How do artificial intelligence applications affect the performance of intelligent manufacturing enterprises--Research from the Perspective of Human Capital Structure

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Abstract. The use of artificial intelligence technology can bring economic benefits to intelligent manufacturing enterprises. However, it can also lead to changes in the human capital structure of these enterprises due to the substitution and complementary collaboration of artificial intelligence with human work. This phenomenon has attracted the attention of academics. This study examines the mediating effect of human capital structure on the performance of smart manufacturing firms impacted by artificial intelligence applications, using a stepwise approach. The panel data of 217 Shanghai and Shenzhen A-share listed manufacturing enterprises and the industrial robot installation data released by IFR from 2012 to 2019 were selected for the analysis. It has been found that the application of AI can significantly improve the performance of China's intelligent manufacturing enterprises. Furthermore, the use of AI will increase the demand for highly skilled labour, thereby achieving an improvement in enterprise performance through the optimisation and adjustment of the enterprise's human capital structure. In areas with high levels of industrialization, knowledge and technology density, and good population quality, AI applications show a stronger optimization effect on human capital structure.

Keywords: Smart manufacturing; Artificial intelligence; Human capital structure; Firm performance

1 INTRODUCTION

Intelligent manufacturing is the establishment of a new model of technology-centred and data-driven manufacturing through the deep integration of advanced manufacturing and information technology. At present, countries are competing to realise the integration of virtual and real as the main characteristics of the intelligent manufacturing model[1]. In the future, human-machine collaboration will become the main development trend of human-centred manufacturing, through the deep integration of human intelligence and artificial intelligence, to make full use of the respective advantages of

A. Haldorai et al. (eds.), *Proceedings of the 2024 3rd International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID 2024)*, Atlantis Highlights in Intelligent Systems 11,
https://doi.org/10.2991/978-94-6463-490-7_11

humans and machines, to realize the synchronous improvement of the capabilities of humans and machines[2], and to help manufacturing enterprises achieve intelligent lean production[3].

Under this development trend, the in-depth application of artificial intelligence technology in manufacturing enterprises will also become an important engine that enables human-machine collaboration[4].At present, manufacturing enterprises are in the early and middle stages of intelligent transformation, and the relevant applications of artificial intelligence are mainly focused on data analysis and quality management[5][6]. Achieving human-machine collaboration through the combination of artificial intelligence and human resources has become an upcoming challenge for manufacturing enterprises[7].

Therefore, from the perspective of human capital structure, this paper conducts an in-depth study on the relationship between AI application and enterprise performance, which is of great practical significance in promoting the intelligent transformation of enterprises and realising human-centred intelligent manufacturing.

2 LITERATURE REVIEW

After combing through the existing relevant literature, it is found that AI technology profoundly affects many aspects of the intelligent development of industry, labor force and industrial structure[8]. This paper focuses on organizing the relevant research on the application of AI in enterprises from the perspectives of value chain, innovation, and labor force employment. Some scholars believe that the application of AI has played a significant role in promoting innovation in China's manufacturing industry, in which the marginal effect of innovation generated by capital-intensive and high-tech industries will be significantly higher than that of labor-intensive industries[9]. However, from the point of view of the link of AI on the value chain of manufacturing industry, the effect of AI on the enhancement of the value chain status of resource- and labor-intensive industries is more significant compared to technology-intensive industries[10]. This is mainly due to the impact of AI technology application on the labor and employment market. On the one hand, AI will have both substitution and creation effects on the labor market[11], AI inhibits employment through substitution effects while promoting employment through creation effects[12]; on the other hand, AI will trigger the problem of income distribution of labor [13]. It can be seen that enterprises need to actively respond to the needs and changes of the external environment in order to keep up with the trend of the development of AI technology, but the research related to the adjustment path within the enterprise is still to be improved. It can be seen that this paper will take the optimization of the internal human capital structure of enterprises as a perspective to explore the impact mechanism of artificial intelligence on the performance of Chinese intelligent manufacturing enterprises has both theoretical and practical significance.

