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Original Article

The Impact of Artificial Intelligence on High-Quality Development of Manufacturing Enterprises: A Cross-Disciplinary Perspective on Management and Technology

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Abstract:

This paper conducts a thorough investigation into the influence mechanism of artificial intelligence (AI) technology on the high-quality development of manufacturing enterprises, integrating theories from management science, operations research, and industrial economics. Empirical analysis based on data from 2008 to 2022 of Chinese A-share listed manufacturing companies indicates that AI technology exerts a direct impact on enhancing productivity, innovation capacity, product quality, and green transformation in enterprises. Moreover, it functions as an indirect catalyst through two mediating mechanisms: (1) the optimization of the manufacturing innovation chain, rooted in resource allocation theory; and (2) the upgrading of employment structure, informed by human capital management theory. The study also reveals significant regional heterogeneity (moderated by digital infrastructure and policy support) and enterprise-type heterogeneity (differentiated by resource endowment and organizational agility). Specific data show that the eastern region's AI-driven TFP growth is 0.0472 ($p<0.01$), significantly higher than the central region's 0.0321 ($p<0.01$) and the western region's 0.0018 ($p<0.01$). State-owned enterprises (SOEs) exhibit an AI impact coefficient of 0.0322 ($p<0.01$), while non-SOEs reach 0.0592 ($p<0.01$), reflecting distinct advantages. These findings contribute to management theory by integrating technological innovation with organizational development frameworks and provide practical, region- and enterprise-specific policy implications.

Keywords: Artificial Intelligence; High Quality Development; Impact Mechanisms; Regional Heterogeneity; Firm Type Heterogeneity

1. Introduction

1.1Research Background

In the context of globalization, competition in the manufacturing industry is becoming increasingly intense, and enterprises are facing the dual challenges of rising costs and declining profits. Concurrently, consumer demand for personalized, high-quality products continues to increase, while the traditional manufacturing model is characterized by its inability to respond quickly to market changes. The advent of Industry 4.0, a paradigm of intelligent manufacturing, has precipitated a profound metamorphosis in the global manufacturing landscape. Nevertheless, numerous enterprises continue to grapple with the constraints imposed by antiquated technology, languid digital transformation processes, and a plethora of other impediments, impeding their ability to achieve substantial enhancements in production efficiency. In this regard, it is imperative to acknowledge the pressing need for China's economy to foster newfound momentum in its economic growth and to achieve high-quality development in its manufacturing sector. The imperative for this undertaking is further accentuated by the pivotal role that artificial intelligence (AI) plays in cultivating this newfound momentum and in establishing technological competitive advantages. AI, in this sense, emerges as the pivotal technology that is propelling the current era of scientific and technological revolution and industrial transformation, exerting a profound leadership effect through its capacity for strong spillover effects.Data from the World Economic Forum (2023) shows that AI-driven manufacturing enterprises in China have achieved an average 18% reduction in production costs and a 23% increase in product qualification rates, verifying AI's practical value in breaking through traditional model constraints.

1.2 Literature Review

In recent years, the rapid development of artificial intelligence (AI) technology has provided a new impetus for the high-quality development of manufacturing enterprises. This development has been the focus of related research, which has explored the multi-dimensional aspects of technology application, management change, and industrial upgrading. From a technical standpoint, the integration of AI within production processes has been demonstrated to enhance manufacturing efficiency and product quality through the utilization of machine learning, computer vision and natural language processing. For instance, the implementation of predictive maintenance systems has been demonstrated to reduce equipment downtime by means of real-time monitoring of equipment status (Lee et al., 2020).[8] Furthermore, the employment of intelligent quality inspection technology has been shown to result in a significant reduction in the error rate of manual inspection (Zhang et al., 2021).[16] Furthermore, AI-driven flexible manufacturing systems have the capacity to dynamically adjust production plans in order to meet personalized customization needs (Wang et al., 2022),[12] thereby reflecting the advantages of intelligent manufacturing in terms of agility. At the management level, AI reconfigures the enterprise decision-making mode, and intelligent analysis based on big data helps managers achieve accurate resource allocation (Chen et al., 2023),[5]while supply chain intelligence significantly improves inventory turnover and logistics efficiency (Ivanov et al., 2021).[6]

However, the implementation of AI in a deep capacity is not without its challenges. Firstly, the issue of data silos and the opaque nature of algorithmic black boxes has the potential to impede the integration of the technology (Nguyen et al., 2022). [10]Secondly, there is a discordance between conventional organizational structures and the flattened management models that AI engenders (Brynjolfsson & McAfee, 2017).[2]Thirdly, there is a discrepancy between the expense of the technology and the digitalization capabilities of SMEs (Liao et al., 2020).[9] In the context of industrial ecology, the integration of manufacturing and service industries is accelerated by AI, thereby giving rise to a novel paradigm of 'product as service' (Porter & Heppelmann, 2015). [11]However, this development concomitantly exacerbates the controversy surrounding the ethics of technology and the restructuring of employment (Acemoglu & Restrepo, 2020). [7]The following text is intended to provide a comprehensive overview of the subject matter. It is imperative that future research endeavors delve deeper into the synergistic mechanisms that emerge when AI is integrated with technologies such as industrial internet and digital twin. A pivotal focus of these studies should be the examination of policy guidance and its role in facilitating technology inclusion (World Economic Forum, 2023).[13] It is evident that the development of manufacturing that is enabled by AI is a dynamic process of multidisciplinary intersection. In order to achieve a balance between technological innovation, institutional adaptation and social responsibility, it is essential to recognize the significance of this multifaceted endeavor. A review of the extant literature reveals that the majority of studies focus on the analysis of a specific dimension of AI and manufacturing development. Fewer studies focus directly on the impact of AI on the high-quality development of manufacturing enterprises. This paper explores the direct impact of AI technology on the high-quality development of manufacturing enterprises. It does so by examining the employment structure of the two mechanism variables from the perspective of the manufacturing innovation chain. This is done in order to explore the indirect impact of AI technology on the high-quality development of manufacturing enterprises. The paper then puts forward an optimization strategy for AI technology that will promote the high-quality development of enterprises.

