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Artificial Intelligence and Carbon Emissions in Manufacturing Firms: The Moderating Role of Green Innovation

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Abstract: Carbon emissions have gained worldwide attention in the industrial era. As a key carbon-emitting industry, achieving net-zero carbon emissions in the manufacturing sector is vital to mitigating the negative effects of climate change and achieving sustainable development. The rise of intelligent technologies has driven industrial structural transformations that may help achieve carbon reduction. Artificial intelligence (AI) technology is an important part of digitalization, providing new technological tools and directions for the low carbon development of enterprises. This study selects Chinese A-share listed companies in the manufacturing industry from 2012 to 2021 as the research objects and uses a fixed-effects regression model to study the relationship between AI and carbon emissions. This study clarifies the significance of enterprise AI technology applications in realizing carbon emissions reduction and explores the regulatory mechanism from the perspective of the innovation effect. The results show that the application of enterprise AI technology positively impacts carbon emissions reduction. Simultaneously, green technological innovation, green management innovation, and green product innovation play moderating roles; in other words, enterprise green innovation strengthens the effect of AI on carbon emissions reduction. This study clarifies the necessity of intelligent manufacturing and enriches theories related to AI technology and carbon emissions.

Keywords: artificial intelligence; carbon emissions; green technology innovation; green management innovation; green product innovation

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1. Introduction

Since the Industrial Revolution, the harm caused by global warming has drawn attention, and countries have introduced policies to mitigate global warming and pursue sustainable development. Carbon emissions from energy consumption are the main cause of climate change; therefore, reducing carbon emissions has become the key to reversing environmental degradation. Greenhouse gas (GHG) emissions accompany economic growth, especially in developing and emerging countries [1]. Therefore, initiatives to address climate change in developing countries are crucial for achieving carbon emissions reduction. As the largest developing country, China accounts for approximately 30% of the world's CO_2 emissions, of which approximately 90% originate from fossil fuels. To meet the requirements of the Paris Agreement, China has pledged to achieve peak carbon by 2030 and carbon neutrality by 2060, emphasizing low-carbon development [2]. In achieving this carbon reduction goal, the focus is on guiding traditional industrial changes and intelligent transformations.

Scientific and technological development can lead to industrial upgrades, economic transformations, and energy restructuring. The Industrial Revolution promoted economic growth, but traditional economic development also led to excessive energy consumption and emissions, which, in turn, produced environmental pollution. Carbon emissions are macro-environmental defects in industrial development. The emergence of intelligent technology has led to cutting-edge technological interventions in traditional economic growth [3] that make human life and work more efficient and reduce the impact of practical activities on the environment [4]. Artificial Intelligence (AI) is a collective term for the science of artificial intelligence, including theories, methods, technologies, and application systems, consisting of different fields such as machine learning, language recognition, image recognition, natural language processing, etc., which is a simulation and extension of human intelligence [5]. Energy consumption during the production and operation of enterprises generates carbon emissions, and emission intensity increases with each process step of the supply chain [6]. AI is one of the three top technologies of the 21st century, which has brought about great changes in technological innovation, production and operation, and even social life, and it is the driving force for technological and industrial transformations [7]. The "Made in China 2025" plan highlights the deep integration of the new generation of information technology into the manufacturing industry to create "intelligent manufacturing." Therefore, AI technology is closely related to the manufacturing industry. This study focuses on artificial intelligence technologies in the manufacturing industry and examines the level of utilization of AI technology by manufacturing companies.

Previous studies discussed the low carbon economy of smart manufacturing, confirming that the development of AI technology can reduce carbon intensity [8–10]. Therefore, AI can serve the dual purpose of achieving economic growth and alleviating environmental pressure and is an important tool for achieving carbon neutrality and carbon reduction [11]. In several fields, AI can reduce carbon emissions by optimizing industrial structures, strengthening information facilities, and improving green innovations. For example, in the electric power industry, AI technology can coordinate carbon and electricity coupling [12]. In the medical industry, AI can reduce carbon emissions by optimizing processes and improving care models [13]. Industry is the largest energy-consuming sector, accounting for approximately 70% of China's total energy demand, and low carbon improvements are critical to ensuring sustainability [14]. The use of AI technology can improve energy efficiency and reduce resource waste, thereby realizing low carbon development [15]. In addition, AI technologies provide more opportunities for traditional supply chains to transition to green supply chains by reducing carbon emissions [16]. However, scholars have opposing views on this topic. First, the advancement of AI has led to a decrease in energy costs, prompting companies to expand resource extraction, production, and consumption, which has exacerbated energy consumption and created a "rebound effect" [17]. Second, when the smart transformation process is not sufficiently stable, additional data management support is required, leading to increased energy consumption and carbon emissions [18].

