Social Science and Management
Print ISSN: 3007-6854
Online ISSN: 3007-6862
DOI: https://doi.org/10.61784/ssm3083

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ENTERPRISE INCOME DISTRIBUTION

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Abstract: As the most representative general technology at present, artificial intelligence is profoundly reshaping the organizational form, operating model and operating mechanism of enterprises, and bringing unprecedented impact to the income distribution structure within enterprises. Therefore, based on the panel data of China's Shanghai and Shenzhen A-share non-financial listed companies from 2010 to 2022, this paper explores whether the development of AI will trigger new changes in the interest pattern between corporate profits and labor compensation. Based on basic theories such as capital-labor substitution principle and factor reward theory, this paper explores how AI can promote enterprises to adopt different income distribution modes by improving marginal output of capital and substituting low-skilled labor from the perspective of technology bias. At the same time, the key factor of financing constraint is considered to hinder the enterprise's choice of technology level, which leads to the change of its corresponding distribution effect. Finally, the group regression is carried out from the two perspectives of the ownership structure and the industry to find the different responses of different types of enterprises to the income distribution changes brought by this new technology. This study attempts to outline the basic picture of the evolution of enterprise income distribution mechanism in the era of artificial intelligence, and also provides certain theoretical support and practical evidence for coordinating the relationship between technological innovation process and social distribution justice.
Keywords: Artificial intelligence; Financing constraints; Income distribution structure

1 INTRODUCTION

At present, a new round of global scientific and technological revolution and industrial transformation are accelerating, and digital technologies such as artificial intelligence, big data and cloud computing are reshaping the path of global economic growth. At the same time, geopolitical conflicts, increased trade barriers, and the trend of technological "decoupling" continue to spread, combined with the weak recovery of the world economy, and enterprises are facing unprecedented uncertainties and challenges. In the context of the transformation of the domestic economy from a stage of high-speed growth to a stage of high-quality development, scientific and technological innovation has been placed in the core position of the overall development of the country, and artificial intelligence, as a key breakthrough field, is becoming a key force to promote the transformation and upgrading of traditional industries, improve the efficiency of factor allocation and competitive advantage. The report of the 20th National Congress of the Communist Party of China proposed to accelerate the development of the digital economy, the deep integration of the real economy and the promotion of digital technology and stressed the need to improve the distribution mechanism to achieve higher quality and more sustainable common prosperity[1].
While improving the production efficiency and profitability of enterprises, artificial intelligence is also profoundly affecting the income distribution structure within enterprises. On the one hand, artificial intelligence technology has enhanced the output capacity of capital elements, and the substitution effect on low-skilled labor has become increasingly significant, and enterprises' dependence on labor has gradually weakened, and the income distribution structure has tilted toward capital. On the other hand, the empowering effect of artificial intelligence has begun to appear in some high-tech enterprises, forming a positive incentive for highly skilled talents, but the imbalance risk of the overall distribution pattern is still intensifying. In this context, corporate financing constraints, as an important factor affecting technology allocation and allocation decisions, are becoming a key variable to understand the mechanism of AI. It is suggested that enterprises with limited financing rely more on "machine instead of labor" to alleviate the cost pressure, which may further compress the income distribution of employees; On the other hand, enterprises with loose financing are more likely to release production potential and improve employee compensation through AI empowerment. Therefore, it is pointed out that clarifying how artificial intelligence and financing constraints jointly affect the income distribution of enterprises not only has important theoretical value, but also provides practical reference for promoting the development strategy of technology innovation and distribution equity[2].

