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Original Research

Artificial Intelligence and Carbon Emission Embodied in Manufacturing Production: Effect and Impact Mechanism

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Abstract

At present, the deep integration of artificial intelligence and manufacturing has become an important engine for global green development. Based on data from 54 countries worldwide, this paper finds that AI has a significant inhibitory effect on carbon emissions embodied in manufacturing production. Mechanism analysis indicates that this abatement effect is realized by improving production technology levels, promoting the optimization and upgrading of industrial structure, and strengthening industrial agglomeration. Heterogeneity tests show that while these decarbonization benefits are particularly pronounced in high-income economies and nations with advanced AI adoption, the impact varies considerably across individual countries and different industries. Finally, the paper finds that "Industry 4.0" policies enhance the carbon reduction potential of AI, with the effect reaching its peak in the fourth lag period. Therefore, only by fully leveraging the technological dividends of AI and enhancing the transmission effect of production technology, industrial structure optimization, and industrial agglomeration can the potential of AI in manufacturing carbon reduction be better released.

Keywords: sustainable development, artificial intelligence, carbon emissions embodied in manufacturing production

Introduction

As a pillar industry of the global economy, the manufacturing sector, while contributing to GDP and driving global economic growth, has, due to its long-standing production model of high input, high energy consumption, and low output, become the main source of carbon emissions. Therefore, promoting the high-end, intelligent, and green development of manufacturing is an important guarantee for achieving global environmental sustainability.

Technological advances have long been recognized as an important driving force to reduce carbon emissions [1]. As a key driving force behind the new round of scientific and technological as well as industrial revolutions, Artificial Intelligence (AI), represented by industrial robots, has brought about profound transformations in global productivity and production models. Its widespread application in manufacturing has not only made intelligent production

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a new direction for current manufacturing modes but has also turned smart manufacturing into a new focal point of international competition among countries. For example, the United States has introduced the "National Artificial Intelligence Initiative Act 2021", and Germany has implemented the "Artificial Intelligence Strategy". In China's "Made in China 2025", China not only highlights the deep integration of the new generation of manufacturing and information technology, but also, in the "14th Five-Year Plan" for Intelligent Manufacturing Development, suggests the "two-step" strategy of intelligent manufacturing.

Theoretically, AI can achieve carbon emissions reductions by upgrading production technologies and reducing the consumption of energy inputs [2]. However, the rebound effect generated by AI-driven expansion of production scale in turn fuels an increase in carbon emissions. Therefore, under the overarching goal of global carbon reduction, it is imperative to systematically examine the complex relationship between AI and manufacturing carbon emissions and to elucidate the specific transmission mechanisms through which AI operates to maximize its technological dividends.

At present, the environmental implications of AI for carbon emissions have attracted widespread attention in the academic community, yet no unified consensus has been reached regarding the nature of this relationship; existing research can broadly be grouped into three main perspectives. The first perspective highlights the emission-reduction effects of AI [3]. As a form of skill-biased technological change [4], AI is regarded as capable of lowering direct carbon emissions by optimizing industrial structure [5], improving energy efficiency [6], and strengthening information infrastructure [7]. In addition, some studies show that AI can accurately estimate costs and identify key cost drivers at the early stages of product design, thereby contributing to carbon abatement at the source [8]. The second perspective regards AI as a new source of environmental pressure, emphasizing that the large-scale deployment of AI systems may substantially increase carbon emissions due to the additional energy demand from data center operations, hardware manufacturing, operation, and related digital infrastructure [9]. Freitag et al. [10] point out that the "direct impacts" of hardware production and data center electricity consumption often outweigh the "enabling effects" generated by information and communication technologies. Luan et al. [11] further reinforce this concern: based on data from 74 countries, they find that the diffusion of industrial robots has exacerbated air pollution, implying that, in the absence of a deeply decarbonized energy system, the spread of AI is more likely to shift emissions upstream rather than genuinely eliminate them. The third perspective holds that the relationship between AI and carbon emissions is inherently complex and non-monotonic [12]. Only when the level of AI development exceeds a certain threshold do its emission-reduction effects truly emerge [13]. The studies by Cheng et al. [14] and Li et al. [15] both document an inverted U-shaped impact of AI on carbon emissions, suggesting that economies often have to pass through a transitional phase characterized by a "green penalty" before they can ultimately enjoy the environmental dividends of AI.

Building on this, some studies further extend the analytical perspective from direct emissions to embodied carbon emissions. On the production side, AI helps reduce embodied emissions in the production process by increasing the level of automation, optimizing production processes, and improving resource allocation [16]. On the consumption side, the application of AI can enhance human capital, narrow income gaps, and, by reshaping consumption structures and patterns, influence carbon emissions over the full life cycle of products and services [17]. On the export side, the use of industrial robots helps to lower the embodied CO_2 emissions contained in manufacturing exports, although the relationship between the two is U-shaped [18]. Tang et al. [19] further point out that in developing countries, an increase in the use of industrial robots often leads to a rise in embodied carbon outflows through exports, thereby exacerbating the risk of carbon leakage to other regions.

With the widespread application of AI in manufacturing production, another strand of the literature has begun to focus on the impact of AI–manufacturing integration on carbon emissions. Most studies suggest that AI helps promote the green transformation of manufacturing and reduce manufacturing-related carbon emissions [20-22], but the magnitude and direction of this effect display pronounced heterogeneity across countries and regions. Existing evidence shows that the emission-reduction effect of AI is more salient in high-emission, high-income [23], or economically advanced economies. In contrast, in regions with weaker economic foundations and energy systems that remain heavily dependent on high-carbon fuels, the diffusion of AI may instead be accompanied by rising emissions [24]. Based on case studies of China, the United States, and Japan, Zhang et al. [25] find that AI exerts a positive effect on carbon emissions in these major economies. From the perspective of countries participating in the Belt and Road Initiative, Long et al. [26] find that AI can promote low-carbon and green development. On this basis, this paper conducts a comparative evaluation of the existing literature with respect to the research region, time span, analytical perspective, and transmission mechanisms, as shown in Table 1.

However, there are still obvious issues in the literature. On the one hand, these studies do not examine the global relationship between AI and manufacturing-related carbon emissions. In essence, carbon emissions, as a global public good, are spatially dependent. By simply focusing on one country, it is easy to "see trees but not the forest". On the other hand, existing studies have not yet linked AI with

Table 1. Comparative analysis of literature.

Author	Study Region	Time Span	Analytical Perspective	Transmission Mechanism
Li et al. (2022)	35 countries	1993-2017	Carbon emissions intensity	Production efficiency, factor structure, technological innovation
Geng et al. (2024)	39 countries	2000-2011	Carbon emissions intensity	Energy consumption structure, global value chains
Zhang et al. (2025)	38 countries	2000-2014	Carbon emissions intensity	Factor allocation, global value chains
Long et al. (2024)	Belt and Road countries	2004-2020	Low-carbon green performance	Technological progress, labor productivity, human capital
Yao et al. (2024)	OECD and BRICS countries	1993-2015	CO_2 emissions	Economic growth, technological progress, structural transformation
Zhang et al. (2023)	China, U.S., Japan	2006-2021	CO_2 emissions	Driving effects
Li et al. (2020)	China	2006-2020	CO_2 emissions	R&D investment, labor substitution
Chen et al. (2023)	China	2012-2021	CO_2 emissions	Green technological innovation, managerial innovation, product innovation

the carbon emissions embodied in manufacturing. Within the carbon accounting framework, embodied carbon emissions and direct carbon emissions are two closely related but conceptually distinct notions. Embodied carbon emissions refer to the total amount of CO_2 released throughout the entire life cycle of a product's production and supply chain. This includes not only the direct emissions from energy combustion during a firm's production process, but also the indirect emissions embodied in the upstream intermediate inputs used in production. In contrast, direct carbon emissions are limited to the emissions resulting from a firm's own energy consumption during its production activities, excluding the carbon released in the production of raw materials and intermediate goods. From a theoretical perspective, direct carbon emissions reflect the energy efficiency of an individual production stage and emphasize emission control within firms or industries. In contrast, embodied carbon emissions reveal the mechanism of carbon responsibility transfer and redistribution under the global value chain division of labor, highlighting the embodied relationship and transnational transmission pathways of carbon emissions among production, trade, and consumption. From a methodological perspective, direct carbon emissions are usually estimated based on energy consumption data or emission factors within a single sector, whereas embodied carbon emissions rely on input–output models, which trace intersectoral linkages and trade flows to depict the movement of carbon content. This approach offers a more comprehensive representation of the distribution of carbon responsibility within and across global production networks.

