementation of industrial intelligence more strategically oriented and long-term. In the context of strong green innovation capabilities, enterprises are more likely to use intelligence as a tool to achieve energy conservation, carbon reduction, and environmental performance, rather than just improving production efficiency, so as to enhance the marginal reduction effect of intelligent paths on carbon emissions. The following hypotheses are put forward in this paper:

Hypothesis 5: *The level of green technology innovation has a moderating effect on the impact of industrial intelligence on carbon emission reduction.*

3 Study Design

3.1 Research Methodology

This study adopts partial least squares structural equation modeling (PLS-SEM) as the main analytical approach. PLS-SEM is a causal modeling technique that aims to maximize the explained variance of latent variables while simultaneously assessing measurement model quality. Compared with covariance-based SEM (CB-SEM), PLS-SEM is more flexible with respect to sample size, model complexity, and the number of indicators per construct. As a result, it can address a broader range of research problems and has been widely applied in economics, management, and psychology.

The modeling procedure consists of two stages. In the first stage, the measurement model is evaluated to assess internal consistency reliability and construct validity, including Cronbach's alpha, convergent validity, and discriminant validity. In the second stage, the structural model is analyzed to examine and validate the

path coefficients and explanatory power of the proposed relationships, thereby assessing the overall reliability and validity of the latent constructs [15].

The proposed research framework is a second-order model. Second-order constructs can be classified into four types: formative–formative (FF), formative–reflective (FR), reflective–formative (RF), and reflective–reflective (RR). Correspondingly, two main estimation approaches are commonly used: the repeated indicators approach and the two-stage approach [16,17]. An increasing number of studies advocate the use of hierarchical latent variable models rather than models composed solely of lower-order constructs, as higher-order structures allow for greater theoretical parsimony and reduced model complexity [18–20].

This study adopts a typical reflective–reflective (RR) second-order model. In such a model, the lower-order constructs are themselves measured reflectively and are conceptually distinct yet correlated. Lohmöller (1989) referred to this type of structure as a “hierarchical factor model” in which the higher-order construct represents the common factor underlying several specific dimensions [21]. Specifically, industrial intelligence level is conceptualized as a higher-order construct composed of four first-order dimensions: internet investment, intelligent application and market efficiency, each measured by multiple indicators. PLS-SEM is particularly appropriate for estimating second-order models, especially those involving formative components, as covariance-based SEM techniques such as LISREL cannot adequately estimate second-order formative structures [22,23]. Moreover, Hair et al. argue that PLS-SEM is well suited for studies that emphasize prediction and theory development. Since the primary objective of this study is to predict whether industrial intelligence level influences carbon emission, PLS-SEM is an appropriate methodological choice for analyzing the proposed research model.

3.2 Model Setting

In this paper, a structural equation model is constructed with the help of SMART-PLS 4.0 software to analyze the causal relationship between industrial intelligence level and carbon emissions in China's provinces.

The first stage uses the measurement model to verify the suitability of the latent variable and the corresponding observed variable, and the formula is as follows:

$$X_i = \lambda_i \xi + \varepsilon_i \quad (1)$$

where X_i denotes the observed indicator, ξ represents the corresponding latent variable, λ_i is the factor loading, and ε_i is the measurement error term.

In the second stage, the structural model is used to verify the path effect between exogenous and endogenous latent variables, and the formula is as follows:

$$\eta = \beta_1 \xi_1 + \beta_2 \xi_2 + \beta_3 \xi_3 + \zeta \quad (2)$$

where ξ_1, ξ_2, ξ_3 denotes the exogenous latent variables, η is the endogenous latent variable, $\beta_1, \beta_2, \beta_3$ represents the structural path coefficients, and ζ is the structural disturbance term.

In addition, this paper also needs to consider the mediating role of industrial structure upgrading and the moderating role of green technology innovation, and the formula is as follows:

$$UIS = \mu_1 \xi_1 + \mu_2 \xi_2 + \mu_3 \xi_3 + \zeta_1 \quad (3)$$

$$CE = \gamma_1 IIL + \gamma_2 UIS + \zeta_2 \quad (4)$$

$$CE = \delta_1 IIL + \delta_2 GTI + \delta_3 (IIL * GTI) + \zeta_3 \quad (5)$$

Eqs. (3) and (4) represents mediation effect, where UIS denotes industrial structure upgrading, CE represents carbon emissions, μ_1, μ_2, μ_3 and γ_1, γ_2 are path coefficients, and ζ_1, ζ_2 are error terms.