2 RESEARCH LITERATURE

In recent years, the academic community has gradually explored how to build quantitative indicators of enterprise AI development level based on text data. Li Mengnan (2022) proposed to use natural language processing technology to identify keywords related to artificial intelligence in the annual reports of listed companies, and extract word frequency and distribution information from them to measure the strategic investment and technology implementation of

enterprises in the field of artificial intelligence[3]. This method not only improves the efficiency of information extraction, but also enhances the objectivity and comparability of index construction. On this basis, Wang Baichuan and Du Chuang (2022) further analyzed the diffusion path of keywords (such as "machine learning", "deep learning" and "big data") and their influencing factors and explored the regulatory role of government policies in technology diffusion, providing a more systematic empirical basis for quantifying enterprise AI activities from text data[4].
The problem of internal revenue is an important one in economic analysis, especially under the condition of new technology. Especially when the development of the new generation of information technology represented by artificial intelligence accelerates, the income distribution situation will change greatly. For example, Li Yuanyuan and Gao Shuaike (2024) pointed out that "under the rapid development of the new generation of artificial intelligence technology, the proportion of labor factor income in enterprises presents a negative growth" [5], indicating that the development of new science and technology has a huge impact on labor force. “AI will not only lead to significant increases in productivity, it will also put certain types of workers at risk of losing their jobs."。The results of the artificial intelligence quasi-natural experiment conducted in the artificial intelligence innovation and development experiment zone show that due to the obvious difference between technical capital and human capital, the wage rate of high-skilled workers increases greatly, while that of low-skilled workers decreases greatly. Therefore, in order to explain this new pattern of income distribution, the theory of income distribution needs to reconsider how to coordinate the relationship between technological progress and social equity
In the development of artificial intelligence, the improvement of capital returns has played a decisive role in the distribution of corporate income. He Danni (2024) also pointed out that the application of artificial intelligence in the manufacturing industry, especially the introduction of automated production systems, enhanced the capital accumulation of manufacturing enterprises, and gradually decreased the proportion of labor income in total income [6]. Theoretically, this is closely related to Malthus' income distribution model and Keynes' capital accumulation theory. AI technology is perceived as an upgraded form of capital, thus further boosting capital income growth and undercutting the income share of workers, especially low-skilled workers[7].
Although the existing research provides a preliminary understanding of the relationship between artificial intelligence and enterprise income distribution, there are still some shortcomings[8-10]. These studies mainly focus on how artificial intelligence can improve enterprise productivity and profits, but there is relatively little analysis on the mechanism of income distribution, especially on the regulatory role of financing constraints [11]. Secondly, the existing literature mainly focuses on different types of enterprises, and rarely analyzes the differences of organizational structure and industry background of different enterprises. Further research should consider factors such as financing constraints, industry characteristics and enterprise size, and comprehensively analyze the application and impact of AI in different enterprises.
The innovation point of this paper is to explore how artificial intelligence affects the income distribution of enterprises under the background of capital constraints, especially in different types of enterprises and industries. By further improving the research in this field, it can provide more accurate theoretical support and practical guidance for policy makers and enterprise decision makers.

3 EMPIRICAL ANALYSIS OF THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ENTERPRISE INCOME DISTRIBUTION

3.1 Model and Variable Selection

This paper takes China's Shanghai and Shenzhen A-share non-financial listed companies from 2010 to 2022 as the research object, combines the research theme of artificial intelligence technology development and enterprise income distribution, and constructs panel data samples. According to the methods of the existing literature, this paper carries out several processing on the original data to improve the data quality and the reliability of the results. Firstly, ST and *ST enterprises are excluded to avoid financial anomalies interfering with the regression results. Hu Yan, Dong Haoxiang, and Tang Rui (2024) point out that financial industry companies are excluded because their asset structure and income distribution mechanism have significant particularities [12]. Thirdly, the observed value of "cash paid to and for employees" is less than or equal to 0, and the sample of key variables are seriously missing; Finally, a 1% tail reduction was applied to all continuous variables to reduce the effect of extreme values. After processing the above steps, 27,984 valid observations were obtained, covering thousands of listed companies.
The financial data at the enterprise level are mainly from the CSMAR database. Text data such as annual reports are used to extract AI-related keywords to quantify the degree of application of AI technology at the enterprise level; For data at the city and regional level, refer to China City Statistical Yearbook and data released by local Statistical bureaus. In order to further ensure the accuracy and consistency of variables, some missing values are completed by robust interpolation method. The multidimensional data set constructed in this paper provides a solid data basis for empirically testing the impact of artificial intelligence on enterprise income distribution[13].
In order to test the direct impact of artificial intelligence technology on enterprise income distribution, this paper first constructs a benchmark regression model, sets the enterprise income distribution level (indis) as the explained variable, and the application degree of artificial intelligence (AI) as the core explanatory variable. It also controls factors such as enterprise size, asset-liability ratio, profitability, enterprise age, ownership concentration, combination of two positions and board size, and introduces fixed effects of industry, region and year. The model Settings are as follows:

