ISSN 2616-5902 Vol. 8, Issue 8: 51-56, DOI: 10.25236/AJBM.2026.080807

Research on the Impact of Artificial Intelligence Development on Income

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Abstract: *Against the backdrop of rapid development in artificial intelligence (AI) technology, this paper uses panel data from 31 provinces in China from 2008 to 2023 to explore the impact of AI technology on residents' labour income. The study finds that AI technology can significantly promote the growth of residents' labour income. This conclusion remains robust after separately excluding early samples and municipalities. Furthermore, the labour income of residents in central and low-income regions is significantly affected by AI technology. Based on these findings, this paper proposes policy recommendations: constrain and regulate the development of AI technology to ensure its benefits are shared by the people. Central regions should strengthen the popularisation of AI technology; western and northeastern regions should address the shortcomings in AI application; and eastern regions should optimise their distribution mechanisms. Increased policy and resource allocation should be directed towards low-income regions to leverage AI technology and narrow regional income gaps.*

Keywords: *Artificial intelligence technology, residents' labour income, labour skills structure*

1. Introduction

With the rapid development of artificial intelligence (AI) technology, it has become a crucial driving force for socio-economic transformation and changing development models. AI technology is not only reshaping social production methods and industrial structures but also profoundly impacting the distribution of residents' labour income. The impact of AI technology on residents' labour income distribution is mainly concentrated in two aspects: First, from the perspective of industrial restructuring, AI technology will gradually eliminate traditional jobs with high repetition and low technical barriers, while simultaneously creating more competitive, high-skilled jobs, thus promoting adjustments to the skill structure of the workforce and optimising income distribution. Second, AI technology has a significant knowledge spillover effect; its application and impact boundaries are constantly expanding. Through deep integration and efficient collaboration with various jobs, it can significantly improve production and work efficiency, helping workers upgrade their skills and further amplifying labour value, creating greater income growth opportunities for workers. While reshaping production methods and industrial structures, the development of AI technology also poses multiple challenges to individual skills and the labour market. Against this backdrop, a thorough theoretical and empirical analysis of the impact of AI technology on residents' labour income has become a problem of both theoretical and practical significance.

A review of existing literature reveals that current research on AI technology primarily focuses on both macro and micro levels. From a macro perspective, existing studies mainly explore the relationship between AI technology development and economic growth and productivity improvement. As a general-purpose technology, AI can significantly improve productivity and achieve technology inclusion under sound policies and regulations[1]. From an employment perspective, the adoption of AI technology may create new job opportunities in software development, but it may also replace or even reshape the jobs of low- and medium-skilled workers[2]. Furthermore, AI's contribution to total factor productivity improvement is low and that it will widen the gap between capital income and labour income[3]. At the micro level, research mainly focuses on household income. Current research on the impact of AI technology development on household income presents two main viewpoints: On the one hand, some scholars argue that there is a significant positive statistical correlation between AI technology application, AI capital stock accumulation, and wealth inequality[4]. Other researchers argues that AI technology may widen the urban-rural income gap, especially in regions with better digital infrastructure, more government support, and more advanced industrial technologies[5]. On the

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other hand, artificial intelligence will exacerbate wealth inequality in the short term, while the long-term outcome depends on the extent of AI's impact across different technological fields and may reduce income inequality[6]. Some studies argue that, mechanistically, AI increases average wages through three mechanisms: improving productivity, crowding out low-wage routine jobs, and creating high-wage creative and social jobs, but ultimately reduces wage inequality between executives and ordinary employees[7].

Compared with previous studies, this paper has two main innovations. First, it uses provincial panel data from China from 2008 to 2023 and employs a two-way fixed effects model to empirically examine the impact of AI technology development on residents' income, providing empirical evidence for further leveraging AI technology to promote residents' income. Second, it verifies the rationality of the results based on actual circumstances, providing a basis for government and enterprises to formulate policies that balance technological development and residents' income. The subsequent structure of this paper is as follows: Part II presents the relevant theoretical analysis; Part III introduces the data sources and model construction; Part IV presents the empirical results of the data analysis, including benchmark regression results and heterogeneity analysis; and finally, Part V provides conclusions and corresponding policy recommendations.

2. Theoretical Analysis

Currently, the main view in economics is that the development of AI technology affects residents' labour income primarily through multiple mechanisms, including technological progress, industrial restructuring, and labour market redistribution.

First, from the perspective of the impact of technological progress on total production, AI technology enhances enterprise productivity by facilitating new production methods[8]. AI technology has high technological penetration, can continuously evolve, and can complement existing technologies. This allows AI to be integrated into enterprise production systems, changing production paradigms and thus driving improvements in enterprise production efficiency. The characteristics of AI technology enable it to improve the efficiency of enterprise factor allocation and optimise production organisation. By embedding data and algorithms into production processes, it overcomes the shortcomings of traditional methods that are limited by fixed technological boundaries and rigid factor combination patterns, enabling real-time monitoring and dynamic adjustment of resource inputs, thereby optimising enterprise production paradigms. The paradigm shift in production brought about by the introduction of AI technology effectively alleviates efficiency losses caused by information asymmetry, allowing capital, labour, and data to be combined more suitably, achieving higher output efficiency with a given input level. The transformation of production paradigms by artificial intelligence technology is not only reflected in the optimisation of production processes, but also in the overall adjustment of production organisation methods. The application of artificial intelligence technology requires enterprises to adjust their management models, business processes, and organisational structures. This adjustment of production organisation methods and the optimisation of production processes work together to increase the capital income of enterprises and ultimately affect residents' labour income.