Eq. (5) represents moderation effect, where GTI denotes green technology innovation, $IIL * GTI$ represents the interaction term capturing the moderating effect of green technology innovation on the relationship between industrial intelligence and carbon emissions, $\delta_1, \delta_2, \delta_3$ are path coefficients, ζ_3 is the error term.

3.3 Key Indicator Selection and Construction

This article selects panel data from 30 provinces and municipalities in China from 2011 to 2022 as the research sample. After collecting the sample data, this article processes the data according to the following methods: first, the variables are reduced in size; second, missing values are marked as “999”.

1. Industrial intelligent measurement index

The connotation and extension of industrial intelligence are relatively complex, involving a very wide range of resources, and there are difficulties in accounting. Based on the characteristics of China's industrial intelligence development and combined with the existing literature, this paper constructs a comprehensive evaluation system for the level of industrial intelligence from three perspectives: intelligent investment, intelligent application, innovation, and market benefits [4,24], as shown in Table 1.

Table 1: Industrial intelligent measurement index system.

Latent Variable	First-Level Indicators	Secondary Indicators	Measurement Method	Variable
Industrial Intelligence Level	Internet Investment	Internet Equipmenture Investment	Fixed asset investment in the information and communication software service industry	III
		Intelligent Funding Investment	R&D expenditure in high-tech manufacturing	II2
		Intelligent Talent Investment	Number of R&D personnel in high-tech manufacturing	II3
	Intelligent Application	Smart Product Development	Revenue from embedded systems/main business revenue of industrial enterprises	IA1
		Smart Enterprise Development	Main business revenue of high-tech enterprises/main business revenue of industrial enterprises	IA2
		Degree of Smart Technology Application	New product sales in high-tech industries/main business revenue of industrial enterprises	IA3

(Continued)

Table 1 (continued)

Latent Variable	First-Level Indicators	Secondary Indicators	Measurement Method	Variable
	Market Efficiency	Industrial Economic Efficiency	Main business revenue of high-tech manufacturing/number of employees in high-tech manufacturing	ME1
		Industrial Production Efficiency	Energy consumption per unit of regional GDP	ME2
Carbon Emissions			CO ₂ emissions	CE
Upgrading Industrial Structure			Proportion of primary, secondary, and tertiary industries in regional GDP	UIS
Green Technological Innovation			Number of Green Invention Patent Applications	GTI1
			Number of Green Utility Model Patent Applications	GTI2

Note: Data Source: China Statistical Yearbook; China Science and Technology Statistical Yearbook; China High-Technology Industry Statistical Yearbook.

2. Carbon emission measurement indicators

The carbon emissions data for this study are derived from the Emissions Database for Global Atmospheric Research (EDGAR) jointly released by the European Union Joint Research Center (JCR) and PBL Netherlands Environmental Assessment Agency (PBL). EDGAR data accounts for carbon emissions based on different energy types, including energy activity carbon emissions, partial industrial carbon emissions, partial non-energy carbon emissions, and fuel spontaneous combustion emissions [25,26].

3. Measurement indicators of industrial structure upgrading

This paper draws on the research of many scholars to calculate the industrial structure upgrading coefficient [27,28], and the specific formula is:

$$UIS = \sum_{j=1}^3 Y_{i,t,j} \times j, j = 1, 2, 3 \quad (6)$$

$Y_{it,j}$ represents the ratio of the industrial added value of the j industry in i province to the total regional output value in the t period. The value range of UIS is 1–3, and the smaller the value, the lower the value, the lower the industrial structure in the region, and the lagging level of industrial structure upgrading. The higher the value, the higher the industrial structure in the region, the higher the development stage, and the level of industrial structure upgrading is more advanced.

4. Green technology innovation measurement indicators

The number of green patent applications (including the number of green invention patent applications and green utility model patent applications) is used as a measurement index of green technology innovation [29,30].