$$indis_{it}=\beta_0+\beta_1 \cdot ai_{it}+X'_{it}\gamma+\mu_i+\lambda_t+\epsilon_{it} \quad (1)$$

where the explained variable is the level of income distribution (indis), which is measured by the ratio of net profit to cash paid to and for employees. To a certain extent, this index can reflect the enterprise's tendency to distribute benefits to employees on the basis of profits. A higher value indicates that the enterprise retains more profits to itself, and the proportion of income obtained by employees is relatively low, and vice versa. Ji Xiaolin (2024) mentioned that this index can reflect the distribution structure between capital and labor and is an important variable to measure changes in income distribution and has been widely used in relevant literature . The core explanatory variable and control variable are as described in Table 1.

Table 1 Description of Variables

Variable type	variable name	variable symbol	Description of variables
explanatory variable	Corporate income distribution	indis	Net profit of the enterprise/cash paid to and for employees
Core explanatory variables	artificial intelligence (AI)	ai	Total number of occurrences of AI technology and AI application keywords
control variable	Enterprise size	size	Logarithm of total assets
	gearing	lev	Total liabilities/total assets
	profitability	roe	return on net assets
	Age of business	age	Ln (time of establishment + 1)
	shareholding concentration	top	Shareholding ratio of the largest shareholder
	two jobs in one	dual	Whether or not the two positions are combined, yes = 1, no = 0
	Board size	board	Ln (number of board members + 1)
moderator variable	Financing constraints	sa	sa index

3.2 Descriptive Statistics

Table 2 below shows the descriptive statistics of the main variables. It can be seen that the average level of enterprise income distribution (indis) is 0.904, which has a large fluctuation, indicating that there are significant differences in the tendency of profit distribution among enterprises. The mean value of the artificial intelligence variable (AI) is 10.145 with a high standard deviation, indicating that enterprises have significant differences in the degree of AI application. The value of financing constraint index (sa) is concentrated, which reflects that most enterprises are in the state of medium financing constraint. The distribution of other control variables was reasonable and in line with expectations, which provided a good data basis for subsequent empirical analysis[14].

Table 2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
indis	27984	.904	1.57	-4.381	7.825
ai	27984	10.145	25.787	0	164.394
size	27984	22.138	1.353	19.844	26.423
lev	27984	.406	.208	.049	.885
roe	27984	.07	.119	-.511	.353
age	27984	2.893	.337	1.946	3.526
top	27984	.349	.151	.084	.749
dual	27984	.3	.458	0	1
board	27984	2.119	.205	1.609	2.708
sa	27984	-3.8	.265	-4.437	-3.036

3.3 Baseline Regression Result

Table 3 reports the regression results of the impact of artificial intelligence technology application on enterprise income distribution. Columns (1) and (2) are linear model estimates, and columns (3) and (4) add a square term (AI ^{2}) of the artificial intelligence variable on this basis to test its nonlinear relationship. The model controls the characteristic variables of the firm and introduces the fixed effects of industry, region and year. It can be seen from columns (1) and (2) that the coefficient of artificial intelligence variable (artificial intelligence) is significantly negative, indicating that the higher the degree of application of artificial intelligence in enterprises, the lower the level of profit distribution to employees when other factors remain unchanged, reflecting the tendency of artificial intelligence to "squeeze labor remuneration" at the current stage[15].