Essentially, the impact of AI on carbon emissions manifests not only through improvements in energy efficiency at the firm-level production stage, but also through the optimization of production processes and industrial synergies that reshape intermediate input structures and the global division of labor, thereby influencing the embodied carbon intensity of products. Therefore, investigating the impact of AI on carbon emissions embodied in manufacturing production is of both theoretical and practical significance. The main contributions of this paper are as follows: First, we conducted a cross-country comparative analysis using data from 15 manufacturing industries across 54 countries from 2002 to 2018, thereby expanding existing research from a single-country perspective to a global one, which offers distinct advantages in terms of sample breadth and industry granularity. Second, regarding the mechanism of action, we explored the emission-reduction effects through different pathways, such as the upgrading of production technologies, the optimization of industrial structure, and the agglomeration of manufacturing industries, providing more detailed empirical evidence for understanding how AI reshapes the carbon emission pathways of the manufacturing sector. Third, from a comparative perspective, we revealed the differential impacts at the national and industry levels, offering empirical evidence for promoting the design of targeted emission-reduction policies and for reference to cross-country experiences. Fourth, addressing the potential endogeneity issue of the AI variable, we designed a corresponding instrumental variable strategy and implemented instrumental variable estimation to enhance the credibility of causal identification. Fifth, we further extended the analysis to the dimensions of "Industry 4.0" policies and time lag effects to examine the policy environment and its temporal evolution characteristics, providing an empirical basis for identifying the timing and rhythm of policy efforts in enabling the low-carbon transformation of the manufacturing industry through AI.

The remainder of the paper is arranged as follows: In the second section, the research hypothesis is presented.

The third section outlines the research design, the model setup, index selection, and data description. The fourth section analyzes our empirical findings. The fifth section discusses the impact of "Industry 4.0" and the time lag effect of AI. The last section reviews the main findings of this paper and puts forward some corresponding policy recommendations.

Materials and Methods

Theoretical Framework

Direct Impact

AI, as a new type of production input factor, is deeply integrated into manufacturing processes, which can promote profound changes in efficiency and production modes [27]. First of all, AI can monitor environmental indicators in the production process in real-time through intelligent perception systems [28], formulate the optimal response through intelligent simulation to improve the processing efficiency of carbon emissions. Second, AI can track the equipment status continuously, optimize the operational efficiency and production performance of equipment by dynamically adjusting the preset control parameters and working mode, and reduce energy loss and waste in the manufacturing process [29]. Finally, AI utilizes platforms with big data to automatically collect and analyze market demand information, helping manufacturing enterprises raise product quality and achieve flexible production based on changing market demand [30].

However, the proper operation and maintenance of AI systems require substantial energy consumption [31], thereby generating additional demand for energy. Meanwhile, AI enhances production efficiency in the manufacturing sector and significantly boosts output levels [32], which in turn increases energy demand and consumption, possibly leading to higher carbon emissions. From the above discussion, the use of AI creates a "rebound effect" on carbon emissions embodied in manufacturing; that is, the rise in energy consumption may partially or entirely counteract energy savings, leading to an increase in carbon dioxide emissions during production [33]. It is important to note that the "rebound effect" may be significantly mitigated in service-oriented manufacturing. This is primarily because such industries rely more heavily on information processing, system integration, and remote operation, whereby the expansion of output does not necessarily lead to a proportional increase in energy consumption or carbon emissions. Existing studies have shown that the servitization of manufacturing can enhance productivity while simultaneously reducing environmental stress, thereby exhibiting a stronger decoupling effect. Accordingly, compared with traditional manufacturing industries, service-oriented sectors are more likely to achieve green upgrading through the application of AI, rather than falling into the dilemma where productivity improvements lead to an emissions rebound. In summary, the effect of AI technology on carbon emissions embodied in manufacturing is the result of a combination of factors. Nonetheless, AI should be regarded as an effective strategy for reducing carbon emissions in manufacturing. Therefore, this paper presents the following hypothesis:

Hypothesis 1 (H1): AI can lower the carbon emissions embodied in manufacturing production.

Indirect Impact

Technological Progress Effect

AI has characteristics such as permeability, spillover effects, and versatility [34]. Its in-depth integration with the manufacturing industry can not only promote technological innovation in manufacturing through knowledge creation, knowledge spillover, research and development, and investment in talent, but also enable the manufacturing industry to fully utilize the innovation effects and technological spillover effects generated by AI, thereby enhancing the driving force for technological innovation. In addition, AI can help manufacturing enterprises gain excess profits in global competition. Undoubtedly, improvements in profit levels will encourage enterprises to increase research and development expenditures, further promoting the progress and optimization of production technologies [35].

Numerous studies have shown that technological progress can significantly reduce carbon emissions [36]. On the one hand, technologies such as new energy development and storage, generated by technological progress, can promote the storage and utilization of new energy sources such as solar energy, geothermal energy, and wind energy, thereby reducing carbon emissions in the manufacturing industry. On the other hand, technological progress can improve the efficiency of energy conversion and utilization, enabling more effective output from the same energy input; at the same time, the promotion of technologies such as the utilization of new clean energy in the production process has, to a certain extent, replaced part of the high-carbon energy consumption, further reducing carbon emissions in the production process. Therefore, this paper presents the following hypothesis:

Hypothesis 2 (H2): AI can reduce carbon emissions embodied in manufacturing production by enhancing production technology.

Industrial Upgrading Effect

AI can optimize the industrial structure and promote the transformation and upgrading of the manufacturing industry. On the one hand, AI can prioritize improving manufacturing production efficiency. Improvements in manufacturing production efficiency further strengthen the effective demand for high-end manufacturing, which is precisely the endogenous driving force for promoting the optimization and upgrading of the manufacturing industry. The expansion of the scale of effective demand for high-end manufacturing promotes large-scale and specialized production in the manufacturing industry, prompting the transformation of the manufacturing industry from traditional industries to high-end ones, thereby promoting the optimization and upgrading of the industrial structure. On the other hand, with the improvement of the quality of life in human society, people's demand structure for products has changed significantly, and intelligent products have become a key trend in future manufacturing. Therefore, the expansion of demand for intelligent products accelerates the shrinking demand for traditional products and traditional industries and promotes the upgrading of manufacturing products towards intelligence.

The transformation and upgrading of the industrial structure are a key approach to emission reduction [37]. In terms of the allocation of input factors, the transformation and upgrading of the industrial structure promote the optimal flow of production factors such as physical capital and human capital within the manufacturing industry and across industries. Efficient resource allocation and utilization improve production efficiency, and, while optimizing the existing stock and expanding incremental output, they accelerate the transformation of the manufacturing industry towards green and environmental protection [38]. In terms of the value chain, the transformation and upgrading of the industrial structure help break the low-end lock-in of the manufacturing industry, promote its transformation to high-value-added and high-end fields, drive the upgrading of the value chain [39], and enhance the effect of energy conservation and emission reduction. Based on this, we propose the following hypothesis:

Hypothesis 3 (H3): AI promotes carbon-emission reduction in manufacturing production by driving the optimization and upgrading of the industrial structure.

Industrial Agglomeration Effect

Technological spillovers, resource sharing, and location advantages are key driving forces behind industrial agglomeration, while AI is the internal force that stimulates such agglomeration. The application of AI can significantly improve the level of intelligence in the manufacturing production process, thereby helping manufacturing enterprises reduce production costs and improve operational efficiency [40]. Driven by profits, enterprises in the same industry will flock to the same region to benefit from knowledge and technology spillovers, thereby promoting the development of industrial clustering [41]. In addition, AI itself is an important form of technological change. Its widespread application will break the traditional geographical spatial pattern, promote the cross-regional flow and reconfiguration of various production factor resources, and thus help the formation of industrial agglomeration [42].