Therefore, we selected 1938 listed manufacturing companies in China's A-share market from 2012 to 2021 to study whether the use of AI by manufacturing companies can reduce carbon emissions. In addition, previous studies found an innovation effect between the intelligent transformation of the manufacturing industry and carbon emissions reduction. Precise emissions, pollution control, and cost reduction are the focus of green innovation by enterprises [19]. According to the theory of ecological modernization, environmental innovation is a foothold for development, and "economic ecologization" and "ecological economization" are effective ways to achieve environmentally friendly development. In combination with previous studies' findings, green innovation may strengthen the relationship between AI and carbon emissions [20,21]. This paper discusses the regulation and influence mechanisms of green innovation in terms of technology, management, and products.

The contributions of this study are as follows. First, while there is a wealth of existing literature on the relationship between AI and carbon performance in cities or regions, studies from a micro perspective are relatively scarce. This study conducted an empirical analysis to verify the relationship between the development level of AI and carbon performance in the manufacturing industry, with a focus on companies. The results enrich the relevant literature and will help businesses achieve sustainable low carbon development. Second, considering the innovation effect and using innovation as the influence mechanism, this study explored the regulation mechanism between the level of enterprise AI and carbon emissions by green technological innovation, green management innovation, and green product innovation, which provides a basis for promoting relevant theories.

The remainder of the paper is structured as follows: Section 2 presents the theoretical background and analyzes and formulates the hypotheses with respect to the research questions. Section 3 covers the methodology. Section 4 presents the empirical analysis. Section 5 discusses the results of the study, the revelations, and the limitations and future perspectives.

2. Theoretical Background and Hypotheses

2.1. Influence of Enterprise AI Technology on Carbon Emissions

In recent years, the world has experienced a boom in digital transformations, and the convenience and practicality of smart technologies have reduced environmental pressures. Research has found that AI is an engine for green economic development [22]. Based on the theory of high-quality development, promoting the low carbon transformation of high-energy-consuming and high-polluting industries is key to realizing a green and low carbon economy. AI, an emerging technology, has the characteristics of versatility and permeability, and it can promote technological revolutions and industrial change from different perspectives. The emergence of AI has brought light to sustainable development, enabling enterprises to realize maximum benefits at the lowest cost.

The theory of eco-modernization suggests that environmental problems can be improved by increasing resource efficiency to improve sustainability [23]. First, technological advances in AI can optimize the production process, which, in turn, reduces the consumption of fossil fuels and other energy sources, conserves resources, and allows for green production. Pollution is a manifestation of the underutilization of resources [24]. AI technology is used in the manufacturing industry to reduce carbon emissions intensity by improving energy efficiency. Simultaneously, intelligent transformation breaks the restrictions of traditional industries in terms of time and space; contributes to the efficient reorganization and rational allocation of manpower, capital, and resources [25]; enables business transformations [26]; drives the rationalization of the industrial structure and structural upgrading; and is conducive to the realization of carbon neutrality. Second, as a digital tool, AI technology can help realize low carbon development in terms of both classification and prediction. From the perspective of classification, different subtypes of AI application tools can improve operational efficiency and process patterns. For example, AI's data mining capability allows for the fine management of energy demand, and machine learning can improve the process and optimize the manufacturing chain to reduce energy costs [27]. In terms of prediction, AI technology can perform technical tracking to predict carbon monoxide and carbon dioxide emissions; assist in detecting, collecting, and organizing data related to carbon emissions; and indirectly promote carbon emissions reduction [28]. Finally, AI can develop systems for tasks that require human intelligence. The use of AI technology by enterprises can improve supply chain operations [29], drive the integration of environmental processes in upstream and downstream enterprises, create a green supply chain [30,31], optimize the market structure, save energy, and reduce emissions. Therefore, this paper argues that AI technology plays a unique role in industrial transformation, resource integration, data monitoring, and so on, and it is an important means of mitigating carbon emissions. Thus, the following hypothesis is proposed:

Hypothesis 1 (H1): *The level of industry AI in manufacturing firms reduces the carbon intensity of firms.*

2.2. Moderating Role of Green Technological Innovation

The theory of eco-modernization centers on technological innovation and how it can change the direction of technological progress. In early research, green technological innovation was recognized as a new basis for sustainable development [32], focusing on technological innovation in new and renewable resources. Increased levels of innovation in green technologies play an important role in mitigating climate change, with the aim of achieving environmental protection and contributing to the economic growth and sustainable development of enterprises [33]. Green technological innovation is centered on environmental protection and pursues the coordinated development of economy, technology, and ecology [34]. Based on AI technology, an intelligent, green, and low carbon manufacturing system can be a carrier of technological innovation [35]. Technological innovation is one of the three major themes of the United Nations Climate Conference (COP24), and green technological innovation is the key to transforming manufacturing methods into green production [36].