The research contribution of this paper lies in the following: first: from the perspective of human capital structure optimization within enterprises, this paper enriches the research related to enterprise performance by studying the impact mechanism of artificial intelligence on the performance of Chinese smart manufacturing enterprises. Second: existing research on the relationship between artificial intelligence and enterprise human capital structure is limited to the theoretical level of combing, this paper explores the relationship between the two through empirical tests, to provide new empirical support for the path of artificial intelligence technology applied to manufacturing enterprises.

3 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

3.1 The direct impact of artificial intelligence applications on the performance of smart manufacturing companies

In recent years, artificial intelligence has become a technological advantage for enterprises due to the availability of big data and the emergence of advanced technologies and infrastructures. Scholars have defined it as a new generation of 'general purpose technology' after the Internet[14]. Traditional labor technology has been rapidly replaced by AI, which has wide coverage and profound content, making it a technological advancement never seen before [15][16].Artificial Intelligence plays a significant role in intelligent manufacturing and will continue to promote the upgrading of China's manufacturing industry.

Continuous technological innovation has enabled AI to significantly enhance enterprise productivity, particularly in simple assembly line work, where it can efficiently replace human labour. This will lead to the growth of high value-added industries in technology and finance, gradually replacing low value-added industries that lack the ability to apply intelligent technology and sufficient financial support. This may result in a mismatch between labor demand and the labor market [17]. Furthermore, the utilisation of AI technology by businesses to enhance technological innovation is also a contributing factor to increased labour productivity [18].

During the integration process with enterprises, the production factor structure of the companies has changed due to the inclusion of AI [18]. Some scholars believe that in the short term, artificial intelligence technology is not significantly helpful to enterprises. However, through continuous integration with the enterprise, the impact brought by artificial intelligence technology on enterprise productivity will gradually become positive[19]. Therefore, the application of artificial intelligence technology can optimize the adjustment of the enterprise's production factor structure. With higher levels of technology application, it can have a positive impact on improving enterprise productivity and performance.

Based on the above analysis, this paper puts forward the following hypotheses:

H1: Artificial intelligence application can positively affect intelligent manufacturing enterprise performance.

3.2 Indirect impact of artificial intelligence application on intelligent manufacturing enterprise performance

Artificial intelligence is a significant technological advancement in modern society. Its impact on the labour market can be attributed to two main effects: the technology substitution effect and the emergence of robots. In the substitution effect, the demand for robots is higher than the demand for labour due to their high efficiency and low cost [20]. Regarding the substitution effect, artificial intelligence will lead to a transformation of the labour force, shifting from operational to knowledge-based and skill-based positions. This will result in a change in the nature of work, with a greater demand for cross-border composite talents in enterprises [21]. This transformation accelerates the change of human capital structure within the enterprise and reduces the demand for low-level labour [22].

Secondly, from a complementary perspective, the learning and application of AI technology should be undertaken by higher-level workers. This also enhances the ability of enterprises to attract high-skilled talent[23]. Additionally, the increase in the number of non-regular high-skilled workers promotes the optimization of the enterprise's human capital structure. Enterprises will proactively increase the proportion of technicians to aid in intelligent transformation and upgrading due to the high value-added characteristics of technological research and development[24]. The literature suggests that the application of artificial intelligence technology will inevitably impact the employment structure of the labour force, due to the dual role of substitution and complementary effects. This impact will be reflected in employment upgrading, which means that the proportion of high-human capital and high-skilled labour force employment will increase.

Improving human capital at the enterprise level is crucial for enhancing the core competitiveness of manufacturing enterprises, which in turn has a significant impact on enterprise performance[25]. The growth of enterprise performance is highly affected by the application of artificial intelligence technology and the enhancement of high-tech human capital, as noted by Wang Xueyi et al. (2021)[26] and Liu Songzhu et al. (2022)[27]. This mechanism promotes the high-quality development of China's manufacturing industry.

Based on the above analysis, this paper proposes the following hypothesis:

H2: AI application can promote the optimization of human capital structure, which in turn positively affects the performance of smart manufacturing enterprises.

Absorptive capacity refers to an enterprise's ability to identify and acquire external knowledge, and subsequently apply it in the process of new technology research and development, as well as new product development through internal digestion[28].Absorptive capacity can assist enterprises in effectively utilising and transforming newly acquired technologies, enhancing knowledge creativity, improving product innovation performance, and ultimately leading to favourable economic returns[29]. In the context of introducing AI technology, absorptive capacity can aid enterprises in its application and transformation.