From the existing literature, industrial agglomeration can effectively lower carbon emissions embodied in manufacturing production through technology spillover, talent agglomeration, and specialized division of labor. From the perspective of industrial mutual benefits, industries with similar energy structures, factor inputs, and production conditions tend to generate strong competition and learning effects when geographically concentrated. Such agglomeration promotes the interactive diffusion of information, knowledge, and technology among enterprises, fosters the development of greener production methods [43, 44], enhances energy efficiency and pollution control, and ultimately reduces the intensity of embodied carbon emissions. In terms of the talent agglomeration effect, industrial agglomeration usually gathers many highly skilled talents to form a high-quality and large-scale talent market, which can provide a professional and efficient labor force for manufacturing enterprises [45]. This, in turn, enhances labor productivity and contributes to carbon-emission reduction in the sector. From the perspective of resource allocation, industrial agglomeration facilitates the formation of a complementary division-of-labor system and strengthens upstream and downstream industrial linkages. Such integration optimizes resource allocation, enables enterprises to share factor resources [46], reduces energy consumption, and ultimately suppresses carbon emissions. Therefore, this paper presents the following hypothesis:

Hypothesis 4 (H4): AI reduces carbon emissions embodied in manufacturing production by improving the level of industrial agglomeration.

Based on the above analysis, we can conclude that AI reduces carbon emissions embodied in manufacturing production through three main pathways: technological progress, industrial upgrading, and industrial agglomeration. The mechanism is illustrated in Fig. 1.

Econometric Model and Data Descriptions

Model Setting

To examine the effect of AI on the carbon emissions embodied in manufacturing production, this article constructs a fixed-effects model grounded in theoretical analysis, expressed as follows:

$$lnCE_{ikt}=\beta_0+\beta_1 lnAI_{ikt}+\sum_k \beta_k X_{ikt} +\alpha_{ik}+\gamma_{kt}+\varepsilon_{ikt} \tag{1}$$

Among them, i represents the country, k denotes the industry, and t indicates the year. CE_{ikt} is the dependent variable, which represents the carbon emission embodied in the production of industry k in country i in year t; AI_{ikt} is the core explanatory variable, representing the level of AI application in industry k of country i

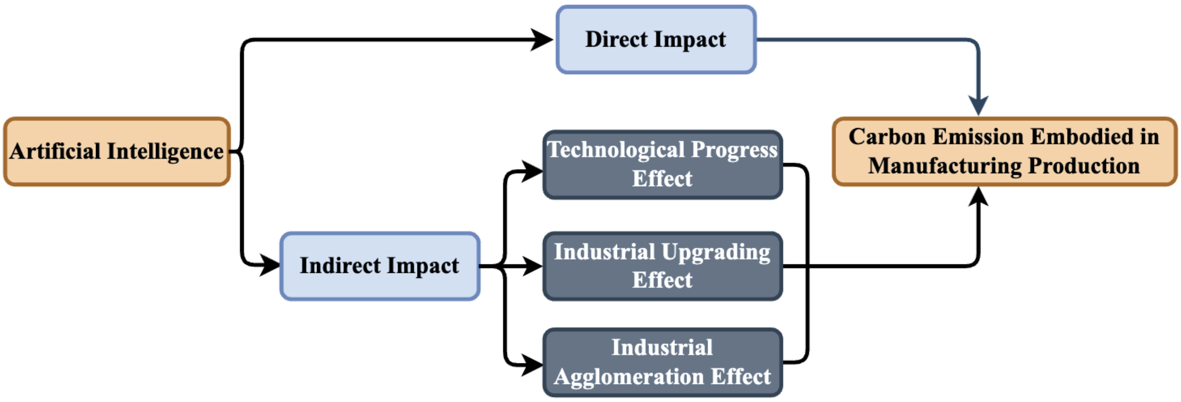

Fig. 1. Mechanism framework.

in year t; X_{ikt} represents control variables that may affect the carbon emissions embodied in manufacturing production. α_{ik} represents the country-industry fixed effect; γ_{kt} represents the industry-year fixed effect; ε_{ikt} is a random error term.

Provided that AI does indeed affect carbon emissions embodied in manufacturing production, we construct the regression model (2) to further test whether Hypothesis 2, Hypothesis 3, and Hypothesis 4 are valid; that is, to judge whether AI will impact carbon emissions embodied in manufacturing production through its influence on manufacturing production technology, industrial structure, and industrial agglomeration. The specific model is constructed as follows:

$$M_{ikt} = \rho_0 + \rho_1 lnAI_{ikt} + \sum_k \rho_k X_{ikt} + \alpha_{ik} + \gamma_{kt} + \varepsilon_{ikt} \tag{2}$$

In model (2), ρ_1 signifies the influence of AI on the technology level, industrial structure, or industrial agglomeration, and its coefficient, whether significant or not, tests if AI affects carbon emissions embodied in manufacturing production by affecting the mechanism variable M.

Variable Construction and Data Sources

Carbon Emissions Embodied in Manufacturing Production

We adopt carbon emissions embodied in manufacturing production as the dependent variable. According to the method proposed by Wang and Han [47], the hypothetical world has M economies, and the number of industrial sectors in each economy is unified to N. To ensure the consistency of production, countries not only need to use intermediate factor inputs from other industries in the country but also need to import related intermediate factor inputs from other economies in the world. Therefore, the total output of each country is expressed as:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_M \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1M} \\ A_{21} & A_{22} & \cdots & A_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ A_{M1} & A_{M1} & \cdots & A_{MM} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_M \end{bmatrix} + \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_M \end{bmatrix} \tag{3}$$

Here, X_i (i = 1, 2..., M) denotes the N*1 order total output vector of i country; Y_i (i = 1, 2..., M) represents the N*1 order final output vector of country i; A_{iM} represents the intermediate input coefficient matrix of N*N order unit output.

By shifting the term of formula (3), we get $X = (I - A)^{-1}Y$, that is:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_M \end{bmatrix} = \begin{bmatrix} I - A_{11} & -A_{12} & \cdots & -A_{1M} \\ -A_{21} & I - A_{22} & \cdots & -A_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ -A_{M1} & -A_{M1} & \cdots & I - A_{MM} \end{bmatrix}^{-1} \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_M \end{bmatrix} \tag{4}$$

Among them, I is the unit matrix. At the same time, B is defined as the Leontief inverse matrix, that is:

$$B = (I - A)^{-1}$$

$$= \begin{bmatrix} I - A_{11} & -A_{12} & \cdots & -A_{1M} \\ -A_{21} & I - A_{22} & \cdots & -A_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ -A_{M1} & -A_{M1} & \cdots & I - A_{MM} \end{bmatrix}^{-1} = \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1M} \\ B_{21} & B_{22} & \cdots & B_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ B_{M1} & B_{M1} & \cdots & B_{MM} \end{bmatrix} \tag{5}$$

On this basis, F_i is defined as the carbon emissions intensity row vector of country i, and $\hat{F}_1$ is converted into a diagonal matrix (F_i), so that the carbon emissions intensity diagonal matrix $\hat{F}$ can be obtained. Similarly, $\hat{Y}$ is the final output of the diagonal matrix. Therefore, the level of carbon emissions caused by production activities in each economy is expressed as follows:

$$\hat{F} B \hat{Y} = \begin{bmatrix} \widehat{F_1} B_{11} Y_1 & \widehat{F_1} B_{12} Y_2 & \cdots & \widehat{F_1} B_{1M} Y_M \\ \widehat{F_2} B_{21} Y_1 & \widehat{F_2} B_{22} Y_2 & \cdots & \widehat{F_2} B_{2M} Y_M \\ \vdots & \vdots & \vdots & \vdots \\ \widehat{F_M} B_{M1} Y_1 & \widehat{F_M} B_{M2} Y_2 & \cdots & \widehat{F_M} B_{MM} Y_M \end{bmatrix} \tag{6}$$

Each sub-matrix of the matrix $\hat{F}B\hat{Y}$ is decomposed to obtain the Carbon Emissions embodied in Production (CEEP) of each manufacturing sector. On this basis, it can be obtained:

$$CE_{ikt} = \frac{CEEP_{ikt}}{Y_{ikt}} \tag{7}$$

CE_{ikt} is the level of carbon intensity induced by the production (domestic production and foreign production) of industry k in country i in this economy. The larger the value is, the more CO_2 is produced in the manufacturing process.