Technological progress and changes in economic structure have been found to help reduce carbon emissions [37]. Technological innovation moderates the relationship between digitization and carbon emissions [38]. Du et al. [39] argued that technological progress is the main driving force for improving low carbon productivity. Improvements in enterprise innovation capability imply technological progress, which promotes the realization of enterprise green development [40]. Li et al. [41] argued that the development of green technological innovation by enterprises implies the possession of higher learning ability and creativity, which in turn promotes the application of enterprise AI technology, increases the green competitive advantage of enterprises, and helps realize sustainable development. Green technological innovation is a dynamic ability; a combination of emissions reduction, energy efficiency, and renewable energy technologies that can strengthen the relationship between AI and carbon emissions. In addition, the development of green technological innovation by enterprises can attract more green and technical talent [42], realize the integration of talent and resources, promote the improvement of human capital efficiency via AI technology, drive the development of intelligence, and encourage green development [43]. Therefore, based on the above analysis, the following hypothesis is proposed:

Hypothesis 2 (H2): *The green technology innovation capacity of manufacturing enterprises strengthens the inhibitory effect of enterprise AI level on carbon emissions intensity.*

2.3. Moderating Role of Green Management Innovation

Green management innovation is an offshoot of the combination of green and management innovation, defined in this study as new management measures for environmental protection introduced or implemented within an enterprise [44]. Based on the performance gap theory, when there is a gap between an enterprise's actual environmental performance and its environmental performance, the enterprise must reduce this gap by introducing environmental management innovations to realize low carbon development [45]. Therefore, if enterprises want to enhance their green capabilities, they must implement green management innovations and focus on the development and utilization of human, business, and technological resources to alleviate environmental pressures [46].

From a management innovation perspective, green management is a key driver of competitive advantage for firms [47] and can improve efficiency, competitiveness, and productivity. Therefore, engaging in green management and implementing environmentally friendly initiatives compels firms to use AI techniques that are more efficient, reduce production waste, and increase productivity. From a green innovation perspective, firms that value this practice have a positive relationship with the natural environment. Viviana Fernandez [48] suggested that high-quality green management innovation contributes to firms' labor productivity and makes them more likely to engage in green development. By adopting environmental management initiatives, companies can communicate with the outside world that they and their management are committed to developing a green economy, thereby improving their social image and enabling green production [49]. At the same time, it attracts more innovative employees [50], provides a strong guarantee for the intelligent transformation of enterprises, and strengthens the impact of the use of AI in manufacturing enterprises on carbon emissions. Therefore, when enterprises implement green management innovation, they emphasize technological change and use AI to mitigate carbon emissions. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3 (H3): *The green management innovation capacity of manufacturing enterprises strengthens the inhibitory effect of the level of corporate AI on carbon emissions intensity.*

2.4. Moderating Effect of Green Product Innovation

Based on organizational learning theory, due to the pressures of environmental pollution and energy waste, enterprises must innovate in the face of high environmental risks [51]. Previous studies focused on green technological innovation in the production process, and green product innovation is important for the development of a low carbon economy. Green product innovation has become crucial for manufacturing companies to maintain green competitiveness in the business environment [52]. According to the literature, green product innovation is defined as reducing environmental harm while increasing energy efficiency; using energy-saving, environmentally friendly, or recyclable materials; designing and developing new products; or improving existing products [53].

As a subfield of green innovation, green product innovation embodies the integration of innovative knowledge, resources, and technologies. Therefore, green product innovation implies that enterprises have sufficient knowledge reserves and resources to develop new technologies, research new products, and promote the use of AI technologies to achieve eco-performance [54]. According to the stakeholder theory, due to contemporary society's concern about the environment, customers and upstream and downstream supply chains will put forward more requirements for green consumption and green products [55]. Therefore, in the process of product development by enterprises, the implementation of green product innovation must improve the environmental performance of their products, which prompts them to utilize AI technology to improve their products' environmental quality [56]. Innovation involves progress and development. Enterprises that emphasize green product innovation and utilize AI technology can reduce waste in developing new products, save costs, and improve their environmental friendliness [57], thus reducing their carbon emissions intensity. Therefore, green product innovation can promote the development of AI technology in enterprises to reduce carbon emissions. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 4 (H4): *The green product innovation capability of manufacturing firms strengthens the inhibitory effect of firms' AI level on carbon emission intensity.*

Figure 1 illustrates the model used in this study.

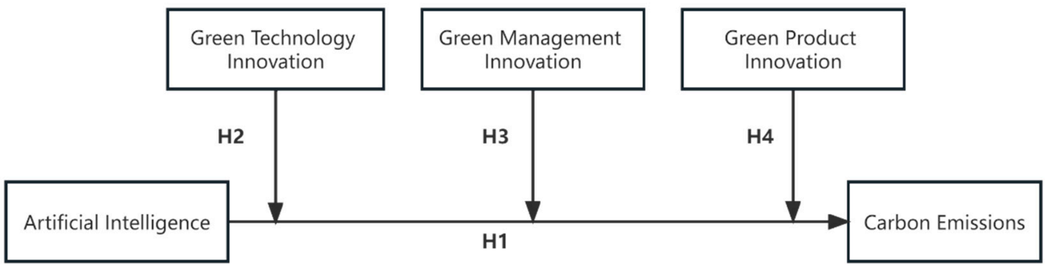

Figure 1. Study model.