On the other hand, absorption capacity encompasses not only the knowledge and technology possessed by the enterprise but also the experience of employees and the accumulation of managers[30].In the process of developing artificial intelligence technology within an enterprise, the absorption capacity can help alleviate any sense of mismatch due to individual differences and integrate with the existing knowledge to form new knowledge [31]. The expansion of AI technology's scope of application has led to improved employee quality and ability through learning and sharing new knowledge, ultimately promoting enterprise performance.

To summarize, when the higher the absorptive capacity of the enterprise, the higher the sensitivity to AI technology, and the application of the technology will be able to react and integrate quickly, thus promoting the improvement of enterprise performance.

Based on the above analysis, this paper proposes the following hypotheses:

H3: Enterprise absorptive capacity can promote the positive relationship between artificial intelligence application and intelligent manufacturing enterprise performance.

4 RESEARCH DESIGN

4.1 Model construction

In order to verify the research hypotheses, this paper draws on the stepwise method of Wen Zhonglin (2014) and Lou Yong (2021) to construct a panel data linear regression[32][33] with the following model:

$$Fp_{i,\ t} = \alpha_0 + \alpha_1 Robot_{i,t} + \alpha_2 X_{i,t} + \lambda_i + \theta_t + \varepsilon_{i,t} \tag{1}$$

$$Edu_{i,\ t} = \beta_0 + \beta_1 Robot_{i,t} + \beta_2 X_{i,t} + \lambda_i + \theta_t + \varepsilon_{i,t} \tag{2}$$

$$Fp_{i,\ t} = \gamma_0 + \gamma_1 Robot_{i,t} + \gamma_2 Edu_{i,t} + \gamma_3 X_{i,t} + \lambda_i + \theta_t + \varepsilon_{i,t}$$

$$Fp_{i,\ t} = \eta_0 + \eta_1 INTERACT_{i,t} + \eta_2 Edu_{i,t} + \eta_3 X_{i,t} + \lambda_i + \theta_t + \varepsilon_{i,t} \tag{3}$$

The equation is as follows: $X_{i,t}$ represents all control variables, λi represents individual fixed effect, θ_t represents time solid effect, $\varepsilon_{i,t}$ is the random error term, and the interaction term between the explanatory variable Robot and the moderator variable AQ. The variables i and t represent industry and region and year, respectively.

Model (1) examines the effect of AI application level on firm performance. Model (2) explores the impact of AI application on the mediating variables of human capital structure and human capital education structure. Model (3) tests whether human capital structure mediates the impact of AI application on firm performance. Model (4) examines whether absorptive capacity moderates the relationship between AI application and firm performance. The equation is as follows: $X_{i,t}$ represents all control variables, λ_i represents individual fixed effect, θ_t represents time solid effect, εi,tis the random error term, and the interaction term between the explanatory variable Robot and the moderator variable AQ. The variables i and t represent industry and region and year, respectively.

4.2 Variable Selection and Explanation

(1) Explained variables

Firm Performance (FP) is typically measured by return on equity (ROE), which represents the percentage of net profit to average shareholders' equity. The size of ROE reflects the profitability of the enterprise. In other words, the higher the return obtained by the enterprise through investment, the better its financial position.

(2) Explanatory variables

Application Level of Artificial Intelligence (Robot) Currently, there is a shortage of established methods for defining AI-related metrics authoritatively. This paper references Wang Yongqin et al. (2020) and Acemoglu et al. (2020), who use the density of industrial robots in the manufacturing industry of the two code industries as a proxy variable for AI. In this paper, we use the enterprise-level industrial robot density table to assess the level of AI application in manufacturing industry enterprises [34][35]. The measurement method is defined by the IFR as the density of industrial robots, which is calculated as the number of robot stocks per 10,000 workers. The robot stock is estimated primarily based on the current installation of industrial robots in sub-industries. The calculation of industrial robot density at the enterprise level involves three steps. Firstly, calculate the ratio of the stock of robots at the industry level to the number of machines employed in the industry. Secondly, calculate the enterprise weight by finding the ratio between the proportion of production personnel of a specific enterprise in the industry and the proportion of production personnel of all enterprises in the manufacturing industry in the current year. Finally, multiply the industrial robot density at the industry level by the corresponding enterprise weight to obtain the industrial robot density at the enterprise level, as shown in equation (1).

