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THE MECHANISM AND EFFECTIVENESS OF AI-DRIVEN ESG RATINGS FOR MANUFACTURING ENTERPRISES

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Abstract: In the continuous evolution and development of artificial intelligence, enhancing the ESG of manufacturing enterprises is of great significance for promoting the high-quality and sustainable development of manufacturing enterprises. This paper uses Chinese manufacturing enterprises from 2009 to 2022 as sample data to empirically examine the impact and mechanism of artificial intelligence on the ESG of manufacturing enterprises. Artificial intelligence can effectively promote the development of ESG in manufacturing enterprises, and this result remains valid after a series of robustness tests. The heterogeneity test results show that AI can effectively promote ESG in state-owned manufacturing enterprises that have not yet applied for patents and have a variable equity structure. Further mechanism studies have shown that AI can effectively enhance the ESG of manufacturing enterprises through three channels: reducing financing constraints and resource misallocation rates, and raising awareness of enterprise risk management. The findings provide empirical evidence and policy implications for improving ESG in manufacturing enterprises from the perspective of artificial intelligence.
Keywords: Artificial intelligence; Manufacturing; ESG

1 INTRODUCTION

Artificial Intelligence (AI), as the core technology field of the new round of technological revolution and industrial transformation, has developed rapidly in recent years in terms of algorithmic innovation, computing power breakthroughs and data resources. It empowers the intelligent transformation of traditional industries and the structural reshaping of emerging business forms. It is triggering a systematic improvement in productivity factor allocation efficiency and a fundamental change in value creation models, and is gradually becoming a core technology driving the deep optimization and transformation of the global industrial structure. In many countries, artificial intelligence is regarded as an important strategy to enhance national economic development and the core technological competitiveness of industries. The report of the clearly states that accelerating the transformation of the production and development mode is an inevitable requirement for promoting the green transformation of manufacturing enterprises and enhancing the diversity, stability and sustainability of the ecosystem to ensure high-quality economic development. The 14th Five-Year Plan for the Development of National Strategic Emerging Industries clearly states that artificial intelligence is a key component of new quality productivity and sets the goal of achieving a breakthrough in basic theory by 2025 and forming global innovation leadership by 2030.

Against the backdrop of global transformation in a century of great changes, Chinese manufacturing enterprises, which are characterized by "large scale but insufficient core competitiveness" in the field of goods trade exports, are facing multiple severe challenges such as sluggish external demand, increased risks of supply chain decoupling and disruption, and technological "choke points" in key areas. However, at the micro enterprise level, questions remain to be explored as to what impact the development and popularization of artificial intelligence will have on manufacturing ESG and in what way. Therefore, this paper, from the perspective of micro enterprises, delves deeply into the impact of artificial intelligence on the ESG of manufacturing enterprises, which is a key link to prompt enterprises to adjust their industrial models and corporate development directions in a timely manner, and is also the key to further promoting the high-quality development of manufacturing enterprises, which is of great significance for promoting the green and sustainable development of manufacturing enterprises.

Through a systematic review of the existing academic literature, this paper finds that the academic achievements closely related to the subject of this study mainly present two research categories. The first category examines the reshaping effect of artificial intelligence on the labor market structure, focuses on the technology empowerment perspective, and focuses on analyzing the adaptive application of intelligent algorithms and automation systems in industrial organizations, verifying through case studies and econometric models its promoting effect on total factor productivity improvement[1-2], product iteration cycle compression, and enterprise operational efficiency; Another category is research related to ESG ratings. On the one hand, ESG assessment may exacerbate the "green labeling" behavior of companies, prompting some to exaggerate the results of their investments in environmental protection and resource management and make unfulfillable commitments in an attempt to obtain higher ESG ratings[3]; On the other hand, corporate management may use ESG information to cover up poor financial performance, distract investors, and distort the information transmission effect into the information masking effect[4].

From the above-mentioned literature classification, it can be seen that although the academic community has conducted multi-dimensional discussions on the microeconomic effects of artificial intelligence, there is still a significant theoretical vacuum in the study of its mechanism of action and impact path on the environmental and social governance (ESG) system of manufacturing enterprises. The existing literature has not yet formed a systematic theoretical framework and chain of empirical evidence in the study of the correlation between technological change and sustainable development indicators of enterprises. This knowledge gap provides an important theoretical innovation space for this study.

This paper uses the word frequency method to conduct relevant text analysis on the annual reports of listed manufacturing enterprises in China and constructs artificial intelligence indicators at the micro enterprise level. The research results show that artificial intelligence significantly improves the ESG rating level of listed manufacturing enterprises in China. The conclusion still holds true after robustness tests such as variable substitution, bilateral tailing and bilateral truncation, and endogeneity tests. In terms of the impact mechanism, in order to leverage the enabling effect of artificial intelligence, enterprises will reduce financing constraints, optimize resource allocation, and enhance the risk management awareness of managers. Further, this paper explores the heterogeneity of AI-enabled ESG ratings for manufacturing enterprises from three perspectives: enterprise ownership type, patent ownership, and equity structure. The research design strictly follows the empirical logical chain of "benchmarking - endogeneity processing - mechanism identification - heterogeneity analysis", and employs panel data models and instrumental variable regression methods to ensure the robustness of the research conclusions. Through this research framework, the aim is to provide theoretical basis and empirical evidence for ESG rating and sustainable development of manufacturing enterprises in the era of intelligent economy.

The marginal contribution of this paper is mainly reflected in the following aspects: First, the research perspective. This paper expands on the literature related to artificial intelligence. This paper delves into the study of the impact of AI on the ESG of manufacturing enterprises from both theoretical and empirical perspectives, providing a fresh theoretical perspective and empirical evidence for AI empowering the ESG development of manufacturing enterprises[5-7]; Second, in terms of theoretical mechanisms. This paper reveals the mechanisms by which artificial intelligence affects the ESG of manufacturing enterprises from three perspectives: financing constraints, resource misallocation, and risk management awareness. Existing literature on the mechanisms of ESG in manufacturing enterprises has mostly focused on factors such as environmental investment, green innovation, and market value (Yang Renfa and Yang Jing), but these factors do not fully explain the intrinsic principles of ESG development in manufacturing enterprises, especially the lack of behavioral analysis of manufacturing enterprise managers. This paper, from the perspectives of ESG financing constraints[8-10], resource misallocation, and risk management awareness in manufacturing enterprises, comprehensively considers the operating conditions of manufacturing enterprises and the awareness of managers, and deeply analyzes the mechanism by which artificial intelligence empowers ESG in manufacturing enterprises; Third, in terms of research dimensions. This paper introduces the analysis research from the external development environment and the internal operating environment, explores the heterogeneity of the impact of artificial intelligence on the ESG development of manufacturing enterprises, and fully reveals the impact of artificial intelligence on the ESG development of manufacturing enterprises, in line with the requirements for the high-quality development of manufacturing enterprises in China's 14th Five-Year Plan.

2 LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Literature Review

(1) Research related to artificial intelligence technology empowerment. Research on the application of artificial intelligence in enterprises originated from theoretical exploration in the field of digital transformation. In the early stages of research, artificial intelligence was often listed alongside big data, cloud computing, blockchain and other technologies as a key technological element driving the intelligent transformation of enterprises[11]. In recent years, with the rapid development of artificial intelligence technology and its increasingly extensive impact on social organizational activities, multiple disciplines, including industrial organization, strategic management, and public administration, have made artificial intelligence an important research topic and conducted extensive discussions. At present, research on the factors influencing the application of artificial intelligence in enterprises is mainly carried out from the following three levels: First, the overall environment level. Industrial policies, science and technology policies, and other innovation policy support have created a favorable institutional environment for the development of artificial intelligence[12], while the construction of new-generation digital infrastructure such as computing power and algorithms provides an important underlying architecture and technical foundation for the application of artificial intelligence technology in enterprises[13]. Second, at the organizational group level. The competitive pressure within the group where the organization is located[14], the embedding of AI patent collaborative innovation networks[15], etc. constitute the organizational group-level factors that affect AI technology selection and innovation activities. Third, at the micro enterprise level. Enterprise strategic orientation[16], data resources generated in the production and operation process[17], and compound talents and artificial intelligence professionals are key drivers of artificial intelligence application at the micro enterprise level[18]. From the perspective of ESG ratings, it further deepens the exploration perspective of AI technology empowerment and expands the research field of AI technology empowerment.

As an important driving force of the new round of technological revolution and industrial transformation, artificial intelligence plays a significant role in improving the ESG ratings of enterprises[19].

(2) Research related to corporate ESG ratings. Since the concept of ESG was proposed, it has received much attention from the academic community. Existing research focuses on analyzing the elements that affect the ESG performance of enterprises. The interaction and superposition of internal and external elements of enterprises jointly affect the ESG performance of enterprises. First, in terms of external factors, government regulation plays a significant role. Studies have

shown that the strengthening of formal environmental regulations such as central environmental inspections, environmental taxes and carbon emission policies, as well as the optimization of the business environment, are all conducive to improving the ESG performance of enterprises. In addition, levels of social trust, regional culture, institutional pressure, institutional investors and non-governmental organizations also affect corporate ESG performance. Second, in terms of internal elements, studies have shown can improve corporate ESG performance, while multiple major shareholders and controlling shareholders' equity pledges have inhibitory effects. Fang et al., Wang Yinghuan and Guo Yongzhen, by analyzing the impact of technology on corporate ESG, found that digital transformation contributes positively to the improvement of corporate ESG performance. Management traits and company size are also important internal factors that affect ESG performance. Zhang Hui and Huang Qunhui pointed out that leading ceos play a significant role in improving the ESG performance of enterprises. Existing literature dissects the economic consequences of conducting supply chain finance business from multiple aspects such as alleviating financing constraints, promoting innovation and enhancing enterprise value, but few studies explore the impact of supply chain finance on sustainable development of enterprises. As an alternative variable for corporate sustainability, although the existing literature summarizes many factors that affect ESG performance, it has not been fully demonstrated from the perspective of the supply chain. In view of this, this paper innovatively incorporates supply chain finance and corporate ESG performance into the same research framework to deeply deconstruct the intrinsic mechanisms by which supply chain finance business affects corporate ESG performance.