1.3 Research Gap and Objectives

Current literature insufficiently addresses: (1) how AI integrates with management processes to drive systemic quality improvement; (2) the moderating role of regional policy ecosystems in AI implementation; (3) the heterogeneous impacts of AI across enterprise types from a management strategy perspective. This research aims to fill these gaps by constructing a cross-disciplinary analytical framework that bridges technology adoption with management effectiveness.

2. Theoretical Mechanisms and Hypothesis Formulation

2.1 Direct Impact Effect

The field of Artificial Intelligence (AI) technology has been shown to make a significant and direct contribution to the high-quality development of manufacturing enterprises. This contribution is primarily reflected in multiple dimensions, including efficiency improvement, innovation drive, quality optimization and green transformation. From an efficiency standpoint, AI has been shown to lead to a significant reduction in downtime and resource wastage in the production process through technologies such as intelligent scheduling, predictive maintenance and automated production lines. Consequently, it has been demonstrated that AI can improve total factor productivity (TFP) and per capita output. To illustrate this point, consider the pervasive integration of industrial robots within contemporary manufacturing enterprises. This integration empowers manufacturers to sustain uninterrupted production for extended periods, thereby reducing errors attributable to manual intervention. Consequently, this enhances overall operational efficiency.[17] In terms of innovation drive, AI has been demonstrated to empower R&D and design, accelerate the development cycle of new products, and optimize processes through deep learning. This has resulted in the manufacturing industry being propelled towards high-end and intelligent development. Research findings indicate that the implementation of AI technology has led to a substantial increase in the number of patents and the proportion of new product sales revenue of manufacturing enterprises, particularly in the eastern region and high-tech manufacturing industries.

Furthermore, the role of AI in quality control cannot be disregarded. Intelligent inspection systems, based on machine vision, have the capacity to identify product defects in real time. This, in turn, has the potential to reduce the rate of defective products, whilst improving the consistency and reliability of products. The result is an enhancement of the competitiveness of enterprises in the global value chain. In the context of green manufacturing, artificial intelligence (AI) assists enterprises in achieving low-carbon production by optimizing energy consumption and reducing waste emissions. For instance, smart grids and energy consumption monitoring systems can dynamically adjust the operating parameters of production equipment, thereby reducing energy consumption per unit of output value. It is important to acknowledge the presence of industry and regional heterogeneity in the impact of AI. The effect of AI is more significant in the promotion of labor-intensive and medium- and high-tech manufacturing industries. The enabling effect of AI is more evident in the eastern coastal region due to the advantages of infrastructure and talent reserves. It is evident that, in general, AI technology directly promotes the transformation of manufacturing enterprises to high-quality development. This is achieved by improving production efficiency, enhancing innovation ability, guaranteeing product quality and promoting sustainable development. However, the effect of AI technology is moderated by factors such as the digital foundation of enterprises, regional policy support and the depth of technology application. It can be displayed like figure 1.[18]

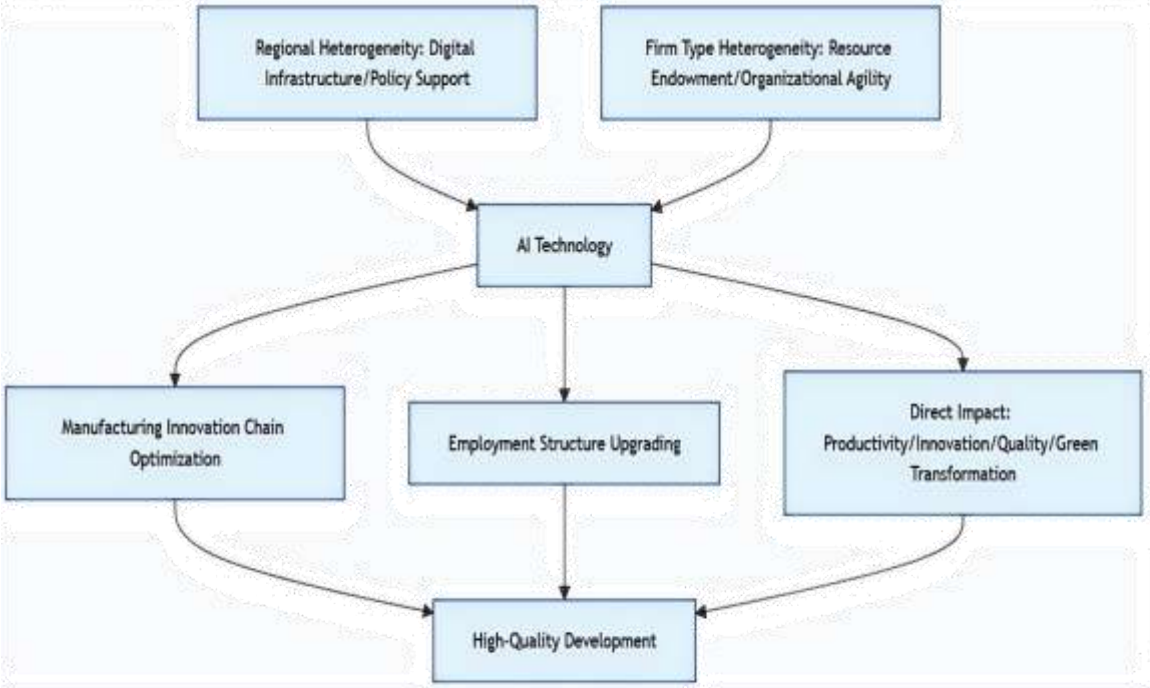

Figure 1: Mechanism Path of AI's Impact on High-Quality Development of Manufacturing Enterprises

Note: The figure illustrates direct and indirect impact paths of AI, with moderating effects of regional and firm-type characteristics.