Artificial Intelligence

We employ the stock of industrial robots as a proxy for AI adoption in the manufacturing sector (denoted as AI_{ikt}). This choice is grounded in three main considerations. First, prior studies widely recognize industrial robots as a representative embodiment of AI applications, with substantial theoretical underpinnings and empirical validation. Second, industrial robots constitute the most direct and tangible form of AI deployment in manufacturing, integrating key AI technologies such as machine learning and computer vision, thereby offering a reliable measure of AI intensity at the production level. Third, data on industrial robot installations are published by the International Federation of Robotics, ensuring high accessibility and cross-country consistency. That said, this proxy also has important limitations. Industrial robots primarily capture the degree of intelligence and automation in the production stage, rather than serving as a comprehensive indicator of AI technologies in the broader economy. As such, it does not fully encompass software-based algorithms, data-driven decision systems, platform-embedded AI services, or other non-robotic AI tools.

Considering the problems of depreciation and phase-out of industrial robots from production, we refer to the research by Graetz and Michaels [48] and assume that the annual depreciation rate of industrial robots is 5%, because in this case, it is closest to the evolution law of industrial robots [49]. Based on this, the robot scale of industry k in country i in year t is expressed as:

$$Robot_{ikt} = 0.95 \times Stock_{ik,t\text{-}1} + Installation_{ikt} \tag{8}$$

Among them, $Stock_{ik,t\text{-}1}$ is the installation stock of i country k industry in the t-1 period, and $Installation_{ikt}$ is the installation quantity of i country k industry in the t period.

Control Variable

The following variables were selected as control variables for better fitting of the model: (1) Manufacturing output scale (OUT): measured using the size of manufacturing output in each economy, with the data from the OECD database. (2) Population size (POP): measured by the total population in each country, data from the WDI database. (3) Proportion of energy-intensive manufacturing industries (Pollution): Referring to Busse [50], paper, chemical, metal, and non-metal manufacturing industries are classified as high energy-intensive industries in the manufacturing sector and are measured using the proportion of high energy-intensive manufacturing output in each economy to total output, with the data obtained from the OECD database. (4) Level of economic development (PGDP): measured using GDP per capita, with data from the WDI database. (5) Energy structure (Energy): Referring to the study by Zhang and Zhu [9], measured using the share of fossil energy consumption in total energy consumption, and the data are obtained from the WDI database. (6) Urbanization level (Urban): measured using the share of urban population in the total population, data from the WDI database. On this basis, this paper takes the log of the non-proportional variables, and their descriptive statistics are presented in Table 2.

Table 2. Descriptive statistics.

Variables	Variable Name	Obs.	Mean	Std.d	Min	Max
lnCE	Carbon emissions embodied in manufacturing production	13770	0.87	1.15	0	7.5
lnAI	Artificial Intelligence	13770	0.22	0.62	0	5.24
lnOUT	Manufacturing output scale	13770	8.89	2.04	0	14.76
lnPOP	Population size	13770	16.8	1.7	12.57	21.06
lnPGDP	Economic development level	13770	9.69	1.07	6.15	11.55
Energy	Energy structure	13770	0.75	0.18	0.05	1
Urban	Urbanization level	13770	0.73	0.15	0.28	1
Pollution	The proportion of energy-intensive manufacturing industry	13770	0.15	0.11	0.16	0.55

Results and Discussion

Benchmark Regression Results

Table 3 presents the results of AI's impact on carbon emissions embodied in manufacturing production. First, in column (1), the coefficient of lnAI is negative and significant, suggesting that AI could significantly reduce carbon emissions embodied in manufacturing production. Second, we add control variables sequentially as represented in columns (2)-(7) in Table 3. The corresponding estimation results are consistent with column (1), which confirms that AI's impact on carbon emissions embodied in manufacturing production is unaffected by other control variables, thus demonstrating the robustness of our findings.

Considering that countries with stronger carbon-reduction capacities may possess superior production conditions and are therefore more likely to adopt AI earlier, such reverse causality may give rise to endogeneity issues. Therefore, this paper constructs appropriate instrumental variables to mitigate the possible endogeneity problem.

First, following the approach of Wang et al. (2022) [51], we use the difference between the total number of industrial robots in a specific global manufacturing subsector and the number of industrial robots in that specific manufacturing subsector of a particular country ($\overline{AI}$) as an instrumental variable for AI. From the perspective of correlation, the increase in the global usage of industrial robots reflects the general trends of technological diffusion, learning effects, and economies of scale. When other countries widely deploy robots in a specific manufacturing subsector, the production methods, cost structures, and technical standards of that industry will undergo systematic adjustments, thereby creating significant competitive pressures and motivations for technological catch-up in a country's own industry. From the perspectives of the exclusion restriction and historical path dependence, this instrumental variable mainly reflects the historical and current robot adoption paths of other countries in the industry, as well as the resulting global technological diffusion shocks. Its changes are mainly determined by factors such as other countries' industrial upgrading strategies, technological innovation capabilities,

Table 3. Benchmark regression results: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)	(5)	(6)	(7)
-	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE
lnAI	-0.0239* (0.0133)	-0.0428*** (0.0123)	-0.0423*** (0.0124)	-0.0445*** (0.0121)	-0.0469*** (0.0121)	-0.0660*** (0.0114)	-0.0648*** (0.0114)
lnOUT	-	0.1405*** (0.0090)	0.1355*** (0.0086)	0.1064*** (0.0095)	0.1047*** (0.0094)	0.1024*** (0.0094)	0.1030*** (0.0095)
lnPOP	-	-	0.6442*** (0.0391)	0.6507*** (0.0391)	0.6148*** (0.0384)	0.5880*** (0.0392)	0.5875*** (0.0392)
lnPGDP	-	-	-	0.0815*** (0.0147)	0.0638*** (0.0143)	0.0622*** (0.0142)	0.0635*** (0.0143)
Energy	-	-	-	-	0.3193*** (0.0427)	0.1529*** (0.0433)	0.1331*** (0.0430)
Urban	-	-	-	-	-	1.2901*** (0.1524)	1.2899*** (0.1525)
Pollution	-	-	-	-	-	-	0.3920*** (0.0626)
Constant	0.8793*** (0.0034)	-0.3653*** (0.0808)	-11.1449*** (0.6653)	-11.7861*** (0.6717)	-11.2339*** (0.6586)	-11.5558*** (0.6618)	-11.6820*** (0.6621)
Country-Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y
R^2	0.9795	0.9806	0.9811	0.9812	0.9813	0.9815	0.9815
N	13,770	13,770	13,770	13,770	13,770	13,770	13,770

Note: The sample covers 54 countries and 15 manufacturing industries from 2002 to 2018, with total observations N = 13,770. lnCE denotes carbon emissions embodied in manufacturing production; lnAI denotes Artificial Intelligence; lnOUT denotes manufacturing output scale; lnPOP denotes population size; lnPGDP denotes economic development level; Urban denotes urbanization level; Energy denotes energy structure; Pollution denotes the proportion of energy-intensive manufacturing industries. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

and factor endowments, rather than being driven by a country's own energy structure, environmental regulation intensity, or carbon emission performance. Although countries and industries that adopted more robots in the early stages often maintain a high level of automation later on, the technological environment created by other countries' accumulated industrial adoption can be treated as an exogenous technological condition for any given country. While technological diffusion may indeed affect the application of robots in various countries through trade, investment, or knowledge spillovers, such impacts can only enhance the availability and willingness to adopt AI, but will not change a country's energy consumption structure or carbon emissions intensity.