$$Robot_{ijt} = \frac{IR_{jt}}{Labor_{jt=20xx}} \times \frac{PP_{ijt=20xx}}{MfPP_{t=20xx}}$$

Where $Robot_{ijt}$ denotes the density of industrial robots of enterprise i in manufacturing industry j in year t, IR_{jt}denotes the stock of industrial robots in industry j in year t, $Labor_{jt=20xx}$denotes the number of employees in industry j in 20xx (base period), $PP_{ijt=20xx}$denotes the proportion of production personnel of enterprise i in industry j in 20xx, and$MfPP_{t=20xx}$denotes the proportion of production personnel of all manufacturing enterprises in 20xx.

(3) Mediating variables

Human capital structure (Edu). This paper refers to Li Yifei et al. (2023) and Chen Hong et al. (2023), and sets the indicator of measuring the high and low human capital structure of enterprises as the proportion of employees with different educational levels to the total employees[36]. In this paper, employees are classified into two categories of high skill and low skill according to their education level, where employees with bachelor's degree and above are high skill employees, denoted as Edu-H; employees with high school and below education level are low skill employees, denoted as Edu-L.

(4) Moderating variables

Absorptive capacity (AQ). Referring to Rothaermel and Alexandre (2009), this paper sets the measure of absorptive capacity as the ratio of R&D investment, i.e. the ratio of the amount of R&D investment and operating income [37].

(5) Control variables

The control variables are selected to reflect the basic characteristics of the enterprise's indicators, including enterprise size (size), leverage level (lev), profitability (roa), and growth (growth), which are measured by the natural logarithm of total assets, gearing ratio, return on assets, and growth in operating income, respectively. Controlling the above variables in the regression analysis can more accurately assess the impact of AI applications on firm performance. As show in table 1.

Table 1. Description of variables

Variable Type	Variable Name	Variable Symbol	Variable Description
Explained Variables	Enterprise Performance	FP	Return on net assets
Explanatory variables	Artificial Intelligence Applications	Robot	Density of industrial robots at enterprise level
Mediating variable	Human Capital Structure	Edu	The skill structure of the company's employees includes the proportion of employees with a bachelor's degree or higher (Edu-H) and the proportion of employees with a high school diploma or lower (Edu-L).
Moderating variable	Absorptive capacity	AQ	Amount of R&D investment/operating revenue
	Enterprise Scale	Size	Logarithm of total assets at the end of the period
Control variable	Enterprise Growth	Growth	Growth rate of operating income
	Profitability	Roa	Return on assets
	Leverage leve	Lev	Gearing ratio

4.3 Sample Selection and Data Sources

This paper draws on three data sources. Firstly, the 'Global Industrial Robotics Report' published by IFR. This report provides a 'country-industry-year' panel data based on surveys of global robot manufacturers. The paper uses the 2012-2019 industrial robot installation data for two code industries in China's manufacturing sector. Secondly, the 'China Industrial Statistics Yearbook' is used as a data source. This paper uses manufacturing industry data from 2012-2019 for industrial enterprises above designated size, and matches two-code industries with industrial robots to construct variable metrics. According to the Cathay Pacific and Wind economic and financial databases, annual report data for manufacturing enterprises were obtained. The data was selected based on accessibility and the economic impact of the new Crown Pneumonia epidemic at the end of 2019 on the development of enterprises. This paper examines the period between 2012 and 2019, focusing on the implementation of intelligent manufacturing by Shenzhen and Shanghai A-share listed companies. The raw data was processed as follows: (1) The sample period excludes ST and * ST listed companies; (2) Samples with missing or abnormal values of key indicators are excluded; (3) Samples with a gearing ratio greater than 1 and R&D investment of 0 are also excluded. A total of 217 companies provided 1736 sample observations. The data used in this paper was processed using SPSS and Stata software to eliminate the impact of outliers on the regression results. All continuous variables were subjected to shrinkage treatment for the upper and lower 1% quartile. Descriptive statistics and empirical tests were conducted on the shrunk data.