As shown in Fig. 1, this study develops a conceptual model that integrates five research hypotheses in Section 2 to examine the relationships among the core constructs and indicators.

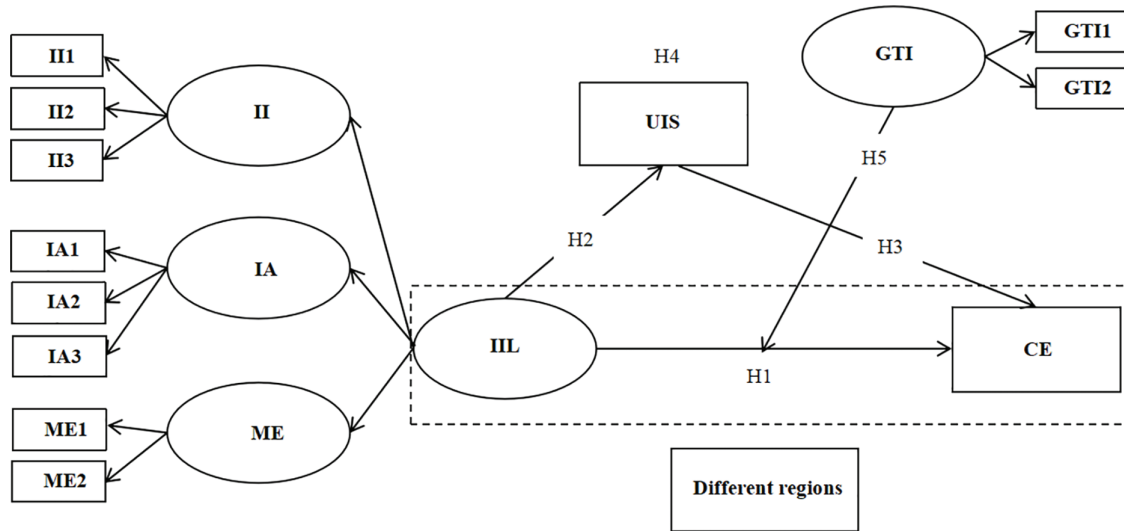


Figure 1: Conceptual model.

4 Empirical Results and Analysis

4.1 Measurement Model Analysis

1. Analysis of industrial intelligent high-order profile measurement model

The measurement model aims to test the structural relationship between latent variables and the observed indicators they represent, and reflect the intrinsic quality of the model. When the factor load coefficient reaches more than 0.70 and passes the significance test (p value < 0.05), it is considered that the observed variable can better reflect the characteristics of the latent variable. The structural equation model constructed in this paper contains a multi-level latent variable system, in which the level of industrial intelligence is reflected by three first-order planes as a high-order plane.

After excluding the observed variables with a factor load of less than 0.70, it can be obtained from Table 2 that the factor load coefficients of each observation index of industrial intelligence are above 0.70, and the corresponding p values are significant, indicating that each selected observation index has a high degree of reliability. At the same time, except for the market benefit variable, the Cronbach's Alpha > 0.8 and the CR value of the other variables > 0.8 , indicating that the measurement model has good internal consistency. The AVE values of each facet were > 0.5 , indicating that the convergence validity was high.

The test results in Table 3 show that according to the Fornel-Larcker criterion, the square root of the AVE value (bold diagonal value) is greater than the correlation coefficient of each facet, which proves that the first-order constructs of the industrial intelligence level constructed in this paper have good differential validity.

Table 2: Industrial intelligent measurement model results.

Higher-Order Configuration	First-Order Configuration	Measurement Indicators	Factor Loading	Cronbach's Alpha	CR	AVE
IIL	II	II1	0.962	0.916	0.948	0.859
		II2	0.976			
		II3	0.836			
	IA	IA1	0.744	0.847	0.908	0.769
		IA2	0.940			
		IA3	0.933			
	ME	ME1	0.902	0.660	0.852	0.743
		ME2	0.820			

Table 3: Differential validity analysis.