Second, we selected the number of fixed-line telephones in various countries in 1980 as an instrumental variable for the AI technology development index. From the perspective of the development history of AI, its popularization and diffusion process largely depend on the construction of information infrastructure, and the early form of information infrastructure originated from the laying of fixed telephone networks and the improvement of communication systems. Therefore, regions with a higher penetration rate of fixed-line telephones in history are also very likely to be regions with a higher level of AI development. In this sense, selecting the number of fixed-line telephones as an instrumental variable for the AI technology development index meets the relevance requirement. From the perspective of the exclusion restrictions and historical path dependence, the number of fixed-line telephones in historical periods essentially depicts a country's endowments and path choices in early communication infrastructure, and its changes are mainly determined by investment factors such as geographical accessibility, transportation conditions, and population distribution, rather than being driven by energy structure or environmental performance. Furthermore, the main function of fixed-line telephones lies in information transmission and social communication. They do not enter the production function of the manufacturing industry, nor do they affect the current energy input, process efficiency, or emission decisions of the manufacturing sector. With the iterative upgrading of technology, the technical connection between fixed-line telephones and current manufacturing production activities has been basically interrupted, and there is no sustainable path for them to affect manufacturing carbon emissions. In this sense, this instrumental variable can meet the exclusion restriction. However, considering that the sample is a balanced panel, using only the 1980 telephone data may introduce measurement difficulties under the fixed-effects model. To address this, following Nunn and Qian [52], we construct an interaction term between each country's 1980 fixed-line telephone stock (capturing cross-sectional variation) and the global number of fixed-broadband subscriptions (capturing time variation) as the final instrumental variable, denoted as ($\widehat{AI}$).

According to Table 4, both stages of estimation show that the coefficients of the instrumental variables are statistically significant at the 1% level. Moreover, the Kleibergen–Paap rk LM statistic and Kleibergen–Paap

Table 4. Instrumental variable regression results: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)
-	First Stage	Second Stage	First Stage	Second Stage
-	lnAI	lnCE	lnAI	lnCE
$\overline{AI}$	-0.0124*** (0.0013)	-	-	-
$\widehat{AI}$	-	-	0.0645*** (0.0095)	-
lnAI	-	-0.0935*** (0.0159)	-	-0.5917*** (0.1350)
Control Variables	Y	Y	Y	Y
Kleibergen-Paap rk LM	48.15*** (0.0000)	48.15*** (0.0000)	36.615*** (0.0000)	36.615*** (0.0000)
Kleibergen-Paap rk Wald F	97.90	97.90	45.466	45.466
Fixed Effect	Y	Y	Y	Y
N	13,770	13,770	13,770	13,770

Note: The sample covers 54 countries and 15 manufacturing industries from 2002 to 2018, with total observations N = 13,770. $\overline{AI}$ indicates the difference between the total number of industrial robots in a specific global manufacturing subsector and the number of industrial robots in that specific manufacturing subsector of a particular country; $\widehat{AI}$ indicates the number of fixed-line telephones in various countries in 1980. Columns (1) and (3) report first-stage regressions; Columns (2) and (4) report second-stage regressions. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

rk Wald F statistic confirm the validity and strength of the selected instruments. Therefore, the results suggest that endogeneity does not materially affect the main estimation outcomes of this study.

Robustness Test

To verify the robustness of the empirical results, we conducted a series of robustness checks, as shown in Table 5.

First, we modify the depreciation rate of industrial robots, with the regression results presented in column (1). The results indicate that the coefficient of lnAI remains significantly negative, even with an increased depreciation rate for industrial robots, consistent with Hypothesis 1.

Second, we adopt the total carbon emissions embodied in manufacturing production to carry out the regression, with results presented in column (2). The coefficient of AI is significantly negative, which is consistent with the above conclusion.

Third, we eliminate the interference period. Considering that the global economic crisis in 2008 impacted the industrial robot market and that the impact continued until 2010 [53], we exclude the data from 2008 to 2010 in the overall sample period, with the estimation results presented in column (3). The coefficient of AI is negative at the 1% significance level, which also affirms the environmental governance effect of AI.

Fourth, we change the sample division interval. Since the application and development of AI is a gradual process, it is challenging for economic variables to adjust fully in a short time frame. Thus, based on the sample information, we split the overall sample into six 3-year intervals, and the results are shown in column (4). The estimated coefficient for AI remains significantly negative, indicating that AI inhibits carbon emissions embodied in manufacturing production, once again confirming the robustness of the above conclusions.

Fifth, we eliminate low-emission samples. Considering that carbon emissions intensity in some manufacturing industries is relatively low, to avoid the influence of outlier samples on the research conclusions, we exclude 10% of the samples with the weakest carbon emissions intensity each year, with the estimation results presented in column (5).

Sixth, we eliminate non-robot industry samples. To better evaluate the environmental governance effect

Table 5. Robustness Test regression results: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)	(5)	(6)	(7)
-	Modify the Depreciation Rate	Replace the Explained Variable	Eliminate Interference Interval	Change the Sample Division Interval	Eliminate Low Emission Samples	Eliminate the Robot-Free Industry	Omitted Variable Problem
-	lnCE	lnCV	lnCE	lnCE	lnCE	lnCE	lnCE
lnAI	-0.0557** (0.0119)	-0.0408** (0.0209)	-0.0588*** (0.012)	-0.0653*** (0.0113)	-0.0674*** (0.0116)	-0.0676*** (0.0114)	-0.0601*** (0.0115)
EF	-	-	-	-	-	-	-0.0968** (0.0483)
TFP	-	-	-	-	-	-	-0.29*** (0.0481)
HC	-	-	-	-	-	-	-0.0967*** (0.0310)
FDI	-	-	-	-	-	-	-0.0079** (0.0033)
Control Variables	Y	Y	Y	Y	Y	Y	Y
Country-Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y
R^2	0.9816	0.9893	0.9804	0.9813	0.9809	0.9817	0.9817
N	13,770	13,770	11,340	13,770	12,410	11,900	13,770

Note: The sample covers 54 countries during 2002–2018, with observations varying across specifications (N = 11,340–13,770). All regressions include the full set of control variables as indicated, with country–industry and industry–year fixed effects. EF, TFP, HC, and FDI represent economic freedom, total factor productivity, human capital, and foreign direct investment. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

of AI, we excluded the samples with an AI installation stock of 0, with the estimation results presented in column (6).

Seventh, we address the issue of omitted variables. Building on the baseline regression, this paper further controls for variables such as economic freedom, total factor productivity, human capital, and foreign direct investment. The regression results are presented in column (7).

All of the above robustness results confirm that the reduction effect of AI on carbon emissions embodied in manufacturing production is robust.

Mechanism Analysis

Based on formula (2), we examine the mechanism by which AI improves the technological level of manufacturing production, optimizes industrial upgrading, and enhances the level of industrial agglomeration, thereby reducing carbon emissions embodied in manufacturing production.

As mentioned above, AI can improve the level of manufacturing production technology, thereby reducing carbon emissions in production. Therefore, we adopt the product of domestic value-added in exports of each manufacturing industry and total factor productivity as a proxy variable of manufacturing production technology level (TEC). The estimation results can be found in regression (1) of Table 6. It is evident that the coefficient of AI on the technology level of manufacturing production is significantly positive, suggesting that AI substantially enhances the production technology level of the manufacturing industry. Therefore, Hypothesis 2 is confirmed. We further use the industrial structure upgrade (IS) as a mechanism variable to estimate formula (2), measured as the ratio of the output value of manufacturing of middle- and high-end industries to the output value of non-middle- and high-end industries. Column (2) shows a significantly positive coefficient for AI, confirming that it can effectively enhance the industrial structure of the manufacturing industry and thus reduce carbon emissions embodied in production. This result supports Hypothesis 3.

While common methods for measuring industrial agglomeration include the Herfindahl index and the location entropy index, the latter is preferred as it accounts for regional differences. Therefore, we use the location entropy index to measure the level of manufacturing industrial agglomeration (LQ), calculated as follows:

$$\mathrm{LQ}_{\mathrm{ikt}} = \frac{\mathrm{Y}_{\mathrm{ikt}}/\mathrm{Y}_{\mathrm{it}}}{\mathrm{Y}_{\mathrm{kt}}/\mathrm{Y}_{\mathrm{t}}}$$

In column (3) of Table 6, the effect of AI on the level of manufacturing industry agglomeration is significantly positive, indicating that AI can improve the level of manufacturing industry agglomeration, thereby inhibiting carbon emissions embodied in manufacturing production. Thus, Hypothesis 4 has been confirmed.