Further, the results of columns (3) and (4) show that the coefficient of the first term of artificial intelligence is negative, and the coefficient of the square term artificial intelligence squared is positive, and both are significant at the 1% level, indicating that the influence of artificial intelligence on the income distribution level of enterprises has a significant

"U-shaped" feature. That is, in the early stage of the application of artificial intelligence, enterprises use technology to replace labor and reduce labor costs, resulting in a decline in employee income distribution; When the level of artificial intelligence investment is high, the overall efficiency and profitability of the enterprise will be improved, which will help improve the compensation structure of employees and realize the shift from negative compression to positive incentive[16].

According to the results of control variables, enterprise size and profitability have a significant positive impact on income distribution, while asset-liability ratio and board size have a negative impact, and other governance variables such as ownership concentration and integration of two positions have no significant impact. On the whole, the explanatory power of the model is good, and the R^2 increases from 0.183 to 0.592, indicating that the regression results are robust and reliable. In summary, the results of benchmark regression and nonlinear test jointly show that artificial intelligence has a significant impact on enterprise income distribution, and the impact is non-linear with a "first decrease and then increase", which provides a theoretical basis for the subsequent analysis of the regulatory role of financing constraints[17].

Table 3 Baseline Regression

	(1)	(2)	(3)	(4)
VARIABLES	indis	indis	indis	indis
ai	-0.00212***	-0.000683***	-0.00407***	-0.00403***
	(-6.106)	(-2.905)	(-4.275)	(-6.061)
ai^2			0.00001**	0.00003***
			(1.987)	(6.108)
size		0.138***		0.139***
		(19.23)		(18.82)
lev		-1.523***		-1.491***
		(-31.96)		(-31.16)
roe		8.086***		8.049***
		(93.53)		(92.56)
age		-0.0675***		-0.0748***
		(-2.972)		(-3.278)
top		-0.0139		-0.0433
		(-0.280)		(-0.837)
board		-0.266***		-0.250***
		(-7.731)		(-7.004)
dual		-0.00355		-0.00879
		(-0.257)		(-0.628)
Constant	0.652	-1.130***	0.536***	-1.498***
	(1.526)	(-6.465)	(3.925)	(-4.987)
Industry Fixed	YES	YES	YES	YES
Area Fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Observations	27,984	27,984	27,984	27,984
R-squared	0.183	0.554	0.111	0.592

Note: ** means p value less than 0.05 (i.e., 10% significance level) *** means p value less than 0.01 (i.e., 1% significance level)

3.4 Robustness Test

This paper selects 2017 as a grouping point, mainly based on the release of the "New Generation of Artificial Intelligence Development Plan" in that year, marking that China's artificial intelligence has officially risen to the national strategy, and enterprise AI applications have entered the stage of accelerated development. In the same period, Liu Shuai (2025) pointed out that the frequency of AI-related words in corporate annual reports increased significantly, indicating that the impact of AI on corporate behavior had a significant stage difference before and after 2017.

Table 4 reports regression results grouped by time. Dividing the sample into two phases before and after 2017, we can find that: Artificial intelligence variables have a significant negative impact on enterprise income distribution in both periods, and the influence coefficient after 2017 (-0.00913) is greater than that before 2017 (-0.000847), indicating that with the accelerated development of artificial intelligence technology, its negative effect on enterprise labor income distribution is further enhanced.At the same time, the coefficient of AI^2 was positive and significant in both periods, continuously verifying the nonlinear "U-shaped" character of AI's influence[18].