The paper puts forward the following hypothesis1:

H1: AI technology can promote high quality development of manufacturing companies

2.2 Indirect Impact Effects

2.2.1mediating Effects in Manufacturing Innovation Chains

The role of artificial intelligence technology in the mediating effect of the manufacturing innovation chain on the high-quality development of manufacturing enterprises is significant. This mechanism is embodied in the innovation input, R&D transformation and market application of the three key links. In the innovation input link, AI technology optimizes the allocation of R&D resources through intelligent data analysis, improves R&D efficiency, reduces trial-and-error costs, and prompts enterprises to increase the intensity of R&D investment. [19]For instance, enterprises in the eastern region have significantly increased the proportion of R&D expenditure with the help of AI technology. As indicated in the R&D transformation link, the utilization of AI-driven intelligent algorithms has been demonstrated to accelerate technological breakthroughs, enhance the efficiency of patent output (particularly the number of invention patents), and concomitantly reduce the development cycle of new products. This has been observed to augment the competitiveness of enterprise innovation in domains such as the automotive manufacturing and electronics industries, as evidenced by the substantial enhancement in yield rate of products achieved through the implementation of AI vision inspection technology. However, the mediating effect of the market application link is relatively weak, indicating that there is still room for improvement in the direct optimization of AI's response to market demand. The integration of AI within enterprises has been demonstrated to facilitate the transition towards intelligence and high-end manufacturing through the optimization of the input and output links within the manufacturing innovation chain. However, it is imperative to emphasize the necessity for the enhancement of the articulation of the market application link to achieve a more comprehensive and high-quality development. The present paper puts forward the following hypothesis 2:

H2: Artificial Intelligence Technology for High Quality Development of Manufacturing Enterprises through the Manufacturing Innovation Chain

2.2.2 The Mediating Role of Employment

Structure Optimization

The impact of artificial intelligence technology on the high-quality development of manufacturing enterprises has been significant, primarily through the mediating effect of employment structure optimization. This mechanism is reflected in three key dimensions: skill structure upgrading, talent effectiveness enhancement and organizational change. In the skill structure dimension, the application of AI technology has prompted manufacturing enterprises to reduce their reliance on low-skilled labor and instead increase the demand for high-skilled talents, such as algorithm engineers, data analysts and other technical positions. [20]This has resulted in a significant increase in the proportion of the human capital structure of the enterprise to high-end transformation. In terms of talent effectiveness, AI-driven automated production processes and intelligent decision-making systems have been shown to have a significant impact on employee productivity. Furthermore, enterprises have seen a notable improvement in the level of employees' digital skills through the implementation of AI training programs. For instance, manufacturing enterprises in the Yangtze River Delta region have increased the proportion of high-skilled talents by more than 30% through the 'digital artisan' cultivation program. In the context of organizational transformation, the integration of AI applications has prompted enterprises to reconfigure their organizational structures, giving rise to novel organizational forms characterized by increased flatter and networked structures. These changes have been shown to enhance decision-making efficiency and teamwork within organizations. It is important to note that there is significant industry heterogeneity in this mediating effect. It is most prominent in technology-intensive industries (e.g. electronic equipment manufacturing, automobile manufacturing) and relatively limited in labor-intensive industries (e.g. textile and clothing).

From a regional distribution perspective, the impact of AI in promoting high-quality development through employment structure optimization is more significant in the eastern coastal region. This is due to the presence of advanced digital infrastructure and a wealth of talent in the area. When observed from the perspective of the time trend, and with the in-depth application of AI technology, it is evident that the employment structure optimization effect exhibits a non-linear characteristic of enhancement and subsequent stabilization. This indicates that a phase change in the technological dividend has occurred. [21]From a comprehensive standpoint, the integration of AI technology within enterprises has the potential to catalyze a shift towards a knowledge-intensive and innovation-driven development model. This transformation is predicated on the reshaping of the employment structure within the manufacturing industry. Nevertheless, it is imperative to exercise caution with regard to the potential short-term employment implications that may arise from technological substitution. To this end, it is essential to facilitate a seamless transition through the collaborative talent cultivation system, a symbiotic relationship between government and enterprise. Based on this, Hypothesis 3 is formulated in this paper:

H3: Artificial intelligence technology promotes high quality development of manufacturing companies through employment structure optimization

2.3 Regional Heterogeneity

The impact of AI technology on the high-quality development of manufacturing enterprises exhibits significant regional heterogeneity characteristics, with this difference primarily manifesting in the eastern, central, western and northeastern regions. The eastern region, with its optimal digital infrastructure, abundant talent pool and dynamic innovation ecology, has the most significant impact on the application of AI technology. Eastern coastal cities, including the Yangtze River Delta and Pearl River Delta regions, have achieved a substantial enhancement in production efficiency. This has been accomplished through the implementation of intelligent factory renovations and the establishment of industrial Internet platforms. Their contribution to the advancement of manufacturing enterprises, at the 1% level, is noteworthy, exhibiting a high coefficient. In the process of industrial transfer from the east in the central region, AI technology primarily fulfils a role in the optimization of production processes, thereby promoting the intelligent upgrading of the traditional manufacturing industry. Despite its relatively limited innovation-driven effect, its promotion of high-quality development remains significant. In the western region, the application of AI technology is primarily concentrated in specific industries that offer a competitive advantage. This is due to a weak digital foundation and talent shortage. Consequently, the overall enabling effect of AI technology has yet to be fully realized. Furthermore, its promotion of high-quality development remains limited.