2.2 Theoretical Analysis and Research Hypotheses

Stakeholder theory breaks through the traditional business philosophy of enterprises, no longer limited to maximizing shareholder interests, but regards enterprises as complex synergy formed by various stakeholders. In the process of strategy formulation[20], enterprises must deeply analyze the internal and external environment they are in, accurately identify the potential challenges and rare opportunities contained therein, and thus effectively respond to the diverse and reasonable interests of stakeholders. The ESG (Environmental, Social and Governance) concept, as an advanced investment and evaluation system, differs from the traditional model that focuses solely on financial performance. It comprehensively considers corporate performance from three key dimensions: environmental responsibility, social responsibility, and corporate governance. The practice of this concept demonstrates the company's high regard for the interests of its stakeholders and aligns with the inherent requirements for sustainable development of enterprises at present[21]. Artificial intelligence, as a key driver of the new round of technological revolution, has successfully integrated a multitude of stakeholders including core enterprises, suppliers, customers and financial institutions, forming a close bond of interests. By optimizing environmental protection initiatives, creating stable job opportunities and enhancing corporate governance, AI not only strengthens the coordination and unity of interests among all parties, breaks down trade barriers, but also injects powerful impetus into the significant improvement of the overall ESG performance of enterprises.

On the one hand, with the rapid development of information technology, artificial intelligence technology, with its outstanding information processing and analysis capabilities, has brought about a wave of change in the field of corporate organizational structure and operational management, reshaping the information transmission mechanism. In the manufacturing industry, the "smart manufacturing" strategy drives the traditional hierarchical structure to a more flexible and collaborative networked, flat organizational form. By building digital information integration platforms, enterprises construct a precise and efficient dynamic monitoring system that can track and accurately diagnose the enterprise's environmental, social and governance (ESG) performance indicators in real time, Accurately grasp its dynamic changing trends. Based on the complexity and variability of stakeholder demands, enterprises have further established a set of investment decision response mechanisms that are in line with them. This deep transformation of the organizational structure not only significantly improves the efficiency and accuracy of ESG resource allocation, but also helps to continuously optimize and spiral the overall ESG performance of enterprises by enhancing their investment adaptability and adjustment capabilities in environmental, social and governance areas.

On the other hand, the data interconnection mechanism constructed in the intelligent economic ecosystem has greatly expanded the space and dimensions of enterprise collaborative governance. With the help of cross-organizational information network platforms built by intelligent technologies, enterprises have achieved extensive horizontal dissemination and in-depth vertical exploration of ESG governance experience. For managers with relatively limited ESG management experience, the benchmark enterprise case library and best practice database provided by the digital platform have become key channels for them to acquire valuable knowledge and experience, effectively promoting the spillover and sharing of knowledge. At the same time, collaborative networks built on the basis of blockchain technology have strongly facilitated the optimization and integration of ESG resource allocation among upstream and downstream enterprises in the supply chain. Through the full play of synergy and amplification mechanisms, corporate governance performance has achieved a multiplication-like significant improvement. This digital technology-driven collaborative governance model encompasses both the one-way transmission of ESG governance experience and knowledge from advanced enterprises to other enterprises and the two-way interaction achieved through resource integration and optimization in the process of enterprises' participation in collaborative governance. The two work together to drive the continuous improvement and enhancement of enterprises' ESG performance.

Based on the above theoretical analysis and practical observations, this paper puts forward the following assumptions:

Hypothesis H1: Artificial intelligence technology may positively affect the ESG ratings of manufacturing enterprises.

First, resource misallocation, as a common structural contradiction in the manufacturing sector, is essentially a systemic efficiency loss caused by the deviation of production factor allocation from the optimal state. It not only directly leads to Pareto degradation of resource utilization efficiency and structural increase in production costs, but also intensifies the carbon emission intensity and ecological load of manufacturing through the transmission mechanism of environmental externalities. It forms a rigid constraint on improving ESG performance. Ai enhances the efficiency of collective task completion by connecting and integrating departments and promoting information sharing and collaboration among departments. This collaborative way of working can not only optimize the allocation of human resources in enterprises[22], reduce unnecessary waste of equipment and human resources, but also enhance the market competitiveness of enterprises. In terms of ESG index, artificial intelligence also plays a significant role[23]. Companies' use of AI to optimize resource allocation, reduce energy consumption and waste emissions helps improve their environmental performance. At the social level, AI can promote corporate social responsibility fulfillment, such as enhancing employee satisfaction and loyalty through fair talent selection and employee development mechanisms, and also use AI technology to create more value for society, such as improving public services and promoting educational equity. In terms of corporate governance, AI can enhance the efficiency and transparency of corporate decision-making, strengthen internal oversight and risk management, and thereby improve corporate governance. In the recruitment process of human resource management, the application of artificial intelligence shows a huge advantage. In the face of a vast number of job seekers' resumes, AI recruitment systems can quickly and accurately screen out candidates who meet the job requirements, not only saving a lot of time and energy for human resources departments, but also reducing the costs caused by recruitment mistakes for enterprises.

Secondly, AI technology has demonstrated significant technological and economic advantages in enhancing total factor productivity, optimizing cost structures, and empowering the innovation ecosystem by driving the paradigm shift in manufacturing. However, the capital-intensive nature of its large-scale application has made enterprises generally face the constraints of capital allocation in the process of technology adoption. As a microcosm of capital market frictions, financing constraints essentially reflect institutional obstacles such as credit rationing, information asymmetry and agency costs that enterprises encounter when obtaining external financing. Such capital availability constraints may affect strategic investment decisions through dual paths: On the one hand, high financing costs or quota controls will prompt management to tend to choose investment projects with short-term cash flow returns, thereby creating a "crowding-out effect" on ESG long-term value creation; On the other hand, capital constraints may force companies to delay or reduce capital spending on cutting-edge technologies such as AI, creating a vicious cycle of "lagging technology adoption - hindered improvement in environmental and social performance." From the perspective of the sustainable development paradigm, ESG performance has become a multi-dimensional performance evaluation framework for measuring the value creation ability of enterprises, especially in the context of manufacturing, where its intrinsic development requires enterprises to achieve systematic upgrades in environmental management (E dimension), stakeholder collaboration (S dimension), and governance modernization (G dimension). This transformation not only requires physical capital investment such as building a clean production technology system and improving supply chain due diligence mechanisms, but also relies on intellectual capital accumulation such as building digital governance capabilities. The embedding of AI technology provides a technological decoupling path to break the capital constraints of ESG investment: In the environmental dimension, AI-based industrial Internet of Things platforms can achieve real-time modeling and optimized control of energy consumption data, and reduce energy consumption per unit of output through predictive maintenance; In the social dimension, blockchain-enabled smart contract systems can enhance supply chain transparency and ensure labor rights protection through traceability technology; In the governance dimension, natural language processing technology can automatically parse regulatory texts and assist in building compliance risk early warning systems. These technology applications essentially form a "technology lever" for ESG investment, which can spread out unit environmental governance costs through efficiency improvements and create a positive cycle of "technological progress - endogenous cost reduction - expanded ESG investment".

Finally, in the modern manufacturing operating environment, risk management awareness constitutes the strategic cognitive framework of decision-makers regarding uncertainties. This awareness is not merely a simple identification of potential risks, but a systematic way of thinking that helps decision-makers assess, predict, and respond to various potential uncertainties in complex operational scenarios. The importance of risk management awareness is particularly prominent in the manufacturing sector, which faces multiple complex and interwoven risk challenges. Environmental compliance risks are an important type of risk that cannot be ignored in manufacturing. As global environmental awareness grows and environmental regulations become increasingly strict, manufacturing enterprises must ensure that their production activities comply with relevant environmental standards. Otherwise, companies will face serious consequences such as hefty fines, production disruptions and even damage to their reputation. For example, the problem of wastewater discharge in the chemical manufacturing industry, if it fails to meet environmental protection requirements, will not only cause damage to the surrounding ecological environment, but also trigger strong public resistance, thereby affecting the long-term development of enterprises. In addition, the risk of governance failure also poses a threat to the sustainable development of manufacturing enterprises. A sound governance structure ensures that the decision-making process of the enterprise is transparent, efficient and meets the expectations of stakeholders. However, if the governance structure is flawed, such as an imperfect internal oversight mechanism, excessive concentration of power, or transfer of benefits, it will be difficult for the enterprise to effectively deal with internal and external risks, leading to strategic failures, waste of resources, or even the collapse of the enterprise. Thus, Hypothesis H2 is proposed: AI affects the ESG ratings of manufacturing enterprises by optimizing resource allocation, easing financing constraints, and enhancing managers' awareness of risk management.