3. Methodology

3.1. Sample Selection and Data Sources

The release of the Interim Measures for the Administration of Greenhouse Gas Voluntary Emission Reduction Trading in 2012 marked the beginning of China's voluntary emission reduction market construction. Considering factors such as data availability, this study selected Chinese A-share listed companies from 2012 to 2021 as the research objects and obtained 9547 research samples. Among them, the data related to corporate patents came from the database of the China Research Data Service Platform (CNRDS), the data on green management innovation came from the database of China Stock Market and Accounting Research (CSMAR), and the other data came from the Wind Economic Database (WIND), information on listed companies' websites, websites in the environmental sector, and the social responsibility and annual reports of listed companies. To reduce the interference of other factors and ensure the reasonableness and accuracy of the data, this study adopted the following treatments: (1) excluding ST (special treatment, which refers to listed companies with losses for two consecutive fiscal years), *ST (special treatment*, which refers to listed companies with losses for three consecutive fiscal years with delisting warnings), PT (special transfer, which refers to the cessation of any trading and waiting for delisting of the listed companies), and delisted companies. (2) To eliminate the effect of extreme values, this study winsorized all continuous variables at the 1% and 99% levels. (3) To eliminate the effect of heteroskedasticity, the main continuous variables were logarithmized. (4) To avoid the problem of covariance, this study centered the continuous variables involved in the interaction terms.

3.2. Definitions of the Variables

3.2.1. Dependent Variable

Carbon emission intensity is a traditional indicator used to measure the carbon performance of enterprises, and fossil energy combustion is the main factor producing carbon monoxide and carbon dioxide emissions [58,59]. With reference to the research of Ping et al. and according to data from the Intergovernmental Panel on Climate Change, this paper holds that total carbon emissions are considered to mainly include direct and indirect carbon emissions generated by fossil fuels and carbon emissions from the production process [60] and takes the natural logarithm on the basis of summation. The formula for calculating carbon emissions intensity is as follows:

$$GI = CEE + CPE + CWD + CLT,$$

where GI is the total carbon emissions of listed companies, CEE is the combustion and escape emissions, CPE is the production process emissions, CWD is the waste emissions, and CLT is the emissions caused by land use transformation (e.g., conversion of forests to industrial land). The data used in the carbon emissions calculation process came from the annual reports of listed companies, social responsibility reports, websites of environmental departments, and various statistical yearbooks published by the National Bureau of Statistics of China.

3.2.2. Independent Variable

AI is based on a new generation of information technology running through design, production, management, service, and other manufacturing activities, with a variety of manifestations. Scholars have often used the number of academic AI studies and the number or penetration rate of industrial robots to measure AI variables [61–63]. However, robotics is only a part of AI applications; therefore, more comprehensive measurements must be conducted. With the development of the Internet and the expansion of related literature, text analysis and machine learning have gradually become important methods in economic research. Therefore, in this study, we referred to Li et al., who used a text mining method to construct an AI vocabulary list in Python to analyze the text content of listed companies' annual reports, extract AI-related keywords, and determine word frequency to obtain an AI index of enterprises [64]. Table 1 is the contents of the AI keywords.

Table 1. AI keywords.

Artificial Intelligence	Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision Aids, Intelligent Data Analytics, Intelligent Robotics, Machine Learning, Deep Analysis, Semantic Search, Biometrics, Face Recognition, Voice Recognition, Identity Verification, Automatic Driving, Natural Language Processing

3.2.3. Moderating Variables

Green Technological Innovation

Academics define green technological innovation as innovation in technology that reduces environmental damage or promotes ecological sustainability [65]. Green technological innovation is the core of green innovation and is one way for enterprises to realize the dual goals of environmental protection and economic performance improvement. Considering that it takes time from patent application to authorization, based on previous research, this study used the ratio of green invention patent applications to total invention patent applications as a measure of the level of green technological innovation in enterprises [66–68]. Patent data for enterprises in the current year were obtained from the CNRDS.

Green Management Innovation

The implementation of green management innovation requires the adoption of new and improved environmental management models or measures [69]. The literature shows that enterprises successfully implement and integrate environmental management measures through environmental management systems (EMS) [70]. Therefore, this study referred to Zhang et al. and used ISO 14001 certification to measure green management innovation [71]. A dummy variable form was used, which was recorded as 1 when a firm was ISO 14001 certified and considered to have achieved green management innovation and 0 otherwise. Data on firms' EMS certifications were obtained from the CSMAR database.