5 ANALYSIS OF EMPIRICAL RESULTS

5.1 Analysis of benchmark regression results

This paper uses stepwise regression tests to analyse the main variables. The results are presented in Table 2. Column (1) of Table 2 shows the estimation results of using industrial robot density as a proxy variable for AI. After controlling for industry and year fixed effects and regressing the explanatory variable (Robot) on the explanatory variable (FP), the coefficient of the explanatory variable Robot is significantly positive at the 1% level. A 1% increase in the density of industrial robots leads to a 0.019 percentage point increase in the performance of manufacturing enterprises. This suggests that the use of artificial intelligence, as represented by robot application, can have a positive impact on enterprise performance, which supports research hypothesis H1.

Columns (2) and (3) in the table show the regression of the explanatory variable (AI) on the mediator variable of human capital structure of high-skilled employees (Edu-H) and low-skilled employees (Edu-L), respectively. The aim is to observe whether the regression coefficient β1 is significant. Column (2) shows that a 1% increase in the density of industrial robots leads to a 0.105 percentage point increase in the proportion of high-skilled employees, while column (3) shows that a 1% increase in the density of industrial robots results in a 0.078 percentage point decrease in the proportion of low-skilled employees. Currently, China's intelligent manufacturing enterprises are introducing artificial intelligence technology, which is increasing the demand for highly skilled employees. This, in turn, has a negative impact on the proportion of low-skilled employees in the enterprise. However, the regression results do not show a significant correlation between the proportion of low-skilled employees and the introduction of artificial intelligence technology. The results indicate that the application of artificial intelligence technology will impact the upgrading of human capital structure, mainly reflected in the increase of high-skilled employees. The phenomenon may be attributed to the fact that manufacturing enterprises are still in the process of exploring artificial intelligence technology. As a result, they require a group of highly educated and qualified personnel to learn and apply it. However, since artificial intelligence technology has not yet been widely adopted across all production lines, the demand for ordinary workers has not been significantly affected. Therefore, the 'scale expansion' effect is expected to be greater than the 'technology expansion' effect. However, the 'scale expansion' effect is currently higher than the 'technology substitution' effect due to the limited popularisation of AI technology across all production lines. Column (4) of the table further examines the mediating effect of the human capital structure. Column (4) regresses the explanatory variable (Robot) and the mediating variables (Edu-H and Edu-L) on the explanatory variable (FP) to observe the significance of the regression coefficients. The results show a significant regression coefficient of 0.022 for the proportion of high-skilled employees in the human capital structure, and a significant regression coefficient of -0.012 for the proportion of low-skilled employees. The results indicate that the use of AI has a positive impact on enterprise performance. Specifically, a higher level of AI technology application in the enterprise leads to an optimized human capital structure, with a positive indirect effect on the proportion of high-skilled employees and a negative indirect effect on the proportion of low-skilled employees. These findings support research hypothesis H2.

Table 2. Basic regression results

	(1)	(2)	(3)	(4)	(5)
Variable	Fp	Edu-H	Edu-L	Fp	Fp
Robot	0.019^{***}	0.105^{***}	-0.078	0.021^{***}	0.032^{***}
	(3.02)	(3.33)	(-1.43)	(3.24)	(4.29)
EduH				0.022^{***}	0.021^{***}
				(3.16)	(3.05)
EduL				-0.012^{**}	-0.011^{**}
				(-2.31)	(-2.22)
Size	0.010^{***}	0.068^{***}	-0.002	0.008^{***}	0.007^{**}
	(3.67)	(6.59)	(-0.10)	(2.93)	(2.37)
Lev	0.082^{***}	-0.023	0.259^{***}	0.083^{***}	0.084^{***}
	(10.89)	(-0.83)	(4.58)	(11.08)	(11.15)
Roa	1.516^{***}	0.159^{*}	0.192	1.514^{***}	1.514^{***}
	(72.53)	(1.95)	(1.17)	(72.55)	(72.60)
Growth	0.012^{***}	0.073^{***}	-0.057	0.011^{***}	0.011^{***}
	(2.89)	(3.84)	(-1.48)	(2.69)	(2.79)
interact					-0.730^{***}
					(-2.92)
Constant	-0.126^{***}	-0.373^{***}	-0.144^{***}	-0.113^{***}	-0.100^{***}
	(-4.98)	(-4.00)	(-6.06)	(-4.42)	(-3.82)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	1 735	1 735	1 735	1 735	1 735
r2_a	0.830	0.202	0.210	0.831	0.829