Table 5 shows the regression results after excluding the municipalities' enterprises. After controlling the structure of the sample region, the coefficient of artificial intelligence is still negative and significant at 1% level, and the coefficient of ai^2 is still positive and significant, indicating that the regression results are not significantly affected by the characteristics of enterprises in a specific region and have strong robustness. In general, whether the samples are adjusted from the time dimension or the space dimension, the negative impact of artificial intelligence on enterprise income distribution and its nonlinear characteristics remain significant, which further enhances the reliability of the above conclusions.

Table 6 shows the regression results when replacing the explained variables. After replacing the income distribution index indis in the original model with indis2, the coefficient of artificial intelligence is still significantly negative in the two columns and is significant at the 1% level. Although the coefficient of ai ² is not significant, it has the same direction. It shows that the negative impact of artificial intelligence on income distribution is still stable under different index Settings. Compared with column (1) and column (2), the direction and significance of the coefficients of the control variables were basically the same, and the R^2 of the model was increased from 0.193 to 0.274, which enhanced the explanatory power. On the whole, the robustness test results of replacing the explained variables further verified the reliability of the main regression conclusion, and the inhibitory effect of artificial intelligence on enterprise income distribution was stable and consistent.

Table 4 Regression Grouped By Time

	(1)	(2)
VARIABLES	Prior to 2017	2017 onwards
ai	-0.000847***	-0.00913***
	(-3.364)	(-4.900)
ai^2		0.00008***
		(4.542)
size	0.114***	0.166***
	(13.44)	(11.59)
lev	-1.243***	-1.972***
	(-21.04)	(-22.33)
roe	7.898***	8.346***
	(77.35)	(48.45)
age	-0.151***	0.0811*
	(-5.326)	(1.747)
top	0.0132	0.0364
	(0.224)	(0.351)
board	-0.210***	-0.269***
	(-5.081)	(-4.063)
dual	-0.0382**	0.00929
	(-2.423)	(0.305)
Constant	-1.018***	-1.797***
	(-4.506)	(-5.001)
Industry Fixed	YES	YES
Area Fixed	YES	YES
Year fixed	YES	YES
Observations	16,200	9,971
R-squared	0.581	0.597

Table 5 Excludes Enterprises in Municipalities Directly under the Central Government

	(1)	(2)
VARIABLES	indis	indis
ai	-0.00110***	-0.00609***
	(-4.215)	(-8.313)
ai^2		0.00004***
		(7.662)
size	0.152***	0.154***
	(17.67)	(17.92)
lev	-1.550***	-1.551***
	(-28.40)	(-28.45)
roe	8.041***	8.045***
	(83.11)	(83.26)
age	-0.0812***	-0.0826***
	(-2.983)	(-3.041)
top	0.0867	0.0807
	(1.576)	(1.470)
board	-0.304***	-0.305***
	(-7.828)	(-7.871)
dual	-0.00145	-0.000209
	(-0.0947)	(-0.0136)
Constant	-1.364***	-1.406***
	(-6.732)	(-6.942)
Industry Fixed	YES	YES
Area Fixed	YES	YES
Year fixed	YES	YES
Observations	20,791	20,791
R-squared	0.576	0.577

Table 6 Replaces the Explained Variables

	(1)	(2)
VARIABLES	Indis2	Indis2
ai	-0.00534***	-0.00620***
	(-7.131)	(-2.720)
ai2		8.92e-06
		(0.628)
size	0.962***	1.006***
	(34.32)	(34.54)
lev	-0.398***	-0.574***
	(-2.977)	(-4.233)
roe	5.135***	4.558***
	(24.26)	(22.04)
age	-0.138*	-0.196**
	(-1.721)	(-2.358)
top	-2.070***	-1.427***
	(-11.90)	(-8.030)
board	0.530***	0.626***
	(4.192)	(4.850)
dual	0.333***	0.225***
	(6.874)	(4.582)
Constant	-14.62***	-7.356***
	(-19.74)	(-5.478)
Industry Fixed	YES	YES
Area Fixed	YES	YES
Year fixed	YES	YES
Observations	26,585	26,585
R-squared	0.193	0.274