	II	IA	ME
II	0.927		
IA	0.741	0.877	
ME	0.598	0.646	0.862

Note: The bold diagonal elements represent the square roots of the Average Variance Extracted (AVE) for each construct, while the off-diagonal elements represent the inter-construct correlation coefficients.

2. Overall measurement model analysis

According to the test results of [Table 4](#), the factor load coefficient of each measurement variable is above 0.70 and the p value is significant. The Cronbach's Alpha of all latent variables > 0.8 and the CR values > 0.7, which proves that the latent variables have good reliability characteristics, can maintain stable measurement results at different times and samples, and the AVE values of the four latent variables face exceed the standard of 0.5, indicating that the aggregation validity of the measurement model is excellent.

Table 4: Overall measurement model results.

Latent Variable	Measurement Indicators	Factor Loading	Cronbach's Alpha	CR	AVE
IIL	II	0.913	0.911	0.930	0.628
	IA	0.918			
	ME	0.799			
CE	CE	1.000	1.000	1.000	1.000
UIS	UIS	1.000	1.000	1.000	1.000
GTI	GTI1	0.958	0.940	0.970	0.941
	GTI2	0.982			

From Table 5, it can be seen that the square root values of AVE for each first-order construct exceed the corresponding inter-construct correlations, indicating satisfactory discriminant validity in the proposed measurement model.

Table 5: Differential validity analysis.

	IIL	CE	UIS	GTI
IIL	0.792			
CE	0.064	1.000		
UIS	0.322	−0.387	1.000	
GTI	0.747	0.200	0.237	0.970

Note: The bold diagonal elements represent the square roots of the Average Variance Extracted (AVE) for each construct, while the off-diagonal elements represent the inter-construct correlation coefficients.

4.2 Structural Model Analysis

In this paper, the structural model is verified by using the Bootstrap method, and 5000 repeated sampling is set to ensure the stability of the results. Table 6 shows that the path coefficients of industrial intelligence on carbon emissions and industrial structure upgrading are −0.224 and 0.322, and the test results are significant, supporting hypothesis 1 and hypothesis 2, proving that industrial digitalization can reduce carbon dioxide emissions and improve the level of industrial structure upgrading. The path coefficient of industrial structure upgrading on carbon emissions is −0.428, and the test results are significant, supporting hypothesis 3, proving that the level of industrial structure upgrading can significantly reduce carbon dioxide emissions.

Table 6: Hypothesis testing.

Research Path	Path Coefficient	<i>p</i> value	Hypothesis
IIL → CE	−0.224	*	H1
IIL → UIS	0.322	***	H2
UIS → CE	−0.428	***	H3

Note: * indicates significance at the 5 per cent level of significance; *** indicates significance at the 0.1 per cent level of significance.

These results reflect the internal logic of how industrial intelligence reshapes production systems. Industrial intelligence enhances production efficiency and promotes cleaner production processes, ultimately weakening the dependence on fossil energy. By accelerating the diffusion of smart manufacturing technologies, enterprises are able to optimize resource allocation, reduce energy redundancy, and transition toward higher value-added industrial activities. Furthermore, the significant role of industrial intelligence also provides theoretical insights for the marine economy. As marine renewable energy development, relies heavily on intelligent equipment manufacturing and automated operational systems, improvements in land-based industrial intelligence create spillover benefits for the marine sector. The intelligent technology in the industrial system can be transferred to the offshore energy platform, thereby reducing operational energy consumption and improving the carbon efficiency of marine energy development.

4.3 Mediation Effect Analysis

According to the test results of Table 7, the indirect effect of industrial intelligence on carbon emissions through industrial structure upgrading is -0.138 , and the VAF value reaches 38.12%, which meets the judgment criteria of some mediating effects, so hypothesis 4 is valid. It is further verified that the positive and negative directions of the indirect path and the direct path are the same, indicating that the two are complementary mediating effects. otherwise, it is a competition mediating effect. It can be seen that the industrial structure has been upgraded to a complementary intermediary, which has enhanced the role of industrial intelligence in carbon emission reduction.

Table 7: Mediated effects test.

Independent Variable	Intermediate Variable	Implicit Variable	Direct Effect	Indirect Effect	Overall Effect	VAF	Hypothesis
IIL	UIS	CE	-0.224^*	-0.138^{***}	-0.362^{***}	38.12%	H4

Note: $*p < 0.05$, $***p < 0.001$.