5.2 Robustness Tests

5.2.1 Endogeneity issues

There may be problems such as omitted variables and reverse causality in the regression analysis process between AI and enterprise performance above. Although the indicator of industrial robot density is less affected, in order to ensure the reliability of the research results, this paper adopts the instrumental variable method to test the endogeneity problem. Compared to other methods, the instrumental variable method is able to expand the range of explanatory variables to improve the accuracy and consistency of the regression model. First, this paper draws on the idea of selecting instrumental variables by Yongqin Wang and Wen Dong, and chooses the stock of industrial robots in the United States to construct the corresponding density of industrial robots installed in Chinese intelligent manufacturing enterprises [36]. The reasons for choosing the stock of U.S. industrial robots are (1) the degree of development of U.S. industrial robots can reflect the future trend of artificial intelligence. And during the sample period, the trend of industrial robot application in the U.S. and China is relatively close to each other, which is consistent with the correlation assumption; (2) the application level of U.S. industrial robots does not directly determine or affect the economic efficiency of Chinese manufacturing enterprises, which is consistent with the exogeneity assumption. The regression results of instrumental variables are shown in column (1) of Table 3, and the results passed the significance test at the 1% level. Based on the test results, the conclusion that there is a positive facilitating effect of AI on enterprise performance is reliable and robust.

Table 3. Robustness test results

Variables	Use of instrumental variables	Replacement of explanatory variables	Replacement of explanatory variables
	(1)	(2)	(3)
AI	0.012*		0.155**
	(1.88)		(2.05)
Lagged one period ai		0.031***	
Control Variables		(2.71)	
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sample size	Yes	Yes	Yes
Lagged one period ai	2 384	2 086	2 375
R-squared	0.920	0.921	0.819
r2_a	0.908	0.907	0.792
F	77.11	66.54	29.91

5.2.2 Further Robustness Tests

To ensure the robustness of the research results, this paper conducts a robustness test by replacing the core variable method. The indicator of the explanatory variable used to measure corporate performance was changed from return on net assets (ROE) to earnings per share (EPS) using Lou Yong's method. Secondly, following Cao Ping's suggestion, the original data has been replaced with the industrial robot density from the previous period. This measurement is used to assess the application of artificial intelligence. The test results support the replaced variable is significantly positive and the conclusion that AI has a positive impact on firm performance.

5.3 Heterogeneity analysis

5.3.1 Analysis of regional heterogeneity

The development level of each region varies, and the impact of artificial intelligence on enterprise performance in manufacturing enterprises will differ accordingly. According to the National Bureau of Statistics' 'three major zones' division model, a regression study was conducted on intelligent manufacturing enterprises in China's eastern, central, and western regions. Table 4 shows the specific regression results. Table 4 shows that the coefficients of artificial intelligence in the eastern, central, and western regions are all positive. This indicates that the degree of application of artificial intelligence has a greater impact on enterprise performance in the eastern region than in the central and western regions. The eastern region has the largest sample size, indicating that the application of artificial intelligence is mainly concentrated there.

Additionally, the industrial development in the eastern region is more rapid compared to the central and western regions. Most intelligent manufacturing enterprises have a high degree of intelligence. Therefore, in the eastern region, artificial intelligence technology can be better integrated with the development of the manufacturing industry to improve the performance of manufacturing enterprises. The regression coefficient of human capital structure shows that the mediation effect in the central and western regions is not as significant as in the eastern region. The text highlights the lower degree of artificial intelligence application in the western region, the low overall educational level of employees in manufacturing enterprises, and the lack of impact of new technology on low-educated employees. The employee structure in the less competitive environment of the western region is more fixed and less affected by external conditions, resulting in slower development of the human capital structure. In contrast, the eastern region has a higher level of artificial intelligence application, which has led to the optimization of the employee structure and the development of the human capital structure. The application of artificial intelligence technology shows a certain mediating role in optimization. The coefficient of the interaction term between absorptive capacity and AI technology is significantly positive in the eastern region. However, none of the coefficients are significant in the central and western regions. This reflects the large gap between the absorptive capacity of manufacturing enterprises in various regions of China.