3 THREE RESEARCH DESIGNS

3.1 Econometric Model Setup

This paper draws on the research results of scholars Zhang Meng and Song Shunlin (2023) to empirically examine the impact of artificial intelligence on the ESG performance of manufacturing enterprises and constructs econometric models as follows[24]:

$$ESG=\alpha_0+\alpha_1 AI_{it}+\varepsilon_{it} \tag{1}$$

Here, represents the constant term, AI represents the level of development of artificial intelligence, represents the parameter estimation coefficient of the level of artificial intelligence in manufacturing, represents the random error term. $\alpha_0 \alpha \varepsilon$In addition to the impact of AI, manufacturing may also be affected by other factors at the enterprise and year levels. Therefore, expand the model further to:

$$ESG=\propto_0+\propto_1 AI_{it}+\propto_j \sum X_{jit}+\mu_{it} \tag{2}$$

Here, i represents region, t represents year, and represents the level of development of artificial intelligence, which is the core explanatory variable of this paper; ESG represents the ESG performance of manufacturing enterprises, and AI is the explained variable in this model. The regression coefficient α1 is the main object of observation in this paper. Based on the sign and significance level of α1, the extent to which the development level of artificial intelligence affects the ESG performance of manufacturing enterprises can be analyzed. X is the control variable, including seven control variables such as enterprise size, return on total assets, shareholding ratio of the largest shareholder, board independence, asset-liability ratio, operating cash flow, and cash holdings, with regional and annual controls. μit is the random disturbance.

3.2 Measurement and Explanation of the Indicators

3.2.1 Metric measurement

(1) Artificial intelligence (AI) This section selects the annual report texts of Chinese manufacturing enterprises with artificial intelligence technology from 1990 to 2022, adds a logarithm to them to form the characteristic word frequency of artificial intelligence technology, and uses this to measure the development level of artificial intelligence in manufacturing. The data used mainly comes from Statistical Yearbooks and Guotai 'an Database.

(2) Enterprise ESG (ESG) The high-quality development of manufacturing cannot do without the synergy and joint efforts of the government and enterprises. Micro enterprises, as the main implementers of high-quality development of the green economy, should actively respond to national policies, cooperate with government macro-control, and strengthen social and environmental governance. The ESG (Environmental, Social and Governance) concept assesses the economic sustainability and corporate social values of enterprises from three different dimensions: environment, society and corporate governance. From an economic perspective, ESG, as a comprehensive evaluation indicator based on the concept of environmental sustainability and extending to corporate environmental friendliness, social responsibility, and corporate management, is ultimately aimed at motivating companies to maximize the external impact of their business practices on the social economy and the ecological environment into internal impacts. And in the process of implementation, redefine the boundary between the enterprise and the market. Therefore, ESG needs to take into account not only the personal social responsibility of corporate stakeholders, but also issues such as sustainable and green development of the social economy, promoting the green transformation of manufacturing enterprises while enhancing the industry and social recognition of enterprises.

Compared with the comprehensive scores of other domestic ESG ratings[25], the comprehensive score of the Huazheng Index ESG evaluation has the advantages of being updated in a more timely manner and having a wider coverage. In addition, the Huazheng ESG comprehensive score evaluation system is based on the connotation of ESG development, and compared with foreign ESG comprehensive score evaluation systems, its evaluation criteria are more in line with China's current actual national conditions. The Huazheng ESG comprehensive Score evaluation takes a range of 0 to 100 points. In the evaluation system, the three first-level indicators of environment (E), society (S), and governance (G) each account for one-third of the weight. Among them, environment (E) includes seven second-level indicators such as energy, air quality, and waste treatment; Social (S) includes six secondary indicators such as community and customers, health and safety, and supply chain; Governance (G) includes eight secondary indicators such as diversity, board composition, and compensation clauses.

(3) Control variables. To ensure the accuracy of the empirical test results, relevant control variables are introduced with reference to the study by Li et al. (2022)[26].

The meanings and measurement methods of the variables in this section are shown in the following Table 1.

Table 1 Variable Meanings and Measures

Variable Types	Variable symbols	Variable name	Variable metrics
Explanatory variables	AI	Artificial intelligence	Ln(1+ AI technology)
Explained variable	ESG	Huazheng ESG Overall Score	The comprehensive ESG evaluation score of the Huazheng Index
Control variables	Size	Business size	Ln (Total Assets of the enterprise)
	Roa	Net profit margin on total assets	Net profit/total assets

Top1	Shareholding ratio of the largest shareholder	Number of shares held by the largest shareholder/total number of shares
Indep	Board independence	Number of independent directors/total number of board members
Lev	Debt-to-asset ratio	Total liabilities/total assets of the enterprise
Cflow	Operating cash flow	Net cash flows from operating activities/total assets
Cash	Cash holdings	(Monetary funds + trading financial assets)/total assets

3.2.2 Data sources and descriptive statistical results

In order to examine the impact of artificial intelligence on the ESG performance of manufacturing and for the comprehensive consideration of the research results, this part of the study will use Chinese manufacturing enterprises from 2009 to 2022 as sample data.

Data on green ESG and seven control variables of manufacturing enterprises are mainly sourced from the CSMAR database. Artificial intelligence data collated the annual reports of Chinese manufacturing enterprises through text analysis, extracted artificial intelligence keywords from manufacturing enterprises using Python, and calculated their word frequency based on this. After merging and matching, 25,629 valid data from 2009 to 2022 were obtained. Descriptive statistics for each variable are shown in Table 2 (Descriptive statistics of Artificial intelligence, ESG performance of manufacturing enterprises and related variables):

Table 2 Descriptive Statistics of Artificial Intelligence, ESG Performance of Manufacturing Enterprises and Related Variables

Variable	Obes	Mean	Std.Dev.	Min	Max	The 25% quantile	50% quantile	75% quantile
AI	25629	72.788	5.320	44.010	90.930	0.000	0.000	0.000
ESG	25629	0.298	0.674	0.000	5.313	69.890	73.160	76.300
Size	25629	21.989	1.199	16.412	27.621	21.828	21.828	22.654
Roa	25629	0.036	0.371	-30.688	22.005	0.014	0.041	0.073
Top1	25629	33.406	14.359	1.840	89.990	22.500	31.150	42.500
Indep	25629	0.376	0.056	0.000	0.800	0.333	0.333	0.429
Lev	25629	0.418	1.237	0.007	178.346	0.237	0.388	0.543
Cflow	25629	0.048	0.078	-1.686	2.222	0.009	0.047	0.088
Cash	25629	0.208	0.147	0.000	0.998	0.102	0.167	0.277

In Table 2 above, the sample observation data values, the mean, standard deviation, minimum value, maximum value, 25% quantile, 50% quantile and 75% quantile results of each variable are presented. It can be seen that the maximum value of the independent variable artificial intelligence (AI) is 90.930, the minimum value is 44.010, and the mean value is 72.788 The standard deviation is 5.320; The maximum value of the dependent variable manufacturing enterprise ESG (ESG) is 5.313, the minimum is 0.000, the mean is 0.298, and the standard deviation is 0.674; In addition, among the seven control variables, the standard deviation of the largest shareholder ratio (Top1) was higher, reaching 14.359, while the standard deviation of the other control variables was all below 1.3. Overall, the standard deviation of most of the data was small, roughly estimating that the data was not very volatile.

Meanwhile, this paper uses the correlation coefficients of each variable to determine whether there is a multicollinearity relationship, and the results are shown in Table 3 (variable correlation coefficients) below. The results show that the coefficients between the variables are all below 0.2, and it can be roughly judged that the multicollinearity between the variables is weak. Therefore, this paper will directly use the variable data for empirical research.

Table 3 Variable Correlation Coefficients

Variables	ESG	AI	size	roa	top1	indep	Lev	cflow	cash
ESG	1.000								
AI	0.053 * * *	1.000							
size	0.184 * * *	0.087 * * *	1.000						
roa	0.095 * * *	-0.006	0.038 * * *	1.000					
top1	0.114 * * *	0.074 * * *	0.110 * * *	0.024 * * *	1.000				
indep	0.062 * * *	0.057 * * *	-0.005	-0.004	0.052 * * *	1.000			
Lev	0.078 * * *	-0.008	0.014 * *	0.595 * * *	0.001	0.000	1.000		
cflow	0.142 * * *	0.018 * * *	0.108 * * *	0.105 * * *	0.091 * * *	-0.003	0.034 * * *	1.000	
cash	0.164 * * *	0.086 * * *	0.170 * * *	0.052 * * *	0.075 * * *	0.002	0.082 * * *	0.180 * * *	1.000

Note: ***, **, * indicate passing the significance test at 1%, 5%, and 10% respectively

Data source: Calculated and compiled by the authors

4 FOUR EMPIRICAL TESTS AND RESULTS ANALYSIS

4.1 Baseline Results Analysis

By controlling for both year and enterprise fixed effects, this paper estimates the basic regression model using the panel fixed effects model and the cluster-robust standard deviation. Table 4 shows the benchmark regression results of the impact of artificial intelligence (AI) on the ESG performance (ESG) of manufacturing enterprises. According to the results shown in Table 4, in column (1), only the fixed effects of enterprises are controlled, and the estimated coefficients of the AI development variable are not significant, indicating that AI has not yet had a significant impact on the ESG performance of manufacturing enterprises; Column (2) controls both corporate fixed effects and time fixed effects, and the results show a significant positive at the 1% level, indicating that when corporate and time fixed effects are controlled, AI can effectively promote the ESG performance of manufacturing enterprises; The regression results in column (3), which further included control variables such as enterprise size and net profit margin on total assets, showed a significant positive result at the 5% level, indicating that after considering time and other external factors that may affect the ESG level of manufacturing enterprises, AI can still significantly promote the development of the ESG level of manufacturing enterprises.