Green Product Innovation

Green product innovation is the key to companies maintaining competitiveness, as it can control environmental pollution at the source and help them meet environmental protection standards. Manufacturing companies develop green products to improve their environmental performance. The measurement of green product innovation is still not standardized. Lee et al. [72] examined innovation outcomes from a long-term perspective and concluded that green product innovation outcomes are closely related to R and D. R and D expenditures represent a firm's propensity to research and develop products, reflecting its ability to provide high-quality innovative products and services [73]. Therefore, this study referred to a study by Ivanka Visnjic et al. and adopted an indicator of R and D intensity to measure the level of green product innovation in enterprises [74]. Relevant data were obtained from the CSMAR database and the annual reports of listed companies.

3.2.4. Control Variables

To mitigate the effects of other possible factors, this study referred to a study by Wu et al. and selected the following seven control variables [75–78]: size of the firm (Size), gearing ratio (Lev), profitability of assets (ROA), whether it is a state-owned enterprise (SOE), total asset turnover (ATO), return on net assets (ROE), and firm age (FirmAge). Additionally, years (YEAR) were controlled. Table 2 presents the definitions and measurements of the variables.

Table 2. Variable definitions and measurements.

Variable	Name	Symbol	Definition
Independent variable	Artificial Intelligence Technology Application	AI	Ln (keyword word frequency + 1)
Dependent variable	Carbon Emissions Intensity	CEI	Ln (total annual corporate carbon emissions)
Moderating variables	Green Technological Innovation	GTI	Number of green invention patent applications/total invention patent applications
	Green Management Innovation	GMI	Whether ISO 14001 certified
	Green Product Innovation	GDI	R&D intensity: R&D investment/revenue
Control variables	Enterprise Size	Size	Ln (book value of total assets at year-end)
	Return on Assets	ROA	Net profit/total assets
	Return On Equity	ROE	Net profit/average balance of shareholders' equity
	Asset–liability Ratio	LEV	Total liabilities/total assets
	Total Asset Turnover Ratio	ATO	Operating income/assets
	State-owned Enterprise or Not	SOE	1 for state-owned enterprise, 0 otherwise
	Years of Establishment	FirmAge	Ln (current year − year of incorporation + 1)

3.3. Research Model

To examine the impact of AI on carbon emissions—that is, to test the validity of Hypothesis 1—this study constructed a panel econometric fixed-effects model (1) as follows:

$$CEI_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_k Control_{i,t} + Year_t + \varepsilon_{i,t} \tag{1}$$

In model (1), i and t represent individual firms and years, respectively; $AI_{i,t}$ represents the AI level of firm i in year t; $CEI_{i,t}$ represents the carbon intensity of firm i in year t; $Control_{i,t}$ represents each control variable; α represents the constant term; $\varepsilon_{i,t}$ represents the random perturbation term; and $Year_t$ represents the fixed effect on year. If the coefficient α_1 in the model is negative and significant, Hypothesis 1 is valid.

To further verify the moderating role of green technological innovation, green management innovation, and green product innovation in the relationship between corporate AI and carbon emissions—that is, to test whether Hypotheses 2 to 4 were valid—this study added the interaction term between moderating variables and corporate AI technology to the baseline model and constructed the following models:

$$CEI_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 GEI_{i,t} + \alpha_3 AI_{i,t} GEI_{i,t} + \alpha_k Control_{i,t} + Year_t + \varepsilon_{i,t} \tag{2}$$

$$CEI_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 GMI_{i,t} + \alpha_3 AI_{i,t} GMI_{i,t} + \alpha_k Control_{i,t} + Year_t + \varepsilon_{i,t} \tag{3}$$

$$CEI_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 GDI_{i,t} + \alpha_3 AI_{i,t} GDI_{i,t} + \alpha_k Control_{i,t} + Year_t + \varepsilon_{i,t} \tag{4}$$

In models (2) to (4), the moderator variables $GEI_{i,t}$ and interaction terms $AI_{i,t}GEI_{i,t}$, $GMI_{i,t}$; $AI_{i,t}GMI_{i,t}$, $GDI_{i,t}$; and $AI_{i,t}GDI_{i,t}$ were added, respectively. If the coefficient of the interaction term α_3 in the model is negative and significant, Hypotheses 2 and 4 are valid. After the Hausman test, the p-value was 0.0000; therefore, a fixed-effect regression model was used.

4. Empirical Analysis Results

4.1. Descriptive Statistics and Correlation Analysis

Table 3 shows that the average value of carbon emissions of manufacturing enterprises was 11.4, the minimum value was 8.84, and the maximum value was 15.18. It can be inferred that the manufacturing industry causes more carbon emissions, and there is a large gap in the intensity of carbon emissions between different enterprises. The maximum value of enterprise AI technology level was 1, the minimum value was 0, the standard deviation was 0.45, and the mean value was 0.18, indicating that the use of AI by different manufacturing enterprises is uneven and the overall level needs to be improved. The minimum value of green technological innovation was 0, the maximum value was 1, and the mean value was 0.08, indicating that manufacturing enterprises do not pay enough attention to green technological innovation. The mean value of green management innovation was 0.33, which indicates that green management innovation needs to be strengthened in manufacturing companies. The minimum value of green product innovation was 0.13, the maximum value was 20.33, and the mean value was 4.52, which indicates that there are large differences in green product innovation ability among different individual enterprises. In addition, some control variables had large standard deviations, such as that of enterprise size being 1.17 and the number of years of enterprise establishment being 2.87, indicating that the differences between sample enterprises were obvious. Table 3 presents detailed descriptive statistics.