Conversely, the Northeast region exhibits a comparatively substantial presence of conventional industrial infrastructure and considerable challenges in undergoing transformation, resulting in constrained promotion of AI technology. Nonetheless, it exhibits a modestly favourable impact. This regional heterogeneity is not only constrained by objective conditions, such as infrastructure and human capital, but also by policy orientation. For instance, the policy dividends of the National Pilot Zone for AI Innovation and Application and the Smart Manufacturing Demonstration City have significantly enhanced the AI application level of local enterprises. In the future, it is necessary to promote AI technology to ensure the high-quality development of the manufacturing industry in a more balanced way across the country through differentiated policy guidance and regional synergistic development mechanisms. The present paper puts forward the following hypothesis, 4:

H4: Regional heterogeneity in the impact of AI technologies on the high-quality development of manufacturing firms

2.4 Heterogeneity of Firm Types

The impact of AI technology on the high-quality development of manufacturing enterprises presents significant heterogeneous characteristics of enterprise types, especially between state-owned enterprises and non-state-owned enterprises. State-owned enterprises characteristically possess robust financial strength, abundant resources, and a more stable market position, endowing them with an inherent advantage in the implementation and promotion of AI technology. SOEs have the capacity to invest significantly in technology, research and development, and the upgrading of equipment. Illustrative examples of this include the construction of intelligent manufacturing systems, the establishment of industrial internet platforms, and the introduction of big data analysis tools. Furthermore, state-owned enterprises benefit from enhanced policy support and streamlined resource integration, enabling more effective utilization of the national policy dividend to facilitate the comprehensive integration of AI technology within the manufacturing sector. This integration has the potential to yield substantial gains in terms of enhanced productivity, optimized product quality and facilitated green transformation. Conversely, non-state-owned enterprises may possess certain advantages in terms of flexibility and innovation. However, these enterprises frequently encounter challenges such as inadequate capital, a paucity of technical talent, and elevated market risks. However, in the context of market competition, non-state-owned enterprises tend to priorities cost control and efficiency enhancement. Consequently, they exhibit a preference for lightweight and modular solutions in the implementation of AI technology, thereby facilitating a rapid response to market fluctuations and accommodating individual customization requirements.

For instance, the implementation of AI-driven flexible manufacturing systems has enabled certain small- and medium-sized non-State-owned enterprises to achieve substantial cost reductions in production and enhance production efficiency, whilst catering to the specific requirements of their clientele. Furthermore, non-SOEs have demonstrated considerable innovation, particularly in the integration of AI technology and business model innovation, as evidenced by the emergence of the new "product-as-a-service" model. This development has been shown to enhance customer experience and boost enterprise competitiveness. It is evident that, in general, AI technology exerts a favorable influence on the advanced development of both SOEs and non-SOEs. However, it should be noted that there are discernible discrepancies in the mechanisms and consequences of its impact. SOEs have been shown to exhibit superior capabilities in the domains of resource investment and technological application depth, while non-SOEs have been identified as having greater potential in terms of flexibility and innovation. In the future, policy guidance and market mechanisms should be used to promote the synergistic development of state-owned enterprises and non-state-owned enterprises in the application of AI technology, and to realize the overall high-quality development of the manufacturing industry. The present paper puts forward the following hypothesis, 5:

H5: The impact of AI technology on the high-quality development of manufacturing firms with firm type heterogeneity

3. Research Design

3.1 Data Sources

The data is primarily derived from the International Federation of Robotics (IFR) robot statistics (2008-2022), CSMAR, WIND, and China Industrial Statistical Yearbook, covering 3,245 A-share listed manufacturing companies, with a total of 28,632 firm-year observations after excluding missing values.

3.2 Variable Selection

3.2.1Explained Variable: Enterprise High Quality Development (EHQD)

The present paper draws on the theoretical framework developed by (Chen & Chen, 2018) in order to provide a novel characterization of the high-quality development of enterprises in terms of their total factor productivity. [4]Moreover, given the plethora of methodologies for measuring total factor productivity – the least squares method (OLS) and the fixed effects method (FE) being notable exceptions that are unable to address the endogeneity problem and address incomplete information – in conjunction with the generalized method of moment estimation (GMM) method's requirement for a sufficiently extensive time span, and the OP method's concomitant issue of substantial data loss due to enterprises' missing investments, this paper draws upon the contributions of Arnold et al. The utilization of the LP method for the calculation of firms' total factor productivity, with its subsequent employment as a proxy variable for firms' high-quality development, is a subject that merits further investigation.

3.2.2Explanatory Variables: AI

The central explanatory variable in this paper is AI applications, which are considered to be a higher-order type of automation technology. The present study draws on the work of Acemoglu and Restrepo (2009) and Wang and Dong (2020),[14]who have utilized industrial robot data as a proxy variable for AI application.[1] The level of AI adoption is characterized in terms of firm-level industrial robot density, measured as follows: Firstly, the industry-level industrial robot penetration is calculated using the ratio of the industry-level industrial robot stock to the industry base-period employment (in tens of thousands of people). Secondly, the ratio of the firm's base-period production staff share to the median of all firms' base-period production staff share in the manufacturing sector is used as a weight. Finally, the ratio of the product of the enterprise weights and the industrial robot penetration degree of the corresponding industry is used as the enterprise-level industrial robot density.

3.2.3 Mediating Variable: Manufacturing Innovation Chain (MIC)

As posited by Chen and Wu (2024), the investment intensity of research and development (R&D) of manufacturing enterprises is expressed as the proportion of R&D expenditure to operating revenue.[3] Optimization of Employment Structure (OES), as referenced by Yin and Wu (2022),[15] is expressed in terms of the proportion of the high-skilled labor force, that is to say, the proportion of individuals in possession of a bachelor's degree or higher qualification, or technical titles.