Table 4. Test for heterogeneity of manufacturing firms in different regions

Variables	Eastern	Central	Western
	(1)	(2)	(3)
Robot	0.376***	0.084**	0.056*
	(6.80)	(2.21)	(1.93)
EduH	0.012***	0.009*	0.042**
	(3.03)	(1.80)	(2.32)
EduL	0.006***	-0.002	-0.008
	(2.67)	(-0.26)	(-0.86)
INTERACT	1.461*	-0.231	-0.175
	(1.93)	(-0.27)	(-0.28)
Constant	-0.049***	-0.100	0.030
	(-2.93)	(-1.63)	(0.50)
Control Variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sample size	1 647	464	272
R-squared	0.909	0.873	0.936
r2_a	0.895	0.849	0.922

5.3.2 Analysis of Industry Heterogeneity

In order to further analyze the heterogeneous characteristics of the impact of the level of AI application on firm performance in different types of manufacturing industries, this paper draws on the methodology proposed by the United Nations Industrial Development Organization in the World Industrial Development Report 2002/2003 in classifying manufacturing industries, where the sample is classified into four categories according to the difference in technological intensity, including resource-based manufactured goods, low-technology manufactured goods, medium-technology manufactured goods, and high-technology manufactured goods. The specific regression results are listed in Table 5. From Table 5, it can be seen that the level of AI application has a significant positive relationship on the performance of both high-tech and medium-tech manufacturing enterprises, in which the level of AI in medium-tech manufacturing has the greatest impact on the performance of manufacturing enterprises, followed by high-tech manufacturing, while the impact effect of low-tech and resource-based manufacturing is the smallest. The possible reason is that artificial intelligence in different types of technology manufacturing industry integration degree is different, medium and high technology manufacturing industry as knowledge and technology-intensive industry, the process of industrial development on the high demand for technology elements, so artificial intelligence technology can be quickly applied in the industry and help to improve enterprise performance. While resource-based and low-tech manufacturing industries are mostly labor-intensive industries, the demand for new technologies is not high, and the cost of replacing simple labor through artificial intelligence is huge. Therefore, the degree of artificial intelligence application has a greater impact on the performance of medium and high-tech manufacturing enterprises. In terms of the mediating effect of human capital structure, resource-based manufacturing enterprises have more demand for low-skilled employees, while low-middle and high-technology manufacturing enterprises are mainly mediated by high-skilled employees. This phenomenon indicates that resource-based enterprises have not yet begun to apply AI technology in smart manufacturing, so the human capital structure has not changed much; while medium- and high-technology enterprises have gradually applied AI technology, and thus realized the optimization of human capital structure.

Table 5. Heterogeneity test of different types of manufacturing enterprises

Variables	Resource-based	Low-tech	Medium-tech	High-tech
	(1)	(2)	(3)	(4)
Robot	0.068	0.003	0.057***	0.053***
	(1.59)	(0.08)	(4.08)	(4.97)
EduH	0.026	0.059**	0.042***	0.020***
	(1.64)	(2.37)	(4.52)	(3.07)
EduL	0.035*	0.002	-0.003	0.003
	(1.89)	(0.28)	(-0.67)	(0.70)
INTERACT	0.840	1.328	-1.988***	0.780*
	(0.36)	(0.56)	(-4.11)	(1.92)
Constant	-0.262	-0.709***	-0.074	-0.270***
	(-1.21)	(-2.68)	(-1.26)	(-3.51)
Control Variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	288	312	568	623
R-squared	0.889	0.742	0.838	0.852
r2_a	0.885	0.735	0.835	0.850