Table 3. Descriptive statistics.

Variables	Mean	Sd	Min	P50	Max	*n*
CEI	11.40	1.34	8.84	11.24	15.18	9547
AI	0.18	0.45	0	0	2.71	9547
GEI	0.08	0.18	0	0	1	9547
GMI	0.33	0.47	0	0	1	9547
GDI	4.52	3.01	0.13	3.93	20.33	9547
Size	22.04	1.17	20.12	21.86	25.61	9547
LEV	0.37	0.18	0.06	0.36	0.77	9547
ROA	0.06	0.05	−0.12	0.05	0.21	9547
ROE	0.09	0.09	−0.28	0.09	0.34	9547
ATO	0.68	0.34	0.17	0.61	2.21	9547
SOE	0.22	0.42	0	0	1	9547
FirmAge	2.87	0.3	1.95	2.89	3.43	9547

4.2. Correlation Analysis

Table 4 presents the results of the correlation analyses. The correlation coefficients between the two explanatory variables were less than 0.8, and the variance inflation factor values for all variables were less than three, indicating that there was no multicollinearity problem.

Table 4. Correlation analysis.

Variables	CEI	AI	GEI	GMI	GDI	Size	LEV	ROA	ROE	ATO	SOE	FirmAge
CEI	1											
AI	0.049 ***	1										
GEI	0.063 ***	0.023 **	1									
GMI	0.052 ***	0.009	−0.002	1								
GDI	−0.365 ***	0.170 ***	0.009	−0.043 ***	1							
Size	0.915 ***	0.070 ***	0.080 ***	0.054 ***	−0.266 ***	1						
LEV	0.562 ***	0.045 ***	0.106 ***	0.042 ***	−0.270 ***	0.555 ***	1					
ROA	0.009	−0.005	−0.044 ***	−0.002	0.027 ***	−0.071 ***	−0.430 ***	1				
ROE	0.165 ***	0.016	−0.015	0.008	−0.047 ***	0.078 ***	−0.194 ***	0.930 ***	1			
ATO	0.473 ***	−0.018 *	−0.022 **	0.052 ***	−0.383 ***	0.188 ***	0.206 ***	0.199 ***	0.272 ***	1		
SOE	0.369 ***	−0.073 ***	0.021 **	0.049 ***	−0.199 ***	0.388 ***	0.312 ***	−0.183 ***	−0.120 ***	0.113 ***	1	
FirmAge	0.204 ***	0.063 ***	−0.054 ***	0.084 ***	−0.081 ***	0.208 ***	0.124 ***	−0.046 ***	−0.013	0.065 ***	0.177 ***	1

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Analysis of Regression Results

The results of model (1) (column 2) in Table 5 show that the regression coefficient of corporate AI utilization (AI) and carbon emission intensity (CEI) was −2.13, which was significantly negatively correlated at the 5% level, indicating that corporations can mitigate their carbon emissions through the use of AI. Therefore, Hypothesis 1 was valid.

Table 5. Regression results.

	(1)	(2)	(3)	(4)
Variable	**CEI**	**CEI**	**CEI**	**CEI**
AI	−0.022 **	−0.023 **	−0.023 **	−0.031 ***
	(−2.13)	(−2.23)	(−2.24)	(−2.67)
GEI		−0.043 *		
		(−1.67)		
AI*GEI		−0.110 *		
		(−1.82)		
GMI			−0.032 ***	
			(−3.06)	
AI*GMI			−0.036 **	
			(−1.98)	
GDI				−0.008 ***
				(−4.74)
AI*GDI				−0.006 **
				(−2.06)
Size	0.888 ***	0.889 ***	0.887 ***	0.887 ***
	(50.26)	(50.35)	(50.21)	(50.64)
LEV	0.293 ***	0.292 ***	0.297 ***	0.273 ***
	(4.79)	(4.79)	(4.87)	(4.49)
ROA	0.474	0.476	0.498	0.346
	(1.21)	(1.21)	(1.27)	(0.90)
ROE	0.090	0.087	0.081	0.109
	(0.43)	(0.42)	(0.39)	(0.53)
ATO	1.155 ***	1.154 ***	1.152 ***	1.145 ***
	(26.72)	(26.71)	(26.73)	(26.61)
SOE	−0.044	−0.044	−0.041	−0.039
	(−1.18)	(−1.20)	(−1.12)	(−1.06)
FirmAge	0.133	0.132	0.131	0.141
	(1.39)	(1.38)	(1.36)	(1.49)
Constant	−9.522 ***	−9.527 ***	−9.495 ***	−9.519 ***
	(−22.26)	(−22.31)	(−22.15)	(−22.38)
Observations	9547	9547	9547	9547
Adjusted R-squared	0.682	0.682	0.683	0.684
Number of id	1938	1938	1938	1938
Year FE (Fixed Effect)	YES	YES	YES	YES