3.2.4 Control Variable

In accordance with extant research, the present study employs a series of indicators as control variables. These include (1) enterprise size (Size), characterized by the natural logarithm of the enterprise's total assets at the end of the period. The term 'enterprise age' (Age) is defined as the natural logarithm of the difference between the current year of the enterprise and the year of its establishment. The market value of the firm, denoted by Tq, is defined as the ratio of the firm's market value to its total assets. The fourth element is the size of the board (Bsize), which is characterized by the natural logarithm of the total number of board members. The proportion of independent directors (Indep) is characterized by the ratio of the number of independent directors to the total number of board members. Table I presents the descriptive statistics of the relevant variables.

Table I Results of descriptive statistics for relevant variables

variant	observed value	average value	standard deviation	minimum value	maximum values
EHQD	13271	15.28	0.923	13.27	16.29
AI	13271	1.62	1.623	0.23	5.22
MIC	13265	2.62	2.622	0.052	3.728
Size	13265	2.732	0.273	0.052	0.287
Age	13265	2.739	1.827	0.273	2.382
Lev	13265	0.927	0.628	13.92	17.29
Bsize	13209	2.83	0.072	0.283	9.28
Indep	13283	21.82	0.648	13.72	17.83

Note: MIC is measured by R&D expenditure/operating revenue.

3.3 Model Construction

In order to test the efficacy of AI technology on the high-quality development of manufacturing enterprises, this paper constructs the following benchmark model:

$$EHQD_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls_{it} + \mu_{i+}\delta_{t+}\varepsilon_{it} \quad (1)$$

In equation (1), the explanatory variable $EHQD_{it}$ denotes the level of high-quality development of manufacturing firm i in year t. AI_{it} denotes the level of technological development of manufacturing firm i in year t. $Controls_{it}$ denotes a series of control variables selected in this paper. μ_{i+} denotes the fixed effects effect of manufacturing firms. δ_t denotes the year fixed effect. δ_t denotes the random error term.

In order to further verify the mediating effect of manufacturing innovation chain and employment structure optimization, this paper constructs the following mediating effect model for testing on the basis of model (1).

$$Med_{it}=\alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls_{it} + \mu_{i+}\delta_{t+}\varepsilon_{it} \quad (2)$$

$$EHQD_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Med_{it} + \alpha_3 Controls_{it} + \mu_{i+}\delta_{t+}\varepsilon_{it} \quad (3)$$

In the above equation, Med_{it}denotes the mediating variable and the other variables are consistent with the above.The models (1)-(3) are tested using Stata 17, with standard errors clustered at the firm level to address heteroscedasticity.

4. Results

4.1direct effect test

The present study employs the baseline effects modelling style constructed above to examine the impact of AI applications on the high-quality development of China's manufacturing firms, and the results are shown in Table II. The first column does not incorporate any control variables, whilst the second adds control variables at each level. It is important to note that each column controls for industry fixed effects and year fixed effects. The findings indicate that the estimated coefficients of AI applications on the high-quality development of China's enterprises are positive at the 1% significance level, irrespective of the inclusion of control variables, thereby suggesting that AI applications contribute to the promotion of high-quality development in the context of Chinese enterprises. Consequently, hypothesis 1 of this paper is proven.

Table II Direct effect results

variant	(1)	(2)
EHQD	0.062^{***} (4.82)	0.027^{***} (2.83)

AI		0.478*** (20.73)
MIC		0.168** (2.91)
Size		0.082* (1.62)
Age		0.027** (2.73)
Tq		0.152** (1.62)
Bsize		0.082* (1.82)
Indep		0.172 (0.72)
constant	14.283*** (110.27)	1.728*** (2.83)
Industry fixed effect	Yes	Yes
Year fixed effects	Yes	Yes
observed value	13271	10283
R^2	0.263	0.527

4.2 Robustness Check

The preceding regression analysis indicates that AI technology exerts a direct impact on the high-quality development of manufacturing enterprises. This verifies the reliability of the results of hypothesis 1 in this paper. The present paper employs three distinct methodologies to undertake the robustness test. Firstly, the explanatory variables are substituted to measure the index. The present study employs a range of analytical methods, including the OLS method, the OP method, the fixed effect method (FE method), the GMM method, and others, with a view to re-measuring the total factor productivity of manufacturing enterprises. The objective is to substitute the indicators and the benchmark regression test with the total factor productivity of manufacturing enterprises. Following the replacement of the explanatory variables, the regression coefficients of the digital transformation of manufacturing enterprises were found to be significantly positive at a minimum of the 5% level. The results were found to be robust, as demonstrated in columns (1) through (4) of Table III.

Table III Robustness test results

variant	(1) OP	(2) OLS	(3) FE	(4) GMM	(5) Outlier handling	(6) Elimination of the sample of enterprises in the computer and communications industry
AI1	0.0172*** (0.0071)	0.0172*** (0.0029)	0.0182*** (0.0018)	0.0182** (0.0082)	0.0281*** (0.0081)	0.0182*** (0.0056)
AI2						
AI3						
AI4						
control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
observed	13271	13271	13271	13271	10272	11832

value						
R^2	0.9822	0.9638	0.9752	0.8622	0.9722	0.9621

Secondly, the issue of outlier treatment is addressed. It is important to note that extreme samples may have an impact on the final regression results. In order to solve the problem of outliers, this paper employs the shrinking-tail treatment at the 5% level for the explanatory variable of high-quality development of manufacturing enterprises and the core explanatory variable of artificial intelligence technology. The final results are shown in Table III(5). As evidenced by the findings, the impact of artificial intelligence technology on manufacturing enterprises remains substantial, with the coefficients demonstrating a positive association at the 5% level after adjusting for outliers in the explanatory variables. This suggests that the benchmark regression results are not influenced by outlier effects. Thirdly, the sample of computer and communication industry enterprises is excluded. In the context of the manufacturing industry, enterprises operating within the computer, communication and other electronic equipment sector demonstrate a higher level of information technology, intelligence and digitalization than other industry sectors. Furthermore, these enterprises exhibit a significantly higher degree of digital transformation willingness and ability. Consequently, this paper makes the decision to exclude the computer, communication and other electronic equipment manufacturing enterprises from the research sample. The subsequent analysis involves conducting a benchmark regression. The findings presented in column (6) of Table 3 demonstrate that digital transformation continues to foster the advancement of manufacturing enterprises of a high caliber, with the exclusion of enterprises operating within the domains of computer and communication-related industries. The robustness of the conclusion is substantiated by the empirical evidence obtained through rigorous testing.