Table 4 Benchmark Regression Results

	(1)	(2)	(3)
	ESG	ESG	ESG
AI	0.0043	0.2371 * * *	0.1860 * *
	(0.085)	(0.090)	(0.085)
size			1.1384 * * *
			(0.101)
roa			0.3461 * * *
			(0.082)
top1			0.0273 * * *
			(0.008)
indep			4.0480 * * *
			(1.000)
Lev			-0.0408
			(0.042)
cflow			-0.3656
			(0.498)
cash			4.3945 * * *
			(0.373)
_cons	72.7870 * * *	72.7176 * * *	44.3726 * * *
	(0.025)	(0.027)	(2.302)
N	25629	25629	25629
r2	0.5177	0.5234	0.5391

*** p<0.01, ** p<0.05, * p<0.1

Note: ***, **, * indicate passing the significance test at 1%, 5%, and 10% respectively

From the above regression results, it can be seen that the impact of artificial intelligence on the ESG level of manufacturing enterprises is significantly positive, and it is independent of whether fixed effects are introduced or random control variables are added. This also indicates that artificial intelligence can effectively enhance the ESG development level of manufacturing enterprises, verifying the previous theoretical analysis results. The development and improvement of the new generation of intelligence provide new channels and perspectives for manufacturing enterprises to measure their own value and the trends of the industry market economy. First, the development and popularization of intelligence have forced manufacturing to optimize and upgrade its industrial structure, indirectly compelling enterprises to pay attention to the social environment, assume their social responsibilities, and maximize regulatory effects through intelligent platforms, big data and other means, suppressing the behavior of top management of enterprises to obtain economic benefits at the expense of high-risk pollution such as the ecological environment; Secondly, manufacturing enterprises that attach more importance to the intelligent upgrading of industrial equipment tend to pay more attention to the internal supervision mechanism and management model of the enterprise, strengthen communication within the enterprise and outside the market, alleviate problems such as agency and information closure within the enterprise, and reduce the probability of wrong decisions made by senior management.

4.2 Robustness Test

4.2.1 Variable substitution

To further ensure the accuracy and credibility of the research conclusions and to avoid differential results due to possible errors in the explained variables, in this section, the ESG composite score of the Business Green Index 2015-2022 was used as the new explained variable indicator to test the robustness of the benchmark regression results, and 2,916 valid data were obtained. According to the results in Table 5, in column (1), the estimated coefficient of the artificial intelligence development variable is significant and positively significant at the 1% level, indicating that, regardless of the time effect, artificial intelligence technology has effectively promoted the development of the ESG level of manufacturing enterprises in each time period. Column (2), which controls for both enterprise fixed effects and time fixed effects, shows a significantly positive result at the 5% level, indicating that artificial intelligence technology can still effectively enhance the ESG level of manufacturing enterprises within specific enterprises and time periods. Column (3) shows the regression results after further adding the seven control variables of enterprise size, net profit margin on total assets, shareholding ratio of the largest shareholder, board independence, debt-to-asset ratio, operating cash flow, and cash holdings. The results are still significantly positive at the 5% level. The development of artificial intelligence technology can still significantly promote the ESG development of manufacturing enterprises after taking into account time and many other external factors that may affect the ESG development level of manufacturing enterprises.

The above benchmark regression results show that there is no significant difference between the benchmark regression results after replacing the measurement method of the explained variable and the benchmark regression results of the original sample, thereby verifying the robustness of the benchmark regression in this study.

Table 5 Results of the Robustness Test of the Replacement Variable

Variables	ESG	ESG	ESG
	(1)	(2)	(3)
AI	0.2650 * * *	0.0761 * *	0.0660 * *
	(0.0357)	(0.0334)	(0.0332)
size			0.3477 * * *
			(0.0763)
roa			0.4247 * * *
			(0.1265)
top1			0.0063
			(0.0049)
indep			07222 * *
			(0.3428)
Lev			0.6393 * * *
			(0.1952)
cflow			0.0925
			(0.2124)
cash			0.0015
			(0.2706)
_cons	4.1915 * * *	4.2967 * * *	4.0708 * * *
	(0.0199)	(0.0186)	(1.7587)
N	2916	2916	2916
r2	0.6946	0.7581	0.7655

4.2.2 Bilateral tail reduction and bilateral tail truncation

To eliminate the influence of the extreme values at the beginning and end of the data sample on the benchmark regression results, this section performs bilateral 1% truncation and bilateral 1% truncation on the ESG levels of manufacturing enterprises respectively. Columns (1) and (2) of Table 6 show the regression results of bilateral truncation and bilateral truncation on the ESG levels of manufacturing enterprises at the 1% level respectively. The results show that in the cases of bilateral 1% tailing and bilateral 1% truncation, the impact of artificial intelligence on the ESG level of manufacturing enterprises is positively significant, and positively significant at the 1% and 5% levels, respectively, indicating that after removing the influence of the head and tail extreme values, artificial intelligence technology can still effectively promote the development of the ESG level of manufacturing enterprises. This results also again demonstrated that there was no significant difference in the benchmark regression results of the original sample data after bilateral 1% tailing and bilateral 1% truncation, respectively, compared with the benchmark regression results of the original sample, once again verifying the robustness of the benchmark regression results of this study.

Table 6 Results of the Bilateral Truncation and Bilateral Truncation Robustness Tests

Variables	ESG (1) Bilateral 1% tailing	ESG (2) Bilateral 1% truncation
AI	0.3343 * * *	0.2290 * *
	(0.089)	(0.089)
size	1.3914 * * *	1.1207 * * *
	(0.127)	(0.101)
roa	9.4828 * * *	0.3444 * * *
	(1.395)	(0.081)
top1	0.0299 * * *	0.0273 * * *
	(0.009)	(0.008)
indep	4.3374 * * *	4.1219 * * *
	(1.451)	(1.005)
Lev	5.2812 * * *	-0.0416
	(0.481)	(0.042)
cflow	2.3597 * *	-0.2982
	(0.737)	(0.502)
cash	3.0281 * * *	4.3652 * * *
	(0.442)	(0.375)
_cons	40.7451	44.7301
	(2.823)	(0.506)

Year fixed effect	Controls	Control
Corporate fixed effects	Control	Control
N	25629	25380
r2	0.5441	0.5384

4.2.3 Endogeneity test

In the econometric analysis framework of this section, the effects of artificial intelligence on energy consumption in manufacturing enterprises may be disrupted by endogeneity issues. Specifically, the endogenous bias can be mainly attributed to two reasons: First, there may be unobserved heterogeneous variables in the model construction process, which may be associated with the application of artificial intelligence through collinearity mechanisms, thereby undermining the exogenous assumption of the error term; Secondly, the energy consumption patterns of manufacturing enterprises may act in reverse on the adoption and deployment of artificial intelligence, forming a reverse causal chain that further exacerbates the severity of endogenous bias.

In order to effectively mitigate the potential bias caused by the endogeneity problem to the benchmark regression results, this section re-estimates the econometric model using the instrumental variable method. By screening exogenous instrumental variables that meet the dual constraints of correlation and exclusivity, the statistical robustness and economic significance of the baseline regression results are systematically verified to ensure that the research conclusions have sufficient reliability and explanatory power.

Given that the calculation results of artificial intelligence in the previous year may cause deviations in the calculation results of artificial intelligence in the current year, the energy consumption level of manufacturing enterprises in the current year will not cause deviations in the calculation results of artificial intelligence in the previous year. Following Li Guo's (2023) approach, this subsection uses the lagging one-period AI index for two-stage regression (Table 7).

Table 7 Endogeneity Test: Two-Stage Instrumental Variable Regression Results

Variables	Phase 1	Phase 2
	AI	ESG
IV	0.516 * * *	
AI	(0.016)	0.0041 * *
		(0.002)
Tagr	-0.011	-0.001
	(0.010)	(0.001)
Cash	0.095 * *	0.001
	(0.047	(0.005)
Lev	0.024	0.000
	(0.034)	(0.004)
Size	0.089 * * *	0.001
	(0.011)	(0.000)
Roe	-0.001	0.000
	(0.002)	(0.000)
Cr	0.027	-0.003
	(0.044)	(0.005)
Roa	-0.024	-0.008
	(0.041	(0.005)
_cons	1.788 * * *	
	(0.238)	
Year fixed effect	Not controlled	Control
Corporate fixed effects	Control	Control
N	20229	20229
r2	0.745	0.000

4.3 Mechanism Testing

According to the previous theoretical analysis, the development of artificial intelligence technology will not only have a direct impact on the ESG level development of manufacturing enterprises, but also have an indirect impact on the ESG of manufacturing enterprises from three dimensions: financing constraints, resource misallocation, and risk management awareness. Therefore, this section mainly examines the mechanism of the mediating effect of the development of artificial intelligence technology on the ESG of manufacturing enterprises based on the previous text.