3.5 Endogeneity Test

Considering that artificial intelligence variables (AI) may be affected by endogenous decision-making factors of enterprises, such as corporate governance structure, development strategy or income distribution mechanism, which may lead to endogenous bias in the model, this paper adopts the instrumental variable method (Two-Stage Least Squares (2SLS)) for endogenous test. Specifically, the one-stage lag term (L. artificial intelligence) of the artificial intelligence variable is selected as the tool variable, and the two-stage least squares estimation is carried out without changing the original model structure. The first-stage regression results show that L. artificial intelligence has a significant explanatory power for the current artificial intelligence variables, and the coefficient is significantly positive, and the Kleibergen-Paap rk Wald F statistic is much higher than the Stock-Yogo critical value, indicating that there is no weak tool problem in the instrumental variables. It has good relevance and effectiveness.

The results of the second stage regression show that in the model after the use of instrumental variables, the coefficient of artificial intelligence variable artificial intelligence is still negative, and the square term ai^2 is still positive, and both are statistically significant, indicating that the negative influence of artificial intelligence on enterprise income distribution and its "U-shaped" feature are still valid after controlling the endogeneity. The results as Table 7 are consistent with the direction of baseline regression, which further strengthens the causal inference basis of AI's impact on enterprise income distribution and verifies the robustness and reliability of the previous empirical conclusions.

Table 7 Endogeneity Test

	(1)	(2)	(3)	(4)
VARIABLES	Phase I	Phase II	Phase I	Phase II
L.ai	-0.00201***		-0.00353***	
	(-8.029)		(-8.389)	
ai		-0.00206***		-0.00437**
		(-6.176)		(-2.377)
ai^2			0.00001***	0.00003**
			(4.374)	(2.403)
size	0.170***	0.169***	0.170***	0.126***
	(21.00)	(23.62)	(21.02)	(18.03)
lev	-1.067***	-1.070***	-1.065***	-1.421***
	(-21.21)	(-23.77)	(-21.18)	(-32.54)
roe	8.131***	8.134***	8.131***	8.192***
	(90.20)	(125.7)	(90.25)	(133.2)
age	0.226***	0.223***	0.226***	-0.0547**
	(7.847)	(8.276)	(7.832)	(-2.141)
top	0.111*	0.105**	0.110*	-0.0251
	(1.925)	(2.013)	(1.904)	(-0.504)

board	-0.271***	-0.272***	-0.271***	-0.274***
	(-6.327)	(-6.915)	(-6.337)	(-7.451)
dual	-0.0259	-0.0247	-0.0269*	-0.00726
	(-1.645)	(-1.439)	(-1.709)	(-0.455)
Constant	-3.009***	-3.555***	-3.014***	-1.364***
	(-9.969)	(-10.01)	(-9.978)	(-7.388)
Kleibergen - Paap rk Wald F	1018.711		975.837	
Stock-Yogo critical values	16.38		16.38	
Industry Fixed	YES	YES	YES	YES
Area Fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Observations	23,718	23,718	23,718	23,718
R-squared	0.528	0.528	0.528	0.563

3.6 Heterogeneity Analysis

In order to further explore whether the impact of artificial intelligence on enterprise income distribution is different due to different organizational structures of enterprises, this paper divides the samples into state-owned enterprise group and non-state-owned enterprise group according to whether the enterprises are state-owned enterprises, and conducts regression analysis respectively, as shown in Table 8. From the results, the coefficient of the artificial intelligence variable (AI) in the sample of non-state-owned enterprises is negative and significant at the 1% level, and the AI ² coefficient is positive and significant, indicating that in non-state-owned enterprises, AI has a significant negative impact on enterprise income distribution and a "U-shaped" feature. In contrast, in state-owned enterprises, the coefficients of both AI and AI ² are not significant, indicating that the effect of AI on income distribution in such enterprises is relatively weak or unstable.