4.3 Mechanistic Effects Test

The preceding analysis demonstrates that AI exerts a significant influence on the advancement of manufacturing enterprises, particularly in regard to the enhancement of their innovative capabilities and the optimization of their employment structures. It is therefore proposed that empirical tests be conducted on the aforementioned two aspects (see Table IV). In Table IV, W is the mechanism test variable. Paragraphs (1) and (2) present the regression results of the manufacturing innovation chain. The findings of this study demonstrate that the impact of AI technology on the manufacturing innovation chain is statistically significant at the 1% level, suggesting that AI technology can indeed promote the enhancement of the manufacturing innovation chain. Concurrently, the findings of (2) indicate that the influence of the manufacturing innovation chain on the high-quality development of manufacturing enterprises is substantial at the 5% level, yielding a positive outcome. This suggests that the manufacturing innovation chain can substantially encourage the high-quality development of manufacturing enterprises. The present study posits that artificial intelligence (AI) technology can facilitate the advancement of manufacturing enterprises of a high caliber, with manufacturing innovation chain serving as the pivotal mediating variable in this process. The second hypothesis presented in this paper has been proven. Furthermore, the impact of artificial intelligence technology on the high-quality development of manufacturing enterprises can also be influenced by the employment structure optimization mediating variable, as illustrated in (3) (4).

As demonstrated in Table IV, the impact of AI technology on the optimization of employment structure is significant at the 1% level, and the coefficient is positive, indicating that AI technology facilitates the enhancement of the optimization of the development of the employment structure of manufacturing enterprises. Simultaneously, it can be observed from (4) that the employment structure optimization of manufacturing enterprises exerts a positive influence on their high-quality development, with a 1% level of significance and a coefficient result that is also positive. This finding suggests that the optimization of the employment structure of enterprises contributes to enhancing their high-quality development. It is evident that, in general, the implementation of AI technology has the capacity to facilitate the advancement of manufacturing enterprises towards a state of optimal development. This progression is facilitated by the employment structure optimization mediating variable, which functions as a pivotal intermediary in the process. This finding serves to verify hypothesis 3 of this paper.

Table IV Mechanism effect test results

explanatory variable	MIC		OES	
	MIC （1）	EHQD （2）	OES（3）	EHQD （4）
Ai	0.0542^{***} （3.72）		0.0273^{***} （5.82）	
W		0.0723^{**} （2.18）		0.7292^{***} （3.92）
Size	0.2832^{**} （2.73）	0.1823^{***} （0.52）	0.0529^{**} （1.72）	0.3721^{***} （1.72）
Age	0.5282^{**} （2.01）	0.2732^{***} （4.92）	0.1522^{***} （20.32）	0.1821^{*} （3.02）
Tq	0.5182^{***} （0.61）	2.7392^{***} （1.28）	0.1982^{***} （2.83）	0.2710^{***} （3.82）
R^2	0.1729	0.2638	0.5822	0.3821

4.4 Tests for Regional Heterogeneity

In order to verify further the impact of AI technology on the regional heterogeneity of manufacturing enterprises, this paper divides China into four regions, namely the eastern, central, western, and northeastern regions, for the purpose of conducting a regional heterogeneity test (see Table V& Figure 2).

Table V Results of the regional heterogeneity test

variant	（1） Eastern Region	（2） Central Region	（3） Western Region	（4） northeastern part of China
	EHQD	EHQD	EHQD	EHQD
Ai	0.0472^{***} （0.0052）	0.0321^{***} （0.0023）	0.0018^{***} （0.0059）	0.0021^{***} （0.0018）
control variable	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
observed value	12082	11821	9082	10823
R^2	0.9623	0.9427	0.9418	0.0902