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

Column 3 in Table 5 contains the regression test results of model (2), which show that the regression coefficient between enterprise AI utilization and enterprise carbon emissions intensity was significantly negatively correlated at the 5% level. Meanwhile, the regression coefficient of the interaction term between AI and green technological innovation was −1.82, which was significantly negatively correlated at the 10% level, indicating that the green technological innovation capability of manufacturing enterprises strengthens the inhibitory effect of corporate AI on carbon emissions intensity. Therefore, Hypothesis 2 was supported.

Column 4 of Table 5 shows that the regression coefficient between corporate AI and corporate carbon emissions was −2.24, which was a significant negative correlation at the 5% level. Meanwhile, the interaction term between AI and green management innovation was significantly and negatively correlated at the 5% level, indicating that the green management innovation capability of manufacturing enterprises strengthens the inhibitory effect of corporate AI on carbon emissions intensity. Therefore, Hypothesis 3 was supported.

As shown in Column 5 of Table 5, the regression coefficient between enterprise AI technology utilization and carbon emissions intensity was −2.67, indicating a significant negative correlation at the 1% level. Meanwhile, the interaction between AI technology and green product innovation was significantly negative at the 5% level, indicating that the green product innovation capability of manufacturing enterprises strengthens the inhibitory effect of enterprises' AI level on carbon emissions intensity. Therefore, Hypothesis 4 was supported.

The empirical analysis of this study verifies the research hypothesis. The results show that the emergence and utilization of AI can reduce the carbon emissions of manufacturing enterprises. The reason may be that enterprises can use AI to reduce resource consumption, improve energy efficiency, reduce labor costs, and so on and then realize the low carbon development of production and operation. At the same time, green technology innovation, green management innovation, and green product innovation play a regulatory role. Green technology innovation is a kind of technological progress, which can promote the application of AI and reduce carbon emissions. Green management innovation is a signal for enterprises to develop low carbon economy, indicating the pursuit of green and high efficiency at the decision-making level. Green product innovation is further implementation of environmental protection by manufacturing companies, which can strengthen the role of AI in carbon emission reduction.

4.4. Robustness Tests

Two-Stage Least Squares Test

This study used a fixed-effects regression to explore the influence mechanism between the development of AI and carbon emission reduction in the manufacturing industry. Issues such as reverse causation and omitted variables may affect the accuracy of the findings. To address possible endogeneity issues and consider the time-lag effect that exists in AI technology [79], this study drew on previous research and used the level of corporate AI (LAI) with a one-period lag as an instrumental variable and the two-stage least squares (2SLS) method to conduct a robustness test [64]. Table 6 presents the results of the 2SLS test. In the first stage of the 2SLS test, the regression coefficient of LAI on AI was 29.54, indicating a positive correlation at the 1% significance level. In the second stage, the regression coefficient of the fitted value of corporate AI on carbon emissions was −1.87, which was significantly negative at the 10% significance level. In addition, the results of the DWH test showed that the Kleibergen-Paap rk *LM* statistic was 59.333, indicating that the instrumental variables were identifiable. Meanwhile, the Cragg-Donald Wald *F* statistic and Kleibergen-Paap rk Wald *F* statistic were 524.712 and 123.726, respectively, passing the weak instrumental variable test.

Table 6. Two-stage least squares test results.

Variable	First Stage	Second Stage
	AI	CEI
LAI	0.477 ***	
	(29.54)	
AI		−0.056 *
		(−1.87)
Size	0.158 ***	0.872 ***
	(2.90)	(40.25)
Lev	0.385 *	0.325 ***
	(1.91)	(4.87)
ROA	−0.089	0.409
	(−0.07)	(0.98)
ROE	0.074	0.046
	(0.12)	(0.20)
ATO	−0.040	−0.062 *

Table 6. *Cont.*

Variable	First Stage	Second Stage
	AI	CEI
	(−0.37)	(−1.75)
SOE	−0.282 **	0.233 **
	(−2.37)	(2.13)
FirmAge	−0.377	−0.056 *
	(−1.08)	(−1.87)
Underidentification test		59.333
(Kleibergen-Paap rk LM statistic)		(Chi-sq(1) *p*-val = 0.000)
Weak identification test		
(Cragg-Donald Wald F statistic)		524.712
(Kleibergen-Paap rk Wald F statistic)		123.726
10% maximal IV size		16.380
Observations	6828	6531
Adjusted R-squared	0.518	0.605
Year FE	YES	YES