This result may be related to the differences in organizational goals and incentive mechanisms of different ownership enterprises. Compared with non-state-owned enterprises that focus on efficiency and cost control, state-owned enterprises usually emphasize social responsibility and employee protection, and their impact on employee income distribution in the process of promoting the application of artificial intelligence is relatively small. Non-state-owned enterprises tend to be more flexible in human resource management, and the impact of artificial intelligence technology on their organizational structure and employment mode is more direct, so the negative effect is more significant. Heterogeneity analysis further shows that the type of firm plays an important moderating role in the relationship between AI and income distribution.

Table 8 Heterogeneity Analysis

	(1)	(2)	(3)	(4)
VARIABLES	state enterprise	non-state enterprise	state enterprise	non-state enterprise
ai	0.000697	-0.000645***	-0.00137	-0.00614***
	(0.918)	(-2.588)	(-0.815)	(-8.429)
ai^2			1.72e-05	3.93e-05***
			(1.210)	(8.464)
size	0.172***	0.137***	0.173***	0.140***
	(15.65)	(13.33)	(15.66)	(13.59)
lev	-1.676***	-1.411***	-1.674***	-1.406***
	(-20.86)	(-23.54)	(-20.84)	(-23.50)
roe	7.905***	8.103***	7.912***	8.109***
	(54.82)	(74.37)	(54.92)	(74.58)
age	0.0283	-0.0836***	0.0286	-0.0851***
	(0.656)	(-3.011)	(0.663)	(-3.070)
top	0.0441	0.190***	0.0431	0.189***
	(0.514)	(3.018)	(0.502)	(2.997)
board	-0.215***	-0.189***	-0.216***	-0.189***
	(-3.600)	(-4.482)	(-3.615)	(-4.489)
dual	0.104***	-0.0601***	0.104***	-0.0613***
	(2.723)	(-3.908)	(2.727)	(-3.990)
Constant	-2.158***	-1.197***	-2.172***	-1.265***
	(-8.043)	(-4.133)	(-8.061)	(-4.374)
Industry Fixed	YES	YES	YES	YES
Area Fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Observations	10,499	17,485	10,499	17,485
R-squared	0.566	0.564	0.566	0.566

At the same time, we will also explore whether the impact of artificial intelligence on the income distribution of enterprises varies according to the industries in which enterprises are located, and divide the samples into manufacturing enterprise group and non-manufacturing enterprise group according to whether the enterprises belong to the manufacturing industry, and conduct regression analysis respectively, as shown in Table 9. According to the regression results, the coefficient of artificial intelligence variable (ai) in manufacturing enterprises is significantly negative, and the coefficient of ai² is positive and significant, indicating that artificial intelligence has a significant negative impact on income distribution in manufacturing enterprises and a "U-shaped" feature. In non-manufacturing enterprises, the coefficients of ai and ai² are not significant, indicating that the influence of AI on income distribution in such enterprises is weak or has not formed a stable pattern.

This result may be related to the characteristics of manufacturing enterprises easier to achieve process standardization, high job duplication, and large artificial intelligence replacement space. AI technology is more direct and deeper in the manufacturing process, resulting in a more obvious impact on the labor cost structure and income distribution mode of enterprises. In contrast, artificial intelligence in non-manufacturing enterprises exists more in the form of decision-making aid or service tools, and its effect on the reconstruction of traditional labor relations is limited, so its impact on income distribution is not significant enough. The heterogeneity analysis further shows that the industry in which the firm is located plays a key moderating role in the income distribution path affected by AI.