Heterogeneity Analysis

National Heterogeneity

Although developed countries started earlier in AI applications, developing countries have advanced rapidly in this area, and the number and stock of installed industrial robots have exceeded those of most developed countries. Therefore, we divide the samples into high-AI-application countries and low-AI-application countries, based on their number of installed industrial robots, to analyze the effect of AI in countries with different AI application levels on carbon emissions embodied in manufacturing production. Columns (1) and (2) of Table 7 display the estimation results. It is clear that AI significantly reduces carbon emissions embodied in manufacturing production in countries

Table 6. Mechanism Test: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)
-	Technological Progress Effect	Industrial Upgrading Effect	Industrial Agglomeration Effect
-	TEC	IS	LQ
lnAI	0.0164*** (0.0022)	0.0484** (0.0197)	0.0195** (0.0083)
Control Variables	Y	Y	Y
Country-Industry Fixed Effect	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y
R^2	0.9058	0.9548	0.9629
N	13,770	13,770	13,770

Note: The sample scope covers 54 countries and 15 manufacturing industries during 2002–2018, with total observations N = 13,770. Country–industry fixed effects and industry–year fixed effects are controlled across all specifications. Columns (1)-(3) report regressions associated with the technological progress effect, industrial upgrading effect, and industrial agglomeration effect, respectively. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

with high AI application levels, but promotes carbon emissions embodied in manufacturing in countries with low AI applications.

Considering that global carbon emissions are largely driven by high-income countries, this article categorizes the overall sample into high- and low-income countries, based on World Bank data, to examine AI's impact on carbon emissions embodied in manufacturing production in countries with different income levels. From columns (3) and (4) of Table 7, it can be found that compared with low-income countries, AI has a more significant impact on reducing carbon emissions embodied in manufacturing production in high-income countries. The reason is that the high capital requirements for AI implementation are more easily met in wealthier countries, leading to more widespread use in high-income countries and more effective carbon-emission reduction outcomes.

Due to significant cross-country differences in technological research and development, industrial coordination, and energy consumption structures, this paper conducts a country-level analysis of the impact of AI on embodied carbon emissions in manufacturing production, with the results presented in Fig. 2.

The world heatmap presents the country-level effect of AI on embodied carbon emissions in manufacturing. The map applies a single-direction color scale in which white represents the lowest values (including countries with missing data or minimal effects), and deeper red shades indicate stronger positive associations between AI adoption and embodied carbon emissions. Most countries appear in very light pink or white, suggesting

Table 7. Analysis of national heterogeneity: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)
-	Low-AI Application Countries	High-AI Application Countries	Low-Income Countries	High-Income Countries
-	lnCE	lnCE	lnCE	lnCE
lnAI	0.1633*** (0.0391)	-0.0753*** (0.0122)	-0.0509** (0.0243)	-0.0748*** (0.0088)
Control Variables	Y	Y	Y	Y
Country-Industry Fixed Effect	Y	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y	Y
R^2	0.9701	0.9824	0.9784	0.985
N	6,885	6,885	3,825	9,945

Note: The sample covers 54 countries and 15 manufacturing industries from 2002-2018. Columns (1)-(2) divide countries by AI application level; Columns (3)-(4) divide by income level. All regressions control for country-industry and industry-year fixed effects. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

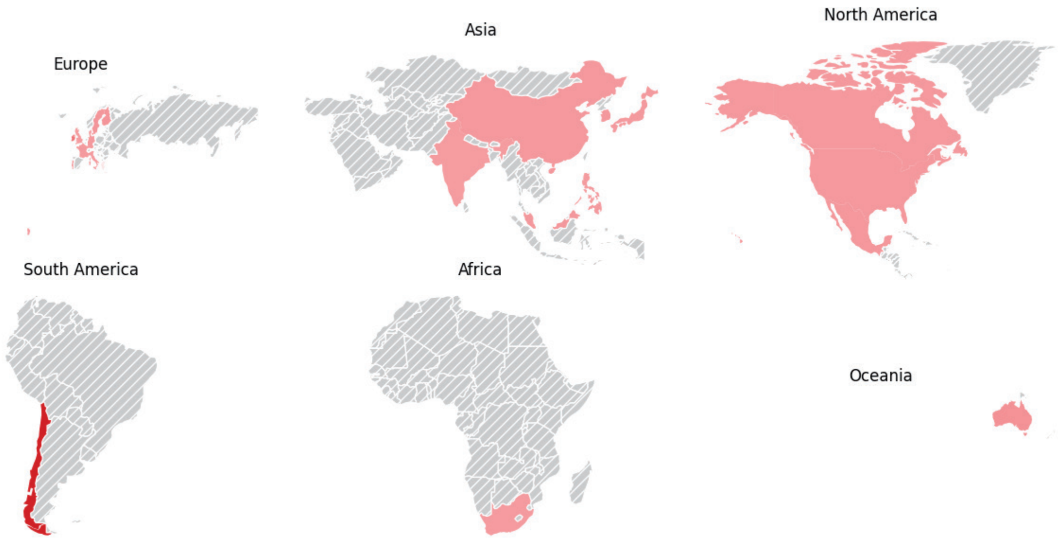

Fig. 2. Country-level effect of AI on carbon emissions embodied in manufacturing production.

that the effect of AI on embodied carbon emissions is small or negligible for the majority of regions. A few countries – such as China, India, Japan, the United States, several European countries, and Australia – show mild positive effects. From the estimation results for China, AI has not yet exhibited a “carbon-reduction” effect, primarily due to the combined constraints of “scale–industry–energy”. In terms of scale, China’s industrial added value reached 39.9 trillion yuan in 2023, accounting for about 30% of global industrial added value. Such a vast production scale drives up energy consumption, thereby offsetting the potential energy-saving benefits brought by AI. In terms of industry, manufacturing remains dominated by heavy industry and energy-intensive sectors. For example, the steel industry emitted 1.89 billion tons of CO_2 in 2023, accounting for 15% of China’s total emissions. The high proportion of carbon-intensive sectors makes the manufacturing industry’s emission “baseline” excessively high, making it difficult to achieve emission reductions through marginal technological improvements alone. In terms of energy, coal accounted for 55% of China’s total energy consumption in 2023, far exceeding the global average. This “carbon-intensive” energy structure further constrained the emission-reduction potential of AI. In contrast, regions such as Africa exhibit little color variation, reflecting either minimal estimated impact or a lack of available data. Overall, the map highlights that while AI’s influence on embodied carbon emissions varies across the world, most countries demonstrate weak effects, with only a small number showing moderate impacts.

Industry Heterogeneity

We mainly carry out the heterogeneity analysis from the following three aspects, namely: technological differences across industries, differences in energy consumption, and the degree of AI application. According to OECD’s industry classification standard, this paper divides 15 manufacturing industries into three types: high-end-technology industries, mid-end-technology industries, and low-end-technology industries.

The heatmap visualizes the industry-level heterogeneity in the impact of AI on carbon emissions embodied in manufacturing, as estimated in Fig. 3. All coefficients are negative, indicating that AI consistently contributes to emission reductions across different industry groups, but the magnitude of this effect varies substantially. Low-end-technology industries exhibit a relatively strong reduction effect compared to mid- and high-end-technology sectors, while high-energy-intensity industries show a slightly weaker reduction effect than medium- and low-energy-intensity ones. The most pronounced reduction is observed in high-AI-intensity industries, where the coefficient reaches –0.191, far larger in magnitude than in any other category, suggesting that sectors already deeply integrated with AI technologies benefit the most in terms of emission mitigation. In contrast, low-AI-intensity industries display a much smaller effect, highlighting how the degree of AI adoption modulates environmental outcomes. Overall, the heatmap underscores clear heterogeneity across technological levels, energy-

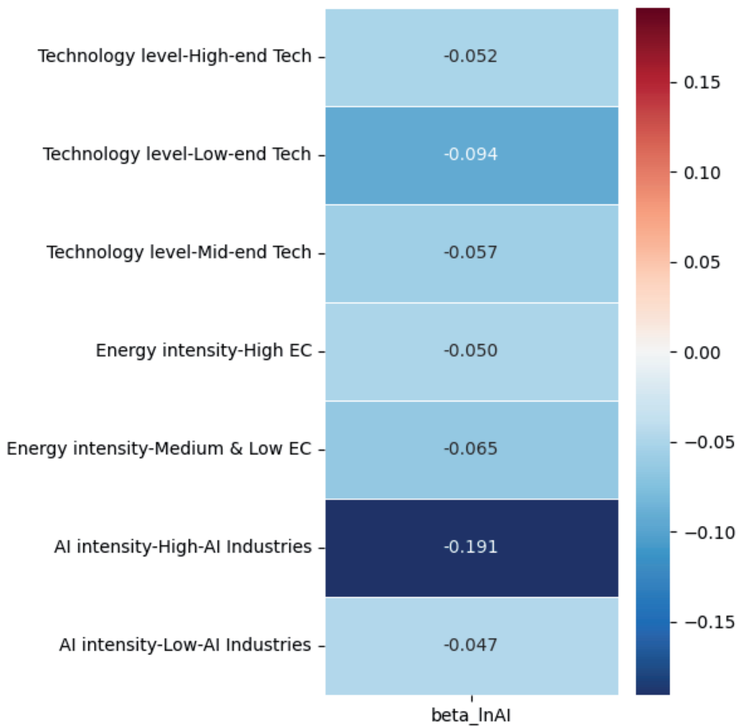

Fig. 3. Industry heterogeneity: effect of AI on carbon emissions embodied in manufacturing production.

intensity levels, and AI-application levels, revealing that AI's decarbonizing effect is strongest where technological readiness and AI penetration are highest.