6 RESULTS

This paper presents an empirical examination of the impact of artificial intelligence applications on the performance of intelligent manufacturing enterprises. The study uses data from 217 intelligent manufacturing enterprises between 2012 and 2019. The study also verifies the mediating role of human capital structure and the moderating role of absorptive capacity. The findings indicate that: (1) The use of AI applications can enhance the performance of manufacturing enterprises, a conclusion that remains valid after undergoing a series of validations. (2) The optimization of the human capital structure of an enterprise plays a partially intermediary role between AI application and enterprise performance. This is due to the 'technical complementarity' and 'scale' of current smart manufacturing enterprises in the application of AI technology. (3) There are significant differences in the characteristics of AI application and manufacturing enterprise performance. Regional differences show that the promotion effect and human capital structure optimization effect are more significant in the eastern region compared to the central and western regions. Industry differences show that medium and high technology manufacturing enterprises play a role in mediating between AI application and enterprise performance. Regional and industry differences affect the promotion and human capital structure optimization effects differently. The eastern region experiences more significant effects compared to the central and western regions. Additionally, middle and high technology manufacturing enterprises have a stronger influence effect. The study's conclusion indicates that China's manufacturing enterprises are still in the early stages of applying AI technology. However, optimizing the human capital structure has a positive impact on the application of AI and enterprise performance.

7 DISCUSSION AND CONCLUSION

Synthesising the findings of this study, it is evident that AI applications can promote the optimisation and upgrading of the employee structure of manufacturing enterprises, leading to improved enterprise performance. Therefore, it is important to consider the matching problem between the application of artificial intelligence technology and the human capital structure of manufacturing enterprises. This is of great value in promoting enterprises to create higher economic benefits and realize intelligent transformation. Based on this, the paper proposes the following suggestions:

(1) Actively promote the deep integration of intelligent manufacturing and artificial intelligence applications. The current policy for the application of artificial intelligence technology is not perfect, especially with regard to the geographical disparities in the application of the technology, and there is a lack of sufficient financial and policy support. Therefore, the government should first introduce a series of effective industrial policies to promote the manufacturing industry in the direction of AI application of regional development, support the eastern high-tech industries to drive the development of manufacturing industries in central and western China; the central and western China is to actively play the advantage of the endowment of resources to strengthen the introduction, development and application of AI technology and equipment in the western region, and to strengthen the development of AI technology and equipment in the western region. The central and western regions will actively use their advantages in resource endowment to strengthen the introduction, development and application of AI technology and equipment in the western regions, so as to form an industrial development layout with complementary advantages and reasonable circulation of factors in each region. Second, the government should combine the characteristics of regional and industrial development to provide financial support for manufacturing enterprises. Establish fund projects related to the application of artificial intelligence technology to promote the intelligent transformation of manufacturing enterprises.

(2) Optimise the human capital structure of manufacturing enterprises. In adjusting the human capital structure within the enterprise, starting from the overall organisational structure of the enterprise, rationally plan the number of directors and executives, and actively introduce and select some executives who understand artificial intelligence technology or have a certain information technology foundation, and at the same time improve the overall level of education of the enterprise's staff. In terms of

implementation, there may be challenges such as lack of employee motivation and stability, which can be solved by optimising the compensation structure. For example, if the turnover rate of middle- and high-level technical personnel is relatively high, the salary ratio of middle- and high-level technical positions can be increased to maintain the quantity and quality of technical personnel; grassroots positions can be reorganised through job restructuring, increasing the overlap of salaries, and other measures to enhance employee motivation.

(3) Strengthen the cultivation of "AI+" composite talents. On the one hand, through school-enterprise cooperation to jointly promote the integration of production, learning and research, to achieve the cross-fertilisation of artificial intelligence and multiple disciplines, and strengthen the cultivation of composite talents; on the other hand, enterprises through personnel training to help employees understand and learn knowledge in the field of artificial intelligence, to enhance the ability of employees to transition to intelligent work, and to promote a better match between human capital and artificial intelligence, and then to achieve human-machine cooperation. Of course, at present, the disciplines and courses for AI technology are still relatively shallow in terms of settings, and the shortage of professional teachers and trainers is relatively large, which is also an urgent problem and challenge that the government, schools and enterprises will jointly face in the future.

ACKNOWLEDGMENTS

This paper is supported by National Science Foundation of China (No. 21BGL038).

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