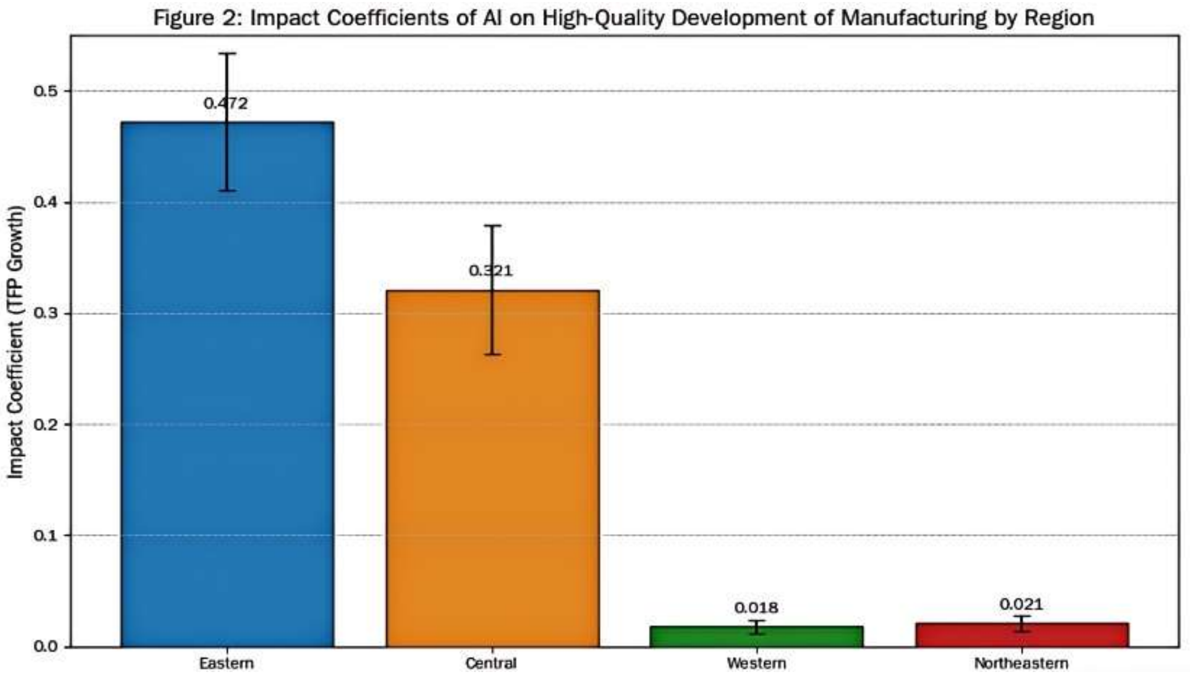

Figure 2: Regional Comparison of AI's Impact Coefficients

As illustrated in Table V, the results of the heterogeneity test pertaining to the impact of AI technology on the high-quality development of manufacturing enterprises across diverse geographical regions are presented. The findings of the study indicate that AI applications in the eastern region play a pivotal role in fostering the high-quality development of manufacturing enterprises, with a coefficient of 0.0472 and a significance level of 1%, suggesting that AI technology can effectively enhance the total factor productivity of enterprises and promote high-quality development in the eastern region. This outcome may be attributed to the well-developed digital infrastructure, substantial talent pool and active innovation ecology in the eastern region, which provide a solid foundation for the in-depth application and innovation of AI technology. The promotion of high-quality development by AI application in the central region is also more obvious, with a coefficient of 0.0321 and significant at the 1% level. This indicates that AI technology mainly plays the role of production process optimization and promotes the intelligent upgrading of the traditional manufacturing industry in the process of undertaking industrial transfer in the central region. However, due to the relative lack of R&D investment in the central region, its innovation-driven effect is relatively limited.

The promotion effect of AI application on high-quality development in the western region is relatively weak, with a coefficient of 0.0018 and significant at the 1% level. This may be attributed to the weak digital foundation and shortage of talents in the western region. Furthermore, the application of AI technology is mainly concentrated in specific advantageous industries, and the overall empowering effect has not yet fully emerged. The coefficient of the promotion effect of AI application on high-quality development in the Northeast region is 0.0021, which is significant at the 1% level. However, the overall effect is not as substantial as that observed in the eastern and central regions. This may be attributable to the fact that the traditional industrial structure of the Northeast region accounts for a significant proportion of the higher transformation difficulty. The impact of AI technology on the high-quality development of manufacturing enterprises exhibits marked regional heterogeneity. The eastern region has the most significant benefits, followed by the central region, while the western and northeastern regions demonstrate comparatively weaker outcomes. This finding indicates that policymakers must consider regional differences when promoting the application of AI technology. To achieve this, they should employ differentiated policy guidance and regional synergistic development mechanisms to promote the high-quality development of the manufacturing industry.

4.5 Tests for Heterogeneity of Firm Types

As illustrated in Table VI, there are substantial variations in the impact of AI technology on the high-quality development of diverse manufacturing enterprises. Specifically, state-owned enterprises and non-state-owned enterprises demonstrate divergent characteristics in terms of the facilitating effect of AI applications. For state-owned enterprises, the coefficient of the facilitating effect of AI application on high-quality development is 0.0322, which is significant at the 1% level. State-owned enterprises characteristically possess robust financial strength and abundant resources, thereby conferring upon them an inherent advantage in the implementation and promotion of AI technology. They are better placed to invest significant financial resources in technological development and the modernization of equipment, for instance in the establishment of intelligent manufacturing systems, the creation of industrial internet platforms and the implementation of big data analysis tools. Furthermore, state-owned enterprises possess a distinct advantage in terms of policy support and resource integration, enabling them to capitalize on the national policy dividend to promote the in-depth integration of AI technology with the manufacturing industry. This integration has the potential to yield substantial results, including significant improvements in productivity, optimization of product quality, and the promotion of green transformation.

Table VI substantial variations in the impact of AI technology

Observed value	(1) State-owned enterprise	(2) Non-state enterprise
	EHQD	EHQD
Ai	0.0322*** (0.0023)	0.0592*** (0.0014)
Control variable	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effect	Yes	Yes
Observed value	12723	11082
R^2	0.8623	0.9082