Given the significant heterogeneity across manufacturing subsectors, we further evaluate the impact of AI on embodied carbon emissions at the disaggregated industry level. The estimation results are presented in Table 8. On the one hand, in sectors such as rubber products, computers, and electrical equipment, AI adoption does not exhibit a statistically significant carbon-reducing effect. Taking the rubber products industry as an example, its production processes – ranging from raw material mixing and molding to vulcanization – are heavily reliant on high-carbon energy sources. The synthesis of rubber itself is highly energy- and carbon-intensive; for instance, producing one ton of synthetic rubber requires approximately three tons of petroleum and 4,645.7 kWh of energy. This structural dependency creates a "hard constraint" on emission reductions. Although AI may contribute to optimizing production scheduling and energy usage, such improvements are only marginal in the absence of a fundamental shift in the energy mix. As for the computer and electrical equipment industries, they are inherently highly automated and digitally advanced. For example, the automation rate in China's electrical equipment sector has exceeded 50%, and most firms have already implemented systems such as Manufacturing Execution Systems. In this context, the marginal benefit of AI in reducing carbon emissions diminishes, as the scope for large-scale efficiency gains is already limited. Moreover, AI applications in these industries tend to focus on precision control and quality inspection, rather than energy-intensive operations, thereby limiting their impact on overall carbon emissions. On the other hand, AI shows significant carbon-reducing effects in sectors such as textiles, apparel, and leather, wood products, printed materials, and coke and refined petroleum products – with the strongest reductions observed in the wood and printed materials industries. These sectors are typically characterized by labor-intensive operations, low levels of standardization, and limited digital infrastructure. They have long relied on manual labor and traditional production techniques, leading to high carbon intensity. Once AI-enabled upgrades are introduced, production becomes more standardized and automated. Through machine learning-based optimization of energy usage and production rhythm, both productivity and energy efficiency improve, resulting in a substantial reduction in energy waste. For instance, AI-assisted color management and layout systems in the printing industry help to reduce material losses while enhancing machine energy efficiency.

The Impact of the "Industry 4.0" Policy and the Time Lag Effect

Since the German government proposed the concept of "Industry 4.0" in 2011, the application of industrial robots in the manufacturing industry has

Table 8. Regression results of specific industries: effect of AI on carbon emissions embodied in manufacturing production.

-	Food, Beverages, and Tobacco	Textiles, Clothing, and Leather	Wood Products	Paper Prints	Coke and Refined Petroleum
lnAI	-0.157***	-1.498***	-0.821***	-2.046***	-0.191***
	(0.038)	(0.207)	(0.240)	(0.152)	(0.049)
R^2	0.980	0.962	0.960	0.983	0.983
-	Chemicals	Rubber products	Other non-metallic minerals	Basic metals	Metal products
lnAI	-0.296***	0.031	-0.198***	-0.078**	-0.069***
	(0.104)	(0.042)	(0.060)	(0.031)	(0.019)
R^2	0.976	0.965	0.985	0.990	0.970
-	Computer and electrical equipment	Mechanical equipment	Automobile manufacturing	Other transportation equipment	Other manufacturing
lnAI	-0.027	-0.186***	-0.054***	-0.165**	0.066
	(0.019)	(0.026)	(0.018)	(0.073)	(0.041)
R^2	0.973	0.972	0.940	0.940	0.959
Control Variables	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y
N	918	918	918	918	918

Note: Each column corresponds to a separate manufacturing industry. All regressions include the full set of control variables, along with country fixed effects and year fixed effects. Each industry-level regression contains 918 observations, corresponding to 54 countries observed annually from 2002 to 2018. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

Table 9. Industry 4.0 and Time Lag Effect Test: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
-	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE	lnCE
lnAI	0.0021	-0.1386***	-0.0626***	-0.0648***	-	-	-	-	-
	(0.0221)	(0.0253)	(0.0113)	(0.0114)	-	-	-	-	-
CN	-	-	-0.0053***	-	-	-	-	-	-
	-	-	(0.0008)	-	-	-0.0053***	-	-	-
L.lnAI	-	-	-	-	-0.0785***	-	-	-	-
	-	-	-	-	(0.0112)	-	-	-	-
L2.lnAI	-	-	-	-	-	-0.0882***	-	-	-
	-	-	-	-	-	(0.0108)	-	-	-
L3.lnAI	-	-	-	-	-	-	-0.0944***	-	-
	-	-	-	-	-	-	(0.0110)	-	-
L4.lnAI	-	-	-	-	-	-	-	-0.0945***	-
	-	-	-	-	-	-	-	(0.0119)	-
L5.lnAI	-	-	-	-	-	-	-	-	-0.0906***
	-	-	-	-	-	-	-	-	(0.0123)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	8,100	5,760	13,770	13,770	12,960	12,150	11,340	10,530	9,720
R^2	0.9883	0.9933	0.9816	0.980	0.981	0.982	0.984	0.984	0.985

Note: CN represents the share of clean energy consumption. L.lnAI, L2.lnAI, L3.lnAI, L4.lnAI, and L5.lnAI denote the first- through fifth-order lags of lnAI. All specifications include the full set of control variables, as well as country–industry and industry-year fixed effects. Sample sizes vary across columns (N = 5,760-13,770) due to lagged-variable availability. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

been significantly improved [54]. IFR data show that after 2011, the number of industrial robots installed has risen rapidly. Therefore, this paper takes 2011 as a demarcation point, dividing the sample into two periods: 2002-2011 and 2012-2018, to examine the impact of "Industry 4.0" on the relationship between AI and carbon emissions embodied in manufacturing production. The regression results are shown in columns (1) and (2) of Table 9. It can be found that between 2002 and 2011, the estimated coefficient of AI was positive but not significant. From 2012 to 2018, the primary coefficient of AI was significantly negative, showing a strong "carbon reduction" effect compared with the previous period. Considering that most countries have implemented clean energy policies since 2011, there is a risk that the parallel development of such policies and the diffusion of AI may jointly influence carbon emissions in the manufacturing sector, thereby introducing identification bias. To address this concern, we incorporate the share of clean energy consumption (CN) as a proxy variable to control for the potential confounding effects of contemporaneous environmental policy changes. The results reported in column (3) show that the coefficient on CN is negative and highly significant, indicating that the expansion of renewable energy has indeed contributed to emission reductions. Crucially, even after controlling for this variable, the coefficient on lnAI remains significantly negative, suggesting that the carbon-reduction effect of AI in manufacturing is robust and not solely attributable to changes in energy structure or environmental policy contexts.

As an emerging technology, AI undergoes a multi-stage and multi-factor intertwined development process involving the preparation of production conditions, breakthroughs in key elements, and implementation in practical applications [55]. There is an inherent lag from R&D investment to deployment and finally to the manifestation of its effects. Therefore, the impact of AI on the embodied carbon emissions of manufacturing production may also exhibit a time-lag effect. From the perspective of technological diffusion, AI must go through several stages, including algorithm optimization, equipment upgrading, talent matching, and institutional adaptation, before moving from R&D to industrialization. Its diffusion process follows a dynamic pattern of "slow start-up, rapid expansion, and steady convergence", which causes the carbon-reduction effects to appear with a delay. From the perspective of capital and factor reconfiguration, the adoption of AI is often accompanied by adjustments in investment structure and factor allocation. In the short term, firms bear high costs for equipment investment and learning. Only after capital and labor skills have sufficiently adapted can improvements in production efficiency and energy efficiency gradually translate into carbon-reduction benefits. From the perspective of the policy environment, standards related to AI, data governance frameworks, and green-technology evaluation mechanisms are still under development. Such institutional lags weaken the immediate carbon-reduction effects of AI technologies. Therefore, it is necessary to explore the time-lag effect of AI from a dynamic perspective. According to the results in columns (4)-(9) of Table 9, the lagged terms of AI are significantly negative at the 1% level, indicating that AI has a statistically significant time-lag effect on reducing the carbon emissions embodied in manufacturing production. Moreover, the reduction effect reaches its maximum in the fourth lag period.