Specifically, Equation 2 reflects the direct impact of the development of artificial intelligence technology on the development of the ESG level of manufacturing enterprises. To better examine the mechanism of how artificial intelligence indirectly affects the green transformation of manufacturing, the mediating variable (MED) is introduced and the mediating effect model is constructed based on this as follows:

$$MED_{it}=\alpha_0+\alpha_1 AI_{it}+\alpha_1 \sum X_{jit}+\mu_{it} \tag{3}$$

$$ESG=\alpha_0+\alpha_1 AI_{it}+\alpha_2 MED_{it}+\alpha_j \sum X_{jit}+\mu_{it} \tag{4}$$

Mediating variables mainly include financing constraints, resource misallocation, and risk management awareness. Among them, the measurement method of financing constraints (Sa) is the same as that in Chapter 6 and will not be repeated here; Resource utilization mainly refers to financial redundancy (FS), measured by the ratio of cash to cash equivalents to total operating costs; Risk management awareness includes both internal risk management awareness and external risk management awareness. Referring to the practices of Bae et al. (2002) and Li Zengquan et al. (2004)[27-28], the degree of major shareholders' embezzlement is used as a measure of internal risk management awareness, where the degree of major shareholders' embezzlement is measured by the ratio of other receivables to total assets of the enterprise; Following the approach of Tang et al. (2024), the number of negative reports on the enterprise by online media is used as a measure of the enterprise's external risk management awareness.

4.3.1 Resource misallocation effect

Table 8 presents the regression results of the mediating effect of resource misallocation on the ESG level development of manufacturing enterprises influenced by artificial intelligence. According to the regression results, column (1) shows the impact of AI on the ESG level of manufacturing enterprises when control variables are introduced, and the result is negatively significant at the 5% level, indicating that AI can effectively enhance the ESG development level of manufacturing enterprises; Column (2) shows the impact of AI on resource misallocation when control variables are introduced, and the result is negatively significant at the 5% level, indicating that AI effectively reduces corporate financial redundancy, reduces corporate resource waste, and further enhances corporate resource utilization; Column (3) shows the impact of AI and resource misallocation on the ESG level development of manufacturing enterprises when control variables are introduced. The results show positive significance at the 5% level, indicating that the combination of AI and resource misallocation can effectively promote the ESG development of manufacturing enterprises. It also demonstrates that resource misallocation is the mechanism by which AI technology promotes ESG development in manufacturing enterprises, and this empirical result supports the theoretical analysis presented earlier.

According to the regression results of the mediating effect, the development of artificial intelligence in manufacturing can effectively reduce financial redundancy in enterprises and promote the development of ESG in manufacturing enterprises. The reasons may be influenced by two aspects: First, the development of artificial intelligence technology may to some extent replace the original human basic workload, significantly reducing the error rate of traditional manual labor, that is, reducing human resource costs and enterprise error tolerance rate, thereby further improving enterprise resource utilization and reducing financial redundancy; The second possibility is that with the continuous development of social civilization, human needs have shifted from the most basic material needs to higher spiritual needs, and the requirements for the ecological environment have also increased accordingly. The development of artificial intelligence technology helps the manufacturing industry to position its development model more accurately, strengthen the awareness of social responsibility and environmental responsibility, strengthen the ESG development concept of enterprises, and promote the green transformation of manufacturing enterprises.

Table 8 Regression Results of Resource Misallocation Mediating Effect

	(1)	(2)	(3)
Variables	ESG	OS	ESG
AI	0.186 * *	0.196 * *	0.191 * *
	(0.085)	(0.098)	(0.084)
Size	1.138 * * *	0.443 * * *	1.150 * * *
	(0.101)	(0.067)	(0.101)
Roa	0.346 * * *	-0.003	0.346 * * *
	(0.082)	(0.093)	(0.082)
Top1	0.027 * * *	0.004	0.027 * * *
	(0.008)	(0.006)	(0.008)
Indep	4.048 * * *	0.752	4.028 * * *
	(1.000)	(0.754)	(1.000)
Lev	-0.041	-0.077	-0.039
	(0.042)	(0.058)	(0.040)
Cflow	-0.366	1.409 * * *	-0.328
	(0.498)	(0.582)	(0.498)
Cash	4.395 * * *	11.024 * * *	4.098 * * *
	(0.373)	(0.759	(0.397)
OS			0.027 *
			(0.015)
_cons	44.373 * * *	10.028 * * *	44.103 * * *
	(2.032)	(1.493)	(2.311)
N	25629	25629	25629
r2	0.539	0.542	0.539

4.3.2 Financing constraint effect

Table 9 shows the regression results of the mediating effect of financing constraints on the impact of artificial intelligence on emissions reduction in manufacturing. According to the regression results, column (1) shows the impact of AI on the ESG level development of manufacturing enterprises when control variables are introduced. The results show positive significance at the 5% level, indicating that AI can promote the ESG development of manufacturing enterprises; Column (2) shows that when control variables are introduced, the impact of AI on financing constraints is negatively significant at 5%, indicating that AI can effectively alleviate the financing constraints of manufacturing enterprises; Column (3) shows the impact of AI and financing constraints on the ESG level of manufacturing enterprises when control variables are introduced. The results show positive significance at the 1% level, indicating that the combination of AI and financing constraints can effectively promote the development of the ESG level of manufacturing enterprises. It also demonstrates that financing constraints are an important mechanism by which AI promotes the development of ESG levels in manufacturing enterprises, and this empirical result supports the theoretical analysis presented earlier.

According to the regression results of the mediating effect, the development of artificial intelligence in manufacturing can alleviate the financing constraints of manufacturing enterprises and promote the development of ESG in manufacturing enterprises. The reasons may be influenced by the following two aspects: First, the development of emerging technologies such as intelligence, digitalization, and big data may have broken down traditional trade barriers, significantly lowering the threshold and difficulty for manufacturing enterprises to raise funds externally; The second possibility is that the financing funds obtained by manufacturing enterprises can be used to strengthen enterprise technological development, boost enterprise productivity, deepen enterprise industrial reform and thereby promote enterprise ESG development.

Table 9 Regression Results of the Mediating Effect of Financing Constraints

	(1)	(2)	(3)
Variables	ESG	Sa	ESG
AI	0.186 * *	0.005 * *	0.157 *
	(0.085)	(0.002)	(0.082)
Size	1.138 * * *	0.031 * * *	1.331 * * *
	(0.101)	(0.005)	(0.107)
Roa	0.346 * * *	-0.008	0.394 * * *
	(0.082)	(0.011)	(0.118)
Top1	0.027 * * *	0.000	0.026 * * *
	(0.008)	(0.000)	(0.008)
Indep	4.048 * * *	0.026	3.888 * * *
	(1.000)	(0.021)	(0.988)
Lev	-0.041	0.007 * * *	-0.085
	(0.042)	(0.003)	(0.053)
Cflow	-0.366	0.027 * * *	-0.198
	(0.498)	(0.011)	(0.505)
Cash	4.395 * * *	0.060 * * *	4.024 * * *
	(0.373)	(0.007)	(0.374***)
Sa			6.167 * * *
			(0.784)
_cons	44.373 * * *	3.147 * * *	63.780 * * *
	(2.032)	(0.106)	(3.444)
N	25629	25629	25629
r2	0.539	0.964	0.542

4.3.3 Risk management awareness effect

Table 10 shows the regression results of the mediating effect of risk awareness within enterprises on the impact of artificial intelligence on the development of ESG levels in manufacturing enterprises. According to the regression results, column (1) shows the impact of AI on the ESG level of manufacturing enterprises when control variables are introduced, and the result is negatively significant at the 5% level, indicating that AI can effectively enhance the ESG development level of manufacturing enterprises; Column (2) shows the impact of artificial intelligence on internal risk management awareness when control variables are introduced, and the impact results are positively significant at the 10% level, indicating that the development of artificial intelligence has effectively enhanced internal risk management awareness in enterprises; Column (3) shows the impact of AI and internal risk management awareness on the development of ESG levels in manufacturing enterprises when control variables are introduced. The results show positive significance at the 5% level, indicating that the combination of AI and internal risk management awareness can effectively promote the development of ESG in manufacturing enterprises. It also demonstrates that awareness of internal risk management is the mechanism by which AI technology promotes ESG development in manufacturing enterprises, and this empirical result supports the theoretical analysis mentioned earlier.

Table 11 shows the regression results of the mediating effect of external risk awareness of enterprises on the development of ESG levels in manufacturing enterprises influenced by artificial intelligence. According to the regression results, column (1) shows the impact of artificial intelligence on the ESG level of manufacturing enterprises when control variables are introduced. The results show that it is positively significant at the 5% level, indicating that artificial intelligence can effectively enhance the ESG development level of manufacturing enterprises; Column (2) shows the impact of AI on external risk management awareness of enterprises when control variables are introduced. The impact results show that it is positively significant at the 1% level, indicating that AI significantly enhances the external risk management awareness of managers in manufacturing enterprises; Column (3) shows the impact of AI and external risk management awareness on the development of ESG levels in manufacturing enterprises when control variables are introduced. The results show positive significance at the 5% level, indicating that the combination of AI and external risk management awareness of manufacturing enterprise managers can effectively promote the development of ESG in manufacturing enterprises. It also demonstrates that external risk management awareness is the mechanism by which AI technology promotes ESG development in manufacturing enterprises, and this empirical result supports the theoretical analysis mentioned earlier.