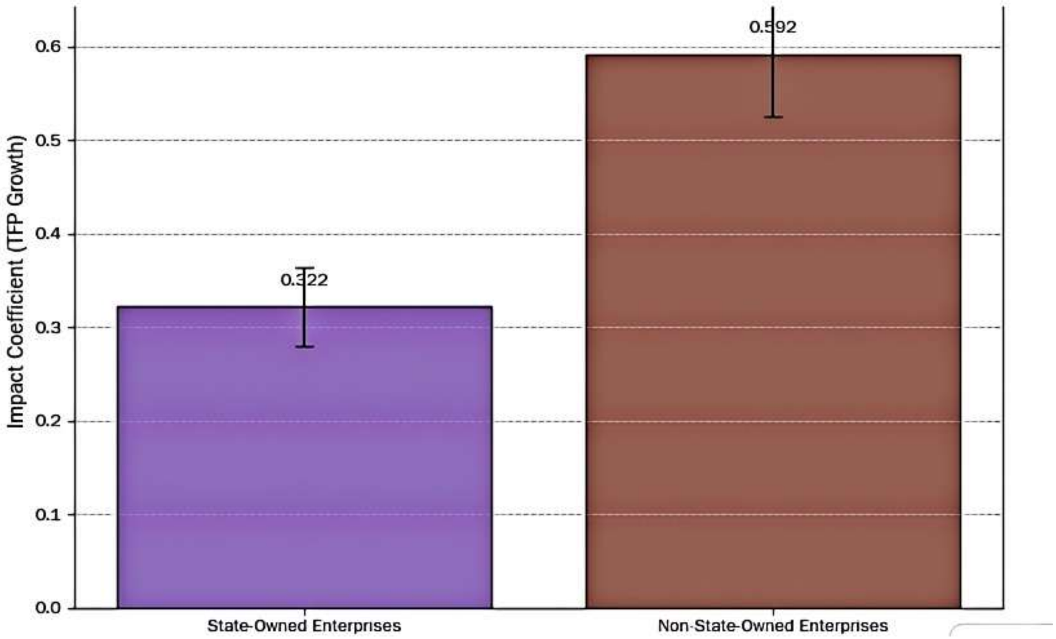

Figure 3: Comparison of AI's Impact on SOEs and Non-SOEs

Conversely, the coefficient on the contribution of AI applications to high-quality development is elevated for non-SOEs, at 0.0592, and once more proves to be significant at the 1 per cent level. Despite the fact that non-SOEs may not possess as substantial financial resources and capital as

SOEs, they can offer distinct advantages in terms of flexibility and innovation. Non-state-owned enterprises frequently encounter challenges such as inadequate capital, a paucity of technical talent, and elevated market risks. Consequently, these enterprises tend to opt for streamlined and modular approaches to AI technology implementation, thereby facilitating expeditious responses to market fluctuations and accommodating bespoke customization requirements. For instance, the integration of AI-driven flexible manufacturing systems has been demonstrated to be a successful strategy for small and medium-sized non-state-owned enterprises in reducing production costs and enhancing efficiency. This has been achieved while catering to the individual requirements of customers. Furthermore, non-State-owned enterprises have demonstrated considerable dynamism in the field of innovation, particularly in the integration of AI technology and business model innovation. Notable examples of this include the new 'product-as-a-service' model, which has been shown to enhance customer experience and enterprise competitiveness.

The overall conclusion of this study is that AI technology exerts a positive influence on the high-quality development of both SOEs and non-SOEs. However, the mechanisms and effects of this influence vary significantly. SOEs have been shown to offer distinct advantages in terms of resource investment and technological sophistication, while non-SOEs have been identified as having greater potential for flexibility and innovation. This discrepancy indicates that policymakers must consider the distinct characteristics of different enterprise types when promoting the implementation of AI technology. Moreover, they should foster the synergistic growth of SOEs and non-SOEs in the utilization of AI technology to achieve the comprehensive high-quality development of the manufacturing industry. This can be accomplished through the provision of targeted policy directives and the establishment of market-driven mechanisms.

5. Conclusion and Implications

5.1Theoretical Contributions

This study explores the impact mechanism of AI technology on the high-quality development of manufacturing enterprises through empirical analyses, and the results demonstrate that AI plays a significant role in promoting the high-quality development of manufacturing enterprises, with this impact being evident in both regional and enterprise type heterogeneity. Specifically, AI technology has been demonstrated to directly enhance productivity, innovation capacity, product quality, and green transformation level of enterprises. Moreover, it has been shown to indirectly promote the high-quality development of enterprises through the optimization of the manufacturing innovation chain and the employment structure via two intermediary mechanisms. In terms of regional heterogeneity, the eastern region has the most significant application effect of AI due to its perfect digital infrastructure and rich talent reserves. In the central region, AI mainly plays the role of production process optimization in the process of undertaking industrial transfer. While the western and northeastern regions have a relatively weak enabling effect of AI due to factors such as a weak digital foundation, a shortage of talent and difficulties in the transformation of industrial structure. The following text is intended to provide a comprehensive overview of the subject matter. With regard to the heterogeneity of enterprise types, state-owned enterprises, benefiting from robust financial strength and substantial resource advantages, demonstrate a more advanced level of AI technology implementation. Conversely, non-state-owned enterprises exhibit greater flexibility and innovation, particularly in the utilization of lightweight and modular solutions.

5.2 Practical Implications

These findings offer significant insights for policymakers: firstly, that AI technologies should be guided by differentiated policies to promote a more balanced role across the country and to encourage the high-quality development of the manufacturing industry; secondly, that precise policies need to be formulated for different types of enterprises to encourage state-owned enterprises (SOEs) to increase their investment in technological R&D, while at the same time supporting non-SOEs to enhance their innovation capabilities and to achieve synergistic development. It is recommended that future research explore the synergistic mechanism between AI and other emerging technologies in greater depth. In addition, the role of policy guidance on technology generalization should be investigated, with a view to providing more comprehensive support for manufacturing enterprises in digital transformation.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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This study did not involve human participants or animals. All data were collected from publicly available databases such as the International Federation of Robotics, CSMAR, WIND, and the China Industrial Statistical Yearbook.

Informed Consent

As this research did not involve human participants, the issue of informed consent does not apply.

Data Availability

The data used in this study are available from the corresponding author upon reasonable request. The data sources include the International Federation of Robotics (IFR) robot statistics (2008 - 2022), CSMAR, WIND, and the China Industrial Statistical Yearbook. However, due to certain data use agreements, some data may have restrictions on public sharing, but can be provided under proper authorization and for legitimate research purposes.

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