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

5. Conclusions and Implications

5.1. Discussion

In recent years, the intelligent development of the manufacturing industry has been the focus of attention. AI is becoming a dominant component of the digital economy [80]. Most scholars believe that the emergence of AI technology can assist enterprises in creating a green supply chain through the Internet of Things and realizing the low carbon development of the industry. However, technological advances can cause harm to the environment [81]. AI technology can bring efficiency and convenience, but it also requires the integration and synergy of different aspects, such as resources, manpower, knowledge, technology, and networks. Therefore, the introduction of AI technology to the manufacturing industry has both positive and negative impacts on environmental performance. For example, AI technology provides new tools that can improve energy efficiency and reduce costs. However, owing to the reduction in costs, this may reverse the process and prompt companies to increase energy inputs, resulting in waste. Therefore, academics do not have a unified view on whether AI is truly conducive to achieving carbon emissions reduction.

To explore this issue in depth, this study examined the level of corporate AI technology and the realization of carbon emissions reduction at the micro level. Simultaneously, the moderating effect of green innovation was verified by considering the role of innovation capability in technology and production operations. The findings were consistent with those of most studies, showing that AI provides more opportunities for environmental protection [82]. AI technology can improve the efficiency of an R and D investment, reduce operational costs, and promote green production [83]. As an example of digital technology, AI improves system efficiency, optimizes processes, and reduces resource waste [84]. Therefore, this study argued that the emergence of AI technology meets the requirements of high efficiency and safety in green manufacturing and that its capabilities, such as information integration, risk assessment, and machine learning, can help realize the green development of enterprises [85].

5.2. Conclusions

With the aggravation of climate change, the manufacturing industry, as a major source of carbon emissions, has attracted considerable attention. In this context, this study selected data on manufacturing companies listed on China's A-share Shanghai and Shenzhen stock exchanges from 2012 to 2021 and adopted a fixed-effect model to explore the abatement effect of corporate AI on the carbon emissions intensity of enterprises. Meanwhile, considering the innovation spillover effect of technological progress combined with mainstream green development, this study further discussed the regulatory mechanism of green technological innovation, green management innovation, and green product innovation on the relationship between AI technology and carbon emissions reduction. The conclusions of this study are as follows: (1) The level of corporate AI negatively impacts corporate carbon emissions intensity. (2) The levels of green technology, management, and product innovation strengthen the inhibiting effect of enterprise AI development on enterprise carbon emissions.

5.3. Implications

Based on the above analysis, this study provides theoretical and practical implications for supporting the use of AI in businesses and mitigating carbon emissions.

The theoretical implications are as follows: First, the research on AI and carbon emissions in this study further confirms the importance of digitalization and intelligence for low carbon development and enriches relevant theories. It also provides a new research perspective and theoretical basis for mitigating climate change hazards. Second, recent research on intelligent manufacturing and carbon emission reduction mainly focused on the macro field, with mostly national, provincial, or regional studies. This study considered listed companies as the research objects and explored the relationship between AI and carbon emission reduction at the individual enterprise level from a micro perspective, thus expanding the field of micro-enterprise research. Finally, the current research focused on internal controls. Based on the direct impact of intelligent manufacturing on industrial upgrading and carbon efficiency, this study expanded the related research ideas by selecting three different aspects of green innovation as moderating variables, with the innovation effect as the criterion.

The practical implications are as follows: First, the government level. The research results prove the positive impact of AI and green innovation on realizing green and low carbon development, illustrate the urgency of intelligent transformation of the manufacturing industry, and provide a reference for the government's macro-control of industrial transformation and upgrading. The government should appropriately introduce or adjust relevant policies to create a green market environment for enterprises that is conducive to the development and transformation of new-generation technologies. Second, the industry level. This study further confirms the importance of digitalization and intelligent technology of the manufacturing industry to improve production and operation efficiency and achieve environmental performance, which provides a direction for the low carbon development of the manufacturing industry. The manufacturing industry should realize intelligent transformation as soon as possible to achieve industrial upgrading and pursue sustainable development of the whole industry. Finally, regarding the enterprise level, the results suggest the necessity of AI, which provides a direction for manufacturing enterprises to develop a green economy and realize sustainable development. At the same time, the research results also show that enterprises should attach importance to the development and utilization of AI, rationally allocate resources, improve energy efficiency, pay attention to environmental management, and improve green innovation ability while pursuing economic benefits, thus realizing low carbon development.

5.4. Limitations and Future Prospects

This study has several limitations. First, it considered listed companies in the manufacturing industry as the research objects, without considering the heterogeneity of the industry or the applicability of non-listed companies and SMEs (small and medium-sized enterprises), and it lacks comparative validation. Second, this study selected three green innovation variables to verify the adjustment mechanism and lacked expansive research on other innovations. Third, this study only examined the level of AI technology in enterprises and did not consider other digital technologies that enhance intelligence. Future research can begin with the above perspectives to supplement and improve the relevant theories.

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