According to the above results, both the internal risk awareness and the external risk awareness of manufacturing enterprises have effectively promoted the development level of ESG in manufacturing enterprises. The main reasons for this are as follows: First, risk management awareness is the prerequisite and foundation for the stable operation of enterprises. Full and accurate risk management awareness enables enterprises to understand in advance the risks and extent of damage they will face, and take corresponding measures in a timely manner to avoid risks, minimize losses to the greatest extent, and ensure the normal operation of enterprises; Second, effective risk management awareness can not only increase the collective sense of security of employees, enhance business confidence, strengthen the decision-making accuracy of managers, and thereby improve the economic benefits of the enterprise; Third, an effective sense of risk management is not only of great significance to enterprises, but also to society. Effective risk management awareness can not only enhance the utilization rate of social resources, avoid potential risks in the economic market, but also ensure the stable operation of the economic market; It can also effectively reduce social and economic risks, enhance the overall economic benefits of society, and thereby indirectly promote the development of ESG in enterprises.

Table 10 Regression Results of the Mediating Effect of Internal Risk Management Awareness

	(1)	(2)	(3)
Variables	ESG	Tun	ESG
AI	0.186 * *	0.01 *	0.197 * *
	(0.085)	(0.001)	(0.083)
Size	1.138 * * *	0.008 * * *	1.054 * * *
	(0.101)	(0.002)	(0.101)
Roa	0.346 * * *	0.018	0.563 * * *
	(0.082)	(0.011)	(0.197)
Top1	0.027 * * *	0.000 *	0.026 * * *
	(0.008)	(0.000)	(0.008)
Indep	4.048 * * *	0.014	4.029 * * *
	(1.000)	(0.008)	(1.000)
Lev	-0.041	0.004	0.008
	(0.042)	(0.003)	(0.014)
Cflow	-0.366	0.044 * * *	0.860 *
	(0.498)	(0.014)	(0.522)
Cash	4.395 * * *	0.022 * * *	4.149 * * *
	(0.373)	(0.003)	(0.372)
Tun			11.268 * * *
			(1.929
_cons	44.373 * * *	0.181 * * *	46.401 * * *
	(2.032)	(0.052)	(2.301)
N	25629	25611	25611
r2	0.539	0.341	0.542

Table 11 Regression Results of the Mediating Effect of External Risk Management Awareness

	(1)	(2)	(3)
Variables	ESG	Neg	ESG
AI	0.186 * *	8.469 * * *	0.191 * *
	(0.085)	(3.149)	(0.085)
Size	1.138 * * *	13.614 * * *	1.162 * * *
	(0.101)	(2.829)	(0.101)
Roa	0.346 * * *	-4.577	0.342 * * *
	(0.082)	(3.846)	(0.080)
Top1	0.027 * * *	0.652 *	0.026 * * *
	(0.008)	(0.212)	(0.008)
Indep	4.048 * * *	52.569	4.189 * * *
	(1.000)	(44.055)	(1.003)
Lev	-0.041	0.090	-0.040
	(0.042)	(0.815)	(0.041)
Cflow	-0.366	34.684 *	-0.441
	(0.498)	(20.318)	(0.499)
Cash	4.395 * * *	2.925	4.452 * * *
	(0.373)	(11.102)	(0.375)
Neg			0.001 * * *
			(0.000)
_cons	44.373 * * *	215.278 * * *	43.904 * * *
	(2.032)	(68.425)	(2.313)
N	25629	25467	25467
r2	0.539	0.683	0.540

5 HETEROGENEITY ANALYSIS

5.1 Heterogeneity Analysis Based on Different Ownership Types of Enterprises

The way of intelligent resource allocation and operational efficiency of enterprises vary by ownership, and the extent to which the development of artificial intelligence technology affects the ESG level of manufacturing enterprises varies under different policy contexts. Therefore, the impact of artificial intelligence technology on the ESG development level of manufacturing enterprises varies by ownership.

This section classifies manufacturing enterprises into state-owned enterprises and private enterprises based on their ownership types, and examines the impact of artificial intelligence technology on the ESG level development of state-owned enterprises and private enterprises respectively. According to columns (1) and (2) in Table 12, artificial intelligence has a significant impact on the progress of green transformation in state-owned enterprises, and the positive impact is significant at the 1% level, indicating that the development of artificial intelligence technology has a significant effect on improving the ESG level of manufacturing enterprises; There is no significant impact on the development of ESG levels in private enterprises. The main reasons for this are as follows: First, state-owned enterprises are mainly distributed in important industries and key fields of the country and enjoy priority in key infrastructure construction and major strategic industrial development, while private enterprises are mainly distributed in ordinary competitive fields of the general market and lack front-end technical industrial support; The second reason is that although the reform of private enterprises is more flexible, compared with private enterprises, state-owned enterprises are not only more stable, but also have greater advantages in terms of economic strength, brand appeal, and the fields involved in technology; Third, compared with the financing problems of private enterprises, the financing constraints of state-owned enterprises are much less difficult. State-owned enterprises not only enjoy the relevant policies of the state, but also enjoy the relevant subsidies of the state, which greatly reduces the financing constraints of enterprises, helps enterprises to further exert their own initiative, strengthen enterprise innovation, improve enterprise management level and promote enterprise development.

5.2 Based on the Heterogeneity Analysis of Enterprise Invention Patents

Patent achievements, as the premise and foundation for enterprises to develop and implement patent strategies, are an important indicator for enterprises to seize the technology market. The economic strength, technical personnel structure, organizational size and other indicators of the enterprise will all affect whether the enterprise can successfully invent patents.

This section divides manufacturing enterprises into two major categories: those that have applied for invention patents and those that have not yet applied for invention patents. Based on this, it examines the heterogeneity of invention patents for the development of ESG levels of manufacturing enterprises by artificial intelligence technology respectively. According to columns (3) and (4) in Table 12, artificial intelligence technology has a greater impact on enterprises that have not yet applied for invention patents, and is positively significant at the 10% level, indicating that artificial intelligence technology can effectively promote the development of the ESG level of enterprises that have not yet applied for invention patents; The impact on enterprises that have applied for invention patents is not significant, indicating that artificial intelligence technology has not yet had a significant impact on enterprises that have applied for invention patents. One possible reason is that with the development of the social economy, the patent application process has become more complex and cumbersome, requiring enterprises to invest more resources such as time, technology and economy; The second possibility is that patent application poses certain risks for enterprises. If an enterprise 's invention patent application is rejected or there is a dispute over interests, the enterprise will have to spend extra, substantial time and money on litigation and rights protection, which greatly increases the development cost of the enterprise and is thus not conducive to the development of the enterprise' s ESG level.

5.3 Based on Heterogeneity Analysis of the Equity Structure of the Enterprise

Equity structure, as a prerequisite for corporate management, determines a number of important issues such as shareholder structure, equity concentration, shareholding ratio of the largest shareholder, and corporate decision-making methods, and thereby affects corporate operation and management models, corporate performance, and corporate ESG levels.

This section examines the heterogeneity analysis of artificial intelligence technology on the development of ESG levels in manufacturing enterprises based on the division of manufacturing enterprises into variable and fixed equity structures. According to the results in columns (5) and (6) of Table 12, artificial intelligence technology has a significant positive impact on the changing equity structure at the 5% level, indicating that artificial intelligence technology can effectively enhance the ESG development level of enterprises with changing equity structure; The impact on fixed equity structure is not significant, indicating that artificial intelligence technology has not yet had a significant impact on fixed equity structure enterprises. One possible reason for this is that with the development and popularization of intelligent technologies, traditional technologies and management models have gradually been phased out of the market, and equity structure has a decisive influence on the formulation and implementation of corporate strategies, and the equity demands and strategic priorities of different shareholders are also different. Compared with the fixed equity structure, The variable equity structure itself is clearly more adaptable to market development and is more conducive to maximizing the role of artificial intelligence technology and enhancing the ESG level of enterprises; The second possibility is that the fixed equity structure itself has problems such as an imbalance in equity structure, excessive concentration of equity, and the loss of power of the supervisory board, which are not conducive to the optimization and reform of the enterprise's industry, hinder the exertion of the functions of artificial intelligence technology, and thereby hinder the development of the enterprise's ESG level.

Table 12 Heterogeneous Results

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	State-owned enterprises	Private enterprises	Applying for an invention patent	No invention patent has been applied for yet	Changing equity structure	Fixed equity structure
AI	0.468 * * *	0.061	0.071	0.233 *	0.218 * *	0.035
	(0.175)	(0.111)	(0.118)	(0.127)	(0.094)	(0.199)
Size	1.509 * * *	1.381 * * *	1.386 * * *	1.295 * * *	1.302 * * *	1.439 * * *
	(0.187)	(0.152)	(0.209)	(0.124)	(0.131)	(0.209)
Roa	0.247	0.317 * * *	1.630	0.328 * * *	0.425 * *	0.111
	(0.483)	(0.073)	(1.372)	(0.078)	(0.198)	(0.236)
Top1	-0.012	0.035 * * *	0.043 * * *	0.021 * *	0.030 * * *	0.020
	(0.012)	(0.012)	(0.012)	(0.010)	(0.009)	(0.015)
Indep	6.199 * * *	2.238	4.287 * * *	3.826 * * *	3.750 * * *	6.170 * * *
	(1.624)	(1.410)	(1.446)	(1.279)	(1.192)	(1.792)
Lev	2.867 * * *	-0.010	5.417 * * *	-0.020	0.007	-0.254
	(0.607)	(0.020)	(0.748)	(0.026)	(0.041)	(0.271)
Cflow	1.478 *	3.980 * * *	1.907 * *	0.155	-0.087	1.302
	(0.833)	(0.487)	(0.913)	(0.605)	(0.661)	(0.096)
Cash	38.211 * * *	39.740 * * *	2.571 * * *	4.407 * * *	4.284 * * *	3.259 * * *
	(4.233)	(3.433)	(0.540)	(0.525)	(0.422)	(0.975
_cons	38.211 * * *	39.740 * * *	41.429 * * *	40.476 * * *	41.040 * * *	36.529 * * *
	(4.233)	(3.433)	(4.578)	(2.863)	(3.021)	(4.666)
Year fixed effect	Controls	Control	Control	Control	Control	Control
Corporate fixed effects	Control	Control	Control	Control	Control	Control
N	6783	15763	10642	13617	17795	5338
r2	0.591	0.579	0.596	0.581	0.556	0.646