This complementary mediation indicates that industrial intelligence not only directly reduces carbon emissions through efficiency gains but also indirectly strengthens carbon-reduction outcomes by promoting industrial upgrading. As industries evolve toward more technologically advanced and service-oriented sectors, energy-intensive and high-pollution activities are gradually reduced. The shift toward cleaner sectors magnifies the environmental benefits of digital technologies, forming a dual-pathway mechanism for emission reduction. A more advanced service-oriented structure promotes the development of scientific research, engineering design, testing and certification services, digital monitoring platforms, and intelligent operation systems. These capabilities are essential for supporting offshore wind installation, marine equipment manufacturing, and smart operation and maintenance in marine renewable energy projects. Therefore, industrial structure upgrading not only serves as a channel through which industrial intelligence reduces carbon emissions on land, but also forms a foundational support system for the technological innovation and equipment needs of the marine renewable energy sector.

4.4 Moderating Effect Analysis

According to the results presented in Table 8, the coefficient of the interaction term is -0.211 and the p -value is less than 0.001, clearly indicating that green technological innovation exerts a significant moderating effect on the relationship between industrial intelligence and carbon emissions. Thus, Hypothesis 5 is supported. This finding suggests that as the level of green technological innovation increases, the suppressive effect of industrial intelligence on carbon emissions is significantly strengthened. In other words, green technological innovation effectively amplifies the marginal carbon-reduction effect of industrial intelligence.

Table 8: Moderating effects test.

rESEARCH PATH	PATH COEFFICIENT	p value	Hypothesis
IIL $\times$ GTI $\rightarrow$ CE	-0.211	$***$	H5

Note: $***p < 0.001$.

The moderating effect reveals that green innovation acts as a catalyst, enabling digital technologies to more effectively translate into environmental performance. Industrial intelligence alone improves efficiency, but green technological innovation introduces cleaner production technologies, advanced pollution-control

equipment, and low-carbon product designs that further enhance the environmental performance of intelligent systems. Offshore renewable energy systems require advanced corrosion-resistant materials, smart fault-detection systems, remote autonomous maintenance, and low-carbon marine transportation solutions. When green innovation capabilities are strong, the intelligent manufacturing of marine equipment becomes more energy-efficient and environmentally friendly. Thus, green innovation not only strengthens the carbon-reducing effect of industrial intelligence on land but also accelerates the decarbonization of emerging marine energy industries through technological spillover and cross-sectoral integration.

4.5 Multi-Cohort Analysis

Considering that there are obvious differences in development levels in different regions of China, this paper divides the sample into three major regions in the east, central and western regions according to the standards issued by the National Bureau of Statistics. After running the multi-group analysis, the relevant indicators can be obtained from Table 9, and the impact coefficient of industrial intelligence on carbon emissions in the eastern region is -0.022 , the impact coefficient in the central region is -0.863 , and the impact coefficient in the western region is -0.309 . It can be seen that industrial intelligence has a greater impact on carbon emissions in the central region. If the p value is less than 0.05 , it indicates that there is a difference in influence between regions, and the results of Table 9 show that there is a significant difference between the eastern and central regions and the central and western regions, but there is no significant difference between the eastern and western regions. The possible reason is that the central region is still in the stage of industrialization, and industrial intelligence can significantly improve energy efficiency, optimize production structure, and have more room for emission reduction. Although the western region has potential, it is subject to infrastructure and technical conditions, and the emission reduction effect is limited; The level of industrial intelligence in the eastern region is relatively mature, the marginal effect tends to decrease, and the potential for carbon reduction is relatively small. In view of the high dependence of the core industries of the blue economy such as offshore wind power and marine equipment manufacturing on intelligent manufacturing capabilities, the above regional differences show that in the future construction of the marine energy industry chain, the central region can participate in the marine equipment supply chain by providing green production capacity and intelligent manufacturing links, while the eastern coastal region will continue to give full play to the advantages of scientific and technological innovation and marine industry agglomeration, and the two form a land-sea linkage and regional complementary development pattern.