Furthermore, Table 10 shows that the coefficients of the lagged AI variable decrease significantly in technology-intensive industries and countries, while exhibiting an upward trend in non-technology-intensive ones. This finding suggests that increasing R&D investment is the key factor in shortening the lag period and strengthening the green effect. Therefore, efforts should be made to enhance the R&D and diffusion mechanisms of AI technologies by shortening

Table 10. Subsample Time Lag Effect Test: effect of AI on carbon emissions embodied in manufacturing production.

-	(1)	(2)	(3)	(4)
-	Technology-intensive industries	Non-technology-intensive industries	Technology-intensive countries	Non-technology-intensive countries
-	lnCE	lnCE	lnCE	lnCE
L4.lnAI	-0.0707***	-0.1218***	-0.0664***	-0.0995*
	(0.0155)	(0.0179)	(0.0111)	(0.0542)
Control Variables	Y	Y	Y	Y
Country-Industry Fixed Effect	Y	Y	Y	Y
Industry-Year Fixed Effect	Y	Y	Y	Y
N	4212	6318	5265	5265
R^2	0.977	0.987	0.992	0.974

Note: L4.lnAI represents the fourth-order lag of lnAI. Columns (1)-(2) group industries by technology intensity categories, and Columns (3)-(4) group countries by technology intensity categories. All models include control variables and both country-industry and industry-year fixed effects. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

the technology-absorption cycle through R&D subsidies, knowledge-sharing platforms, and open-data policies. At the same time, it is necessary to build an institutional environment that integrates AI with green manufacturing – such as tax incentives, innovation subsidies, and carbon-pricing mechanisms – to shorten the "carbon-reduction realization period" of AI and accelerate the transformation of technological dividends into environmental benefits.

Conclusions

Using data from 54 economies from 2002 to 2018, we found that AI has an overall significant inhibitory effect on carbon emissions embodied in manufacturing production. This conclusion remains valid after controlling for endogeneity issues and passing various robustness tests. Heterogeneity analysis shows that AI has a significant emission-reduction effect in countries with high application levels and high-income countries, but there are large differences among different countries. Currently, countries such as China and the United States have not yet entered the emission reduction stage driven by AI. In countries like Mexico and Russia, AI still acts as an "accelerator" for carbon emissions embodied in manufacturing production, while in developed economies such as Germany and Japan, it shows an obvious emission-reduction effect. At the same time, the "carbon reduction" effect of AI varies significantly in four dimensions: industry technological characteristics, energy consumption levels, intensity of AI application, and differences in product structure. Except for rubber products, computers, and electrical equipment, and other manufacturing industries, AI can significantly reduce carbon emissions in other manufacturing industries. Finally, we find that the "Industry 4.0" policy enhances the carbon-reduction effect of AI, and this effect reaches its peak in the fourth lag period.

Based on these findings, we propose several policy considerations. First, governments should fully harness the technological dividends of AI and accelerate the construction of intelligent manufacturing systems. Policymakers should proactively promote the deep integration of AI and the manufacturing sector, thereby achieving a win-win outcome between economic growth and environmental sustainability through intelligent transformation. At the same time, the lagged effects of AI-induced emission reductions must be fully considered to improve policy design. This study finds that the carbon-reduction effect of AI in the manufacturing sector peaks after a four-period lag, indicating a relatively long transformation cycle from technological input to environmental return. In response, governments should, on the one hand, incorporate AI applications into medium- and long-term strategic planning and design rolling support mechanisms in areas such as fiscal subsidies, green credit, and investment guidance to encourage enterprises to make forward-looking deployments. On the other hand, it is essential to strengthen the transformation of scientific research outcomes by establishing emission-reduction-oriented R&D projects and talent support policies, thereby bridging the gap between AI technologies developed in laboratories and their application on production lines, shortening the time lag, and enhancing the practical effectiveness of the technology.

Second, countries should develop differentiated AI adoption pathways based on their respective resource endowments and industrial foundations. This study shows that AI's carbon-reducing effects are concentrated in high-income countries, which typically benefit from systemic advantages in infrastructure and digital technology. These countries should further promote the deep coupling of intelligent manufacturing and low-carbon transformation, leveraging digitalization and enhanced energy efficiency management to unlock the full decarbonization potential of AI. In contrast, developing economies, particularly low- and middle-income countries, face constraints in capital, technology, and infrastructure. They should prioritize the accessibility of AI technologies, focusing on pilot programs in labor-intensive and high-emission traditional manufacturing sectors. In addition, international mechanisms should be strengthened to support inclusive global AI transitions in manufacturing. On the one hand, this includes technology assistance, capacity building, and financial support to help developing countries integrate AI into green manufacturing. On the other hand, a global AI-enabled green manufacturing platform should be established to promote the cross-border sharing of emission-reduction technologies, energy-efficiency datasets, and best practices, fostering a transparent, comparable, and inclusive green transformation. Moreover, developing countries should carefully design their AI investment strategies to overcome the threshold effect identified in this study. Rather than pursuing fragmented adoption, these countries should rely on industrial parks and smart manufacturing pilot zones to scale up AI deployment and reach the critical mass necessary for observable emission reductions. International cooperation and external financing mechanisms can be leveraged to ease capital constraints and ensure that large-scale AI investments deliver timely and measurable outcomes.

Third, policy design should be industry-specific, targeting the heterogeneity of AI's environmental impacts across manufacturing subsectors. Our empirical results highlight significant cross-industry variation in AI's carbon-reduction effect, necessitating tailored pathways based on each sector's technological foundation, energy profile, and development stage. For labor-intensive traditional sectors – such as textiles, apparel, and leather, wood products, and printed materials – common issues include inefficient production flows, high energy intensity, and outdated organizational models. These sectors should be prioritized for infrastructure upgrades in intelligent manufacturing, with government support through subsidies, tax incentives, and targeted interventions in energy-intensive processes. For highly automated industries such as computers and electrical equipment, the focus should shift to AI-frontier technology integration, enhancing system interoperability and synergy to drive a second leap in green manufacturing. In industries with rigid energy structures like rubber products, green-material substitution and intelligent reengineering of core processes should be prioritized. For example, in energy-intensive vulcanization stages, AI-powered systems enabling precise thermal control, real-time parameter correction, and synchronized scheduling can significantly improve energy efficiency. In carbon-intensive sectors such as coke, refined petroleum, and chemicals, AI should be deployed in tandem with energy-saving technologies – such as energy monitoring, process optimization via simulation, and intelligent carbon tracking – to achieve emission reductions through end-to-end carbon chain management. Finally, for advanced manufacturing sectors where marginal gains from emission reduction have plateaued, AI policies should emphasize smart coordination at the production level and green design across the full product lifecycle, thereby enabling the transition toward a systemic, ecosystem-level model of green intelligent manufacturing.

Fourth, we recommend the enhancement of the transmission effects of manufacturing production technology level, industrial structure optimization and upgrading, and industrial agglomeration level on manufacturing carbon-emission reduction. Therefore, the government should take into account existing production processes and characteristics, vigorously develop AI that adapts to the intelligent transformation of the manufacturing sector, promote AI to improve the technical level of the manufacturing industry, and enhance the deep integration of AI and energy conservation and emission reduction technology. In doing so, the government may consider introducing financial incentives. Finally, the government can, through industrial policy means, accelerate the construction of an industrial ecosystem with AI as the core, promote the construction of industrial agglomeration areas, encourage cross-industry cooperation and technology sharing, and achieve efficient use of resources and coordinated reduction of carbon emissions.

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Conflict of Interest

The authors declare no conflict of interest.

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