6 CONCLUSIONS AND COUNTERMEASURES RECOMMENDATIONS

6.1 Research Conclusions

With the advent of the Third industrial revolution, how artificial intelligence technology can be perfectly integrated with manufacturing to create intelligent manufacturing and achieve high-quality development has become an important issue at present. This paper examines the impact of the development of artificial intelligence technology on the ESG development of manufacturing enterprises from the micro perspective of enterprises, using the sample data of A-share listed companies from 2009 to 2022, and reaches the following research conclusions:

First, according to the benchmark regression results, the development of artificial intelligence technology can effectively enhance the ESG development level of manufacturing enterprises; And this conclusion still holds true after changing the measurement method of the explained variable, performing bilateral tapering and truncation of the sample data to eliminate the influence of extreme values, confirming the robustness and reliability of the benchmark regression results.

Second, the study conducted heterogeneity analysis on the research from three aspects: enterprise ownership type, enterprise invention patent, and enterprise equity structure. The study concluded that artificial intelligence technology has a more significant positive effect on the ESG development level of manufacturing enterprises in three cases: state-owned enterprises, enterprises that have not yet applied for invention patents, and enterprises with changing equity structures, indicating that the development of artificial intelligence technology can effectively enhance the ESG development of manufacturing enterprises in these three cases. And further promote the green transformation of the manufacturing industry.

Third, this study conducts mechanism analysis starting from three mediating mechanism variables: financing constraints, resource misallocation, and risk management awareness. The study found that with the development of artificial intelligence technology, financing constraints, resource misallocation, and risk management awareness have all effectively promoted the ESG development of manufacturing enterprises and further facilitated the green transformation of manufacturing. In addition, the development of artificial intelligence technology does not effectively alleviate the financing constraints of enterprises. Instead, it aggravates the financing constraints of enterprises, but at the same time reduces the resource misallocation of enterprises, reduces the financial redundancy of enterprises, and strengthens the risk management awareness of enterprise managers.

6.2 Countermeasures and Suggestions

Based on the above analysis and research, build a manufacturing industry pattern with balanced regional resource allocation and complementary advantages, give full play to the inherent potential of artificial intelligence, and generate spillover effects on the green transformation of manufacturing enterprises. The formation of a comprehensive development group model centered on the country, supported by industries and with enterprises as the main body, and the formation of a multi-dimensional common development environment from macro to meso to micro, cannot be ignored in promoting the high-quality development of China's manufacturing enterprises.

6.2.1 Macro level

With the advent of the intelligent era, China's manufacturing enterprises have also entered a period of accelerated development of artificial intelligence. But at the same time, problems such as the shortage of technical talents and the imbalance between supply and demand of talents have not been solved and are still deepening. Based on this problem, our country should firmly cultivate a large number of compound talents to adapt to the current economic and social development.

(1) Promote reform of the talent market system

With the continuous reform and development of the market economy, manufacturing enterprises are facing increasing competitive pressure, and the demand for high-quality and versatile talents is also gradually increasing. However, the traditional personnel system has drawbacks such as being time-consuming and labor-intensive and unable to meet the demands of the modern market. Therefore, the reform of the talent market system is imminent.

Establish and improve a data-driven employment service system. Encourage relevant government departments to establish and improve an open employment platform system, create a labor and employment information exchange platform among the government, enterprises and job seekers, integrate employment supply and demand information among manufacturing enterprises, gradually improve employment information and achieve timely push and precise matching, improve the professional matching degree of employment talents, reduce employment costs, and reduce talent loss and shortage.

Break the closed framework of talent employment under the traditional employment model. Through the transfer of derivative property rights through market transactions, the social ownership of high-tech talents and the individual ownership of labor force are guaranteed. In addition, legal contracts are used to regulate the behavior of both parties in transactions, thereby recognizing, delineating and safeguarding the autonomous behavioral rights of the three major market entities: the social management entity of talents, the employer entity, and the individual talent entity. This is the fundamental prerequisite for the separation of the final property rights from the production rights derived from talents, and also the fundamental prerequisite for the transaction, transfer, and market positioning of the exchange of rights and interests among talents.

(2) Strengthen macro-control and establish and improve the intelligent network employment system

With the rapid development of a new generation of intelligent technologies such as artificial intelligence, the job market is undergoing profound changes. Market macro-control and intelligent network systems are important measures to adapt to the needs of current economic and social development. They can optimize the allocation of market resources, promote healthy market competition, expand employment opportunities and job positions, improve the quality of market employment, and thereby provide strong support for the prosperity and development of the economy and society.

Strengthen legal aid and protection for talents. Government macro-control can make full use of administrative and relevant laws and regulations and other means to indirectly macro-control the economic market, keep a close eye on the supply and demand status of the talent market, release the market talent supply and demand relationship directory in a timely manner, and release high-authority market-related supply and demand information in the name of the government to regulate the market supply and demand balance. Government macro-control must abandon the traditional, non-focused, multi-faceted, spontaneous and blind approach of the talent market and instead adopt a centralized and holistic regulatory approach, implementing real-name system through the talent social management center, that is, all talent flows in society must be uniformly reviewed and information recorded by the talent social management center. And the talent social management center will provide relevant legal guarantees for talents.

Establish and improve the talent file information database. The Talent Information Network combines information such as talent matching and market supply and demand, and has multiple functions such as talent information reserve, precise matching, dynamic tracking, and information release. The government, enterprises, and employees can conveniently and quickly query the current social market and the supply and demand data of talents in various industries and units. Therefore, the state should fully coordinate the matching system and regulation system of the talent market, build a national talent information network with the help of artificial intelligence, implement unified information entry and file storage for all talents with market access qualifications, facilitate centralized management and dynamic tracking of talent management centers, save time costs for all parties, and increase the success rate of talent employment.

(2) Meso level

Fully integrate intelligent resources to create economic advantages in the green transformation of manufacturing enterprises. Production factors, as essential resources for the operation of the economy and society, are also necessary conditions for promoting the upgrading and green transformation of the manufacturing industry.

6.2.2 Accelerate the development of intelligent manufacturing

Artificial intelligence, which is characterized by high spillover and driving forces, can improve the imbalance in factor allocation ratios among industries through integration with manufacturing industries and play an important role in enhancing industry competitiveness. Therefore, China's manufacturing industry should take advantage of the wave of intelligent economic development to accelerate the development of intelligent manufacturing, achieve full penetration of intelligent technology into manufacturing production, thereby promoting the green transformation of manufacturing and enhancing the international competitiveness of China's manufacturing industry.

Actively build industry demonstration projects. Based on the characteristics of emerging technologies empowering traditional industries and past practical experience, a more effective approach would be to adopt a step-by-step model of "exploration, pilot, promotion, and popularization". Select appropriate enterprises for pilot projects, demonstrate innovative applications of digital economy technologies, explore and form replicable and scalable experiences, then expand to various fields, promote and apply these experiences in various fields and industries, set guiding examples, and encourage more enterprises to actively carry out digital transformation.

Create a leading effect. Strive to be a leader in digital transformation of manufacturing. Relevant departments can benchmark against world-class equipment manufacturing enterprises to cultivate digital transformation leaders with global influence. Focus on key indicators such as competitiveness, innovation, control, influence, and resilience in the manufacturing industry to identify deficiencies and gaps in the green transformation of China's manufacturing industry and take targeted improvement measures.

6.2.3 Optimize the supply of production factors

Production factors are the foundation of manufacturing development and the support of economic development. To achieve the green transformation of manufacturing enterprises and promote their high-quality development, it is necessary to optimize the supply of manufacturing factors, unleash the potential of modern factors, and enhance the efficiency of resource allocation.

Strengthen the foundation of data element supply. The manufacturing industry should establish and improve the standard system of data resources on the basis of compliance with relevant laws and regulations, and enhance the application level of data resources with the concept of "openness and sharing" on the basis of ensuring the accuracy of data sources. In addition, the manufacturing industry should proactively collect relevant data information within the industry, assist government departments in establishing a secure, shared, complete and effective national public data resource system for the manufacturing industry, and fully explore and utilize the potential value of data resources.

Establish and improve the legal framework for safeguarding data and related property rights. When manufacturing processes data, it must ensure the accuracy and reliability of the data source, keep detailed processing records of all original data, clearly define ownership and usage rights, and prevent data theft. In addition, when defining data property rights, industries should develop protection plans based on the inherent characteristics of the data elements and further define ownership and usage rights. In addition, establish a comprehensive data element resource management system, archive manufacturing data, and ensure that each data source is transparent, traceable, and easy to retrieve.

Micro-regulation of the market mainly refers to the self-regulation of enterprises. In terms of the entire economic market, micro-internal regulation of the market is absolutely dominant for the overall precise matching and optimization of talent employment. Enterprises should, based on the economic market price foundation, follow the market interest orientation and economic price laws, actively implement internal micro-regulation of enterprises and work with relevant government departments to promote the balance of supply and demand in the talent market.