Table 9: Mediated effects test.

	β_{east}	β_{central}	β_{west}	E.vs. C.		E.vs. W.		C.vs. W.	
				$\Delta\beta$	p value	$\Delta\beta$	p value	$\Delta\beta$	p value
IIL $\rightarrow$ CE	-0.022	-0.863	-0.309	-0.309	***	0.157		0.021	*

Note: * $p < 0.05$, *** $p < 0.001$.

5 Research Conclusions and Discussion

Based on the existing research results, this paper constructs a theoretical framework for the impact of industrial intelligence on carbon emissions, and analyzes the influence mechanism of 30 provincial-level administrative regions in China except Tibet, Hong Kong, Macao and Taiwan by using the structural equation model method. The main conclusions of the study are as follows: First, industrial intelligence can be measured through four dimensions: intelligent input, intelligent application and market benefits.

Second, industrial intelligence has a significant role in promoting carbon emission reduction. Industrial structure upgrading plays a partial mediating role in the process of industrial intelligence affecting carbon emission reduction, while green technology innovation plays a positive role in this process. Third, the carbon emission reduction effect of industrial intelligence shows significant regional differences. The carbon emission reduction effect was the most significant in the central region, and there were significant differences between the eastern and central regions, and between the central and western regions.

These findings are broadly consistent with international evidence. Existing studies measuring the degree of industrial digitalization in 44 industries in South Africa from the input side, and the empirical results showed that industrial digitalization significantly reduced the intensity of carbon dioxide emissions in the production process, and Brazil, South Africa and China all achieved significant emission reduction effects through industrial digitalization [31]. Similarly, evidence from 27 EU countries shows that digitalization has both direct and partial mediating effects on greenhouse gas emissions, highlighting the importance of digital transformation in reducing greenhouse gas emissions in EU countries [32]. From a broader perspective, the core mechanisms identified in this study are widely applicable to economies undergoing industrial transformation and low-carbon energy transitions. The findings may be generalized to other economies with comparable industrial foundations, digital infrastructure, and decarbonization objectives. Moreover, the observed regional heterogeneity reflects broader dynamics related to development stages, resource endowments, and institutional capacities, indicating that differentiated and context-specific policy pathways are essential when applying industrial intelligence strategies across regions and countries.

Based on the findings of these studies, several feasible policy implications can be derived. First, governments should utilize industrial intelligence as a key tool for reducing carbon emissions, providing targeted incentives such as subsidies for smart manufacturing, digital management systems, and energy-saving technologies. Second, given the mediating role of industrial restructuring, policies should integrate industrial intelligence initiatives with industrial restructuring strategies, guiding resources towards high-value-added and low-carbon industries. Third, the positive moderating effect of green technology innovation highlights the importance of strengthening support for green R&D, innovation platforms, and green finance mechanisms to enhance the synergistic effects of industrial intelligence. Finally, considering the varying effects across different regions, governments should adopt differentiated policy approaches.

These conclusions not only deepen our understanding of how industrial intelligence drives the green transformation of terrestrial industrial systems but also provide important insights for the development of marine renewable energy. The high-efficiency production models, intelligent equipment manufacturing capabilities, and digital management systems fostered by industrial intelligence can generate spillover benefits for the marine energy sector. The regional differences in industrial intelligence levels and associated emission-reduction effects further imply that terrestrial regions will assume differentiated functional roles within the future marine energy equipment supply chain, intelligent operation and maintenance systems, and the broader development of the blue economy.

Despite the contributions of this study, several limitations should be acknowledged. First, the analysis is based on provincial data from China, which may limit the generalizability of the findings to other countries or regions with different industrial structures and digital infrastructures. Second, carbon emissions and industrial intelligence variables, are measured using available proxies, which may not capture all dimensions of the constructs. Future research could address these limitations by extending the analysis to other countries or regions, incorporating additional dimensions and indicators of industrial intelligence, and examining long-term environmental and economic outcomes. Moreover, further studies could explore other potential mediating and moderating mechanisms, such as policy interventions or sector-specific technological adoption, to deepen understanding of how industrial intelligence drives low-carbon development across different contexts.

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