Table 9 Heterogeneity Analysis (Industry Nature)

	(1)	(2)	(3)	(4)
VARIABLES	Non-manufacturing enterprises	manufacturer	Non-manufacturing enterprises	manufacturer
ai	0.000667	-0.00171***	-0.00151	-0.00558***
	(1.203)	(-4.858)	(-0.965)	(-6.479)
ai2			0.0000218	0.00003***
			(1.291)	(4.925)
size	0.163***	0.119***	0.148***	0.121***
	(12.92)	(17.00)	(5.545)	(17.27)
lev	-1.545***	-1.509***	-1.066***	-1.511***
	(-18.34)	(-36.02)	(-9.853)	(-36.08)
roe	8.456***	7.863***	8.616***	7.863***
	(71.22)	(131.7)	(84.00)	(131.7)
age	0.0690	-0.120***	0.867***	-0.120***
	(1.425)	(-5.152)	(4.847)	(-5.157)
top	0.291***	-0.190***	1.191***	-0.192***
	(3.067)	(-3.973)	(6.585)	(-4.012)
board	-0.408***	-0.182***	-0.162*	-0.182***
	(-5.965)	(-5.051)	(-1.730)	(-5.056)
dual	-0.0758**	0.0228	-0.0554	0.0233
	(-2.230)	(1.579)	(-1.519)	(1.615)
Constant	-2.209***	-1.084***	-4.953***	-1.120***
	(-6.910)	(-6.438)	(-6.264)	(-6.655)
Industry Fixed	YES	YES	YES	YES
Area Fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Observations	10,104	17,880	10,104	17,880
R-squared	0.486	0.595	0.486	0.596

4 CONCLUSIONS AND POLICY RECOMMENDATIONS

According to the research results of this paper, aiming at the impact of artificial intelligence technology on enterprise income distribution, It is necessary to provide necessary financial support for small enterprises in a vulnerable position to break the financial difficulties encountered in their development process. In particular, the government and financial institutions can jointly issue loans to small businesses at lower interest rates; Or the government will give certain financial subsidies to reduce the initial investment cost of small enterprises in artificial intelligence research and development, so as to stimulate their technological innovation power in artificial intelligence; Or for the use of artificial intelligence technology for large enterprises to reduce tax burdens, in order to achieve the purpose of reducing operating costs and so on. All of the above methods are conducive to the development and growth of small enterprises and effectively compensate for the problem of income polarization caused by technological innovation.

At the same time, the existence of the above factors may also lead to the unfair phenomenon of income distribution in state-owned enterprises. Specifically, it is reflected in the following two aspects :(1) Enterprise executives and talents who master core technologies can share more of the economic benefits brought by artificial intelligence technology. (2) The growth rate of welfare benefits received by ordinary workers may lag behind the first two groups of people. In addition, compared with non-state-owned enterprises, state-owned enterprises have stronger financing ability to support the occurrence of large-scale artificial intelligence investment activities, but their income distribution will inevitably appear a certaindegree of imbalance. In non-state-owned enterprises, the decision-making mechanism is relatively complex, and the management may face greater pressure from market competition. This structure encourages non-state-owned enterprises to pay more attention to cost-effectiveness and productivity improvement in the introduction and application of AI technology. Due to the limited financing capacity, the artificial intelligence investment of non-state-owned enterprises is often relatively cautious, resulting in a relatively balanced income distribution structure. Especially in the case of limited scope and depth of technology application, the income of ordinary employees is relatively small but can maintain a certain stability.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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APPENDIX

Appendix 1 Word Frequency Ratio of Artificial Intelligence Keyword Classification

Artificial Intelligence Classification	Total word frequency	Byword	Word frequency
Autonomous Driving Class	7710	automatic driving	5163
		unpiloted	2272
		pattern recognition	275
Core technology category	54561	artificial intelligence (AI)	48626
		deep learning	2750
		data mining	2165
Intelligent Applications	2915	business intelligence (BI)	1181
		smart finance	645
		intelligent banking	585
computing platform class	48171	cloud computing	29942
		big data analytics	5988
		Big Data Platform	4346
Computer vision class	6623	virtual reality	3207
		image recognition	1216

		computer vision	1118
else	87932	Internet of Things (IoT)	60293
		smart home	12220
		face recognition	2874

Note: Each category is represented by the three keywords with the highest word frequency ratio