6.2.4 Promote enterprise innovation models

Innovation is an important means for manufacturing enterprises to maintain their competitive edge and seize development opportunities, and it is also an important driving force for the long-term stable development of manufacturing enterprises.

Establish and improve the system of innovation platforms. With the continuous development of new-generation intelligent technologies such as artificial intelligence, the information dissemination state of social resource allocation has evolved from the traditional closed dissemination of unsafe information to the modern fully intelligent open dissemination of information. Manufacturing enterprises can use artificial intelligence to break through the barriers of information dissemination and collect more useful, accurate and complete information in the network information, theoretically having the technical conditions for manufacturing enterprises to match precise resources under the condition of digital complete information openness.

Strengthen the level of cutting-edge technological innovation. With the start of a new round of industrial revolution, cutting-edge technology has also become a key focus for countries to seize market opportunities. Therefore, strengthening the level of cutting-edge technological innovation and seizing the market opportunities of the new round of industrial revolution is another key to the green transformation of manufacturing enterprises. First, keep focusing on the learning of artificial intelligence, constantly tackle new challenges, achieve "human-machine integration", promote the continuous integration of artificial intelligence and technological innovation in manufacturing enterprises, improve the technological innovation level of manufacturing enterprises, increase the technological research and development efforts of manufacturing enterprises, reduce the human resource costs of manufacturing enterprises, give full play to the intelligent effect of artificial intelligence, Provide sustained green innovation drive for the green transformation of manufacturing enterprises.

Adjust the industrial model of enterprises: Under the guidance of the national "dual carbon" strategic policy, the traditional production model of China's manufacturing industry has been gradually phased out. Coupled with the gradual popularization of artificial intelligence, the green transformation and development of China's manufacturing enterprises is imperative.

Vigorously promote clean energy: Manufacturing enterprises in our country should actively adjust production models and outdated equipment structures, and vigorously popularize and apply clean energy. Leverage artificial intelligence to promote the application of new clean energy in the production process of manufacturing enterprises and reduce the total carbon emissions of manufacturing enterprises. However, as new energy sources are currently dominated by electricity, the electricity consumed by artificial intelligence is still based on coal-fired power generation, which to some extent also consumes a large amount of coal energy, thereby affecting the carbon reduction effect of manufacturing enterprises.

Considering the negative impact of new energy on the green transformation of manufacturing, in response to the national "dual carbon" policy and to further reduce carbon emissions, clean energy is chosen as the first choice for the green transformation of manufacturing, and clean energy dominated by natural gas is gradually replacing traditional thermal power sources produced by burning coal. Manufacturing enterprises should actively cooperate with government measures, vigorously develop new types of clean energy, optimize the energy structure of manufacturing production, and gradually reduce the proportion of traditional coal in the energy structure of manufacturing production.

Improve resource utilization: Continuously enhance the deep integration of artificial intelligence with manufacturing enterprises, improve the digital, big data, artificial intelligence and other new-generation intelligent application technologies of employed people, update equipment and machinery in a timely manner, and widely apply intelligent technologies such as computers, big data, digital intelligent trade, remote work, intelligent robots in all aspects of manufacturing enterprises' production, Strengthen the effective integration of artificial intelligence in all industrial links of manufacturing enterprises, strengthen infrastructure construction and establish a systematic intelligent industrial chain to enhance manufacturing production efficiency, reduce production and labor costs, improve resource utilization, and enhance the service level of manufacturing enterprises.

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REFERENCES

[1] Acemoglu D, Restepo P. Robots at work: the impact on productivity and jobs. Journal of political economy, 2020(6): 2188-2244.
[2] Wang Yongqin, Dong Wen. How Does the Rise of Robots Affect the Chinese Labor Market? Evidence from Listed Manufacturing Companies. Economic Research Journal, 2020(10): 159-175..
[3] Research Group of the Institute of the Guangdong-Hong Kong-Macao Greater Bay Area, Guangdong University of Foreign Studies. Media ESG Reputation, Green Overseas Network and the Development of New Quality Productivity of Enterprises. International Trade and Economic Exploration, 2025, 41(05): 4-20.
[4] Li Zhihui, Chang Xinyu, Wei Bin. Responsible Investment and Stock Market Manipulation: A Study Based on ESG Fund Holdings. Securities Market Herald, 2025(04): 54-65.
[5] Mao Qilin, Shi Buchao. The Path to Green Development: Smart Manufacturing and Green Transformation of Enterprises. The Journal of World Economy, 2024, 47(09): 152-182.
[6] Niu Ziheng, Jin Huan. Intelligent Manufacturing, Human Capital Structure and Enterprise Total Factor Productivity. Economic System Reform, 2024(05): 88-96.
[7] Qin Shuyue, Huang Zelin. Digital Investment and the Optimization of Manufacturing Structure: Internal Mechanism and Empirical Evidence. Economist, 2024(04): 98-107.
[8] Tian Jinfang, Li Taebang, Yang Xiaotong. Environmental Regulation Intensity and ESG Rating Quality. Economic and Management Review, 2024, 40(06): 58-69.
[9] Han Zhongxue, He Lu. Non-State Governance, Green Finance and Corporate ESG Performance. Journal of Nanjing Audit University, 2024, 21(06): 68-79.
[10] Yang Renfa, Yang Jing. Research on the Impact of Digital Technology Innovation on Enterprise ESG Performance. Statistics and Information Forum, 2023, 39(11): 93-104.
[11] Pan Shan, Li Jianpei, Gu Naihua. Artificial Intelligence, Industrial Integration and the Transformation and Upgrading of Industrial Structure. China Industrial Economics, 2025(02): 23-41.
[12] Liu Xianjuan, Xue Nianwen. Academic Exploration. 2025(07): 32-38.
[13] Sun Yazhou, Li Xiaosong, Tang Shan Hong, et al. Analysis of the Information Resource Management Function of Generative Artificial Intelligence: Causes, Challenges and Responses. Information and Documentation Work, 2025, 46(05): 24-34.
[14] Qiao Gang, Qian Yuanyuan. Artificial Intelligence Technology, Entrepreneurial Ecosystem and New Firm Entry. Journal of Quantitative & Technical Economics, 2025, 42(08): 110-130.
[15] Tao Yuxiang, Liu Xiangmi, Wu Chuannan, et al. The Formation and Evolution of Digital Technology Innovation Consortia: A Patent Analysis Based on the New Generation of Artificial Intelligence. China Forum of Science and Technology, 2025(05): 60-71.
[16] Zhang Xueming, Lu Bin, Wang Zhenhua, et al. Does the Exit of Enterprise Artificial Intelligence Strategy Inhibit New Quality Productivity? An Empirical Study Based on PSM-Multi-Time Period DID. Journal of Finance and Economics, 2025(01): 92-105.

[17] Wu Xinyu, Wu Zhenxin. Review of the Application Progress of Artificial Intelligence in the Field of Long-Term Preservation of Digital Resources. Journal of Library and Information Science, 2025, 42(01): 146-157.
[18] Du Chunling, Wang Tiezheng, Wang Chenwei. The Current Development Status, Challenges and Countermeasures of China's Artificial Intelligence Chip Technology in the Digital Economy. Science and Technology Management Research, 2023, 43(12): 1-10.
[19] Yang Xiaofeng, Liu Xiang, Li Yaya. Borrowing "Intelligence" to Strengthen "Manufacturing": Can Industrial Intelligence Enhance Corporate ESG Performance?. Commercial Research, 2025(02): 129-140.
[20] Clarkson MBE. A Stakeholder Framework for Analyzing and Evaluating Corporate Social Performance. Academy of Management Review, 1995, 20(1): 92-117.
[21] Mao Qilin, Wang Yueqing. Employment Effects of ESG: Evidence from Chinese Listed Companies. Economic Research Journal, 2023, 58(7): 86-103.
[22] Briscoe F, Rogan M. Coordinating complex work: Knowledge networks, Partner departures, And client relationship performance in a law firm. Management Science, 2016, 62(08): 5449-5460.
[23] Abaku E A, Edunjobi T E, Odimarha O C. Theoretical approaches to AI in supply China Optimization: Pathways to efficiency and resilience. International Journal of Science and Technology Research Archive, 2024, 6(01): 92-107.
[24] Zhang Meng, Song Shunlin. Enterprise Digitalization, Innovation-driven Policies and ESG Performance.Journal of Beijing Technology and Business University (Social Sciences Edition), 2023, 38(06): 34-46+101.
[25] Mao Qilin, Wang Yueqing. Research on the Employment Effects of ESG: Evidence from Chinese Listed Companies. Economic Research Journal, 2023, 58(7): 86-103.
[26] Li Xiuping, Fu Bingtao, Guo Jin. Digital Finance, Heterogeneity of the Executive Team and Enterprise Innovation. Statistics and Decision, 2022, 38(07): 161-165.
[27] Bae KHH, Kang JK, Kim JM. Tunneling or Value Added?Evidence from Merger by Korean Business Groups. The Journal of Finance, 2002, 57(06): 2695-2740.
[28] Zengquan Li, Zheng Sun, Zhiwei Wang. "Tunneling" and Ownership Arrangements: Empirical Evidence from the Occupation of Funds by Major Shareholders of Listed Companies in China. Accounting Research, 2004(12): 3-13+97.