The application of AI technology has led to higher skill requirements for workers in various production stages. This skill bias causes AI to replace most low- and medium-skilled workers and create some high-skilled jobs, thus altering the employment structure[9]. Specifically, the impact of AI on the employment structure is mainly reflected in two aspects. First, AI has a significant substitution effect on low- and medium-skilled workers. These workers primarily perform routine tasks with clear rules and high repetition. When AI and automated systems can complete such tasks at a lower marginal cost, companies will systematically substitute technological input for labour input, leading to a contraction in the demand for low- and medium-skilled labour. Second, AI technology creates more high-skilled jobs. The core characteristic of these jobs is that their work focuses on non-routine abstract cognitive tasks such as abstract reasoning and complex decision-making, which are difficult for AI to perform autonomously. Therefore, companies must create many new high-skilled jobs to develop, train, and monitor AI systems. This shift in labour demand driven by the skill bias of artificial intelligence (AI) technology ultimately leads to a systemic adjustment in the employment structure: the demand for high-skilled labour spurred by AI technology is rising, while the demand for low- and medium-skilled labour, primarily engaged in procedural tasks, is shrinking. Against this backdrop, the distribution of labour resources changes, and the relative positions of different skill groups in the income distribution pattern also shift accordingly.

Finally, from the perspective of wage determination mechanisms, the application of AI technology

ISSN 2616-5902 Vol. 8, Issue 8: 51-56, DOI: 10.25236/AJBM.2026.080807

will enhance both capital and skill premiums[10]. The application of AI technology has brought about a transformation in production paradigms. On the one hand, the deep integration of humans and machines significantly improves overall enterprise production efficiency. After AI takes over many programmed and routine tasks, it not only drastically reduces marginal production costs but also optimises decision-making processes and resource allocation, achieving increasing returns to scale. This increase in production efficiency directly drives up the share of capital income, systematically amplifying the enterprise capital premium. On the other hand, the application of AI technology places higher demands on workers' skill levels. This requires workers to improve their skills to adapt to new tasks and human-machine collaborative production models, thus increasing workers' marginal productivity. Improved enterprise production levels further drive-up workers' wages, ultimately leading to a continuous expansion of the skill premium in the wage distribution structure and a widening income gap between high-skilled and low-skilled workers. Influenced by these mechanisms, skill premiums and capital premiums rise simultaneously, resulting in a trend in the income structure of residents where the income growth of high-skilled groups is faster than that of other groups, and capital income grows faster than labour income.

In conclusion, this paper proposes the hypothesis that the development of AI technology can promote industrial development and ultimately increase residents' labour income.

3. Model Setting

This paper uses a two-way fixed effects model to examine the impact of AI technology on residents' labour income. The model is set as follows:

$$Inc_{it} = \lambda_0 + \lambda_1 AI_{it} + \gamma X_{it} + u_i + \eta_t + \varepsilon_{it}$$

Among them, the dependent variable Inc_{it} represents the income level of residents in province *i* in year *t*, measured by ln (total wages of urban employees); AI_{it} is the core explanatory variable, representing the level of AI technology development in province *i* in year *t*, measured by ln (number of artificial intelligence patents + 1); X_{it} is a series of control variables; u_i is the individual fixed effect; η_t is the time fixed effect; and ε_{it} is the random error term.

Based on existing research, this paper proposes the following control variables: 1. Education development level (*Edu*), measured by ln (number of students enrolled in regular institutions of higher learning); 2. Logistics development level (*Logi*), measured by ln (freight turnover); 3. Economic development level (*GDP*), measured by ln (regional GDP index); 4. Urbanization rate (*Urban*), calculated as urban population/year-end resident population. Descriptive statistics for each variable are shown in Table 1.

Table 1 Descriptive statistics.

Variables	N	mean	sd	min	max
Inc	496	7.7511	1.0341	4.4967	10.1761
AI	496	5.8555	2.1556	0.0000	10.3094
Edu	496	4.1717	0.9685	1.0784	5.6891
Logi	496	8.1033	1.1681	3.5650	10.5092
GDP	496	4.6814	0.0314	4.5497	4.7639
Urban	496	0.5778	0.1383	0.2192	0.8958

4. Empirical Results

4.1. Benchmark Regression

This paper employs a two-way fixed effects model, using data from 31 provinces in China from 2008 to 2023, to empirically test whether AI technology can promote the growth of residents' labour income. Table 2 shows the baseline regression results of the relationship between the development level of AI technology and residents' income level. Column (1) does not include control variables or fixed effects, and the regression results are significant at the 1% level. Column (2) incorporates two-way fixed effects of province and year, and remains significant at the 1% level. Column (3) further

ISSN 2616-5902 Vol. 8, Issue 8: 51-56, DOI: 10.25236/AJBM.2026.080807

incorporates control variables, and AI remains significant at the 1% level, indicating that AI technology has indeed significantly improved residents' labour income level. Overall, for every unit increase in the development level of AI technology, residents' income level increases by an average of approximately 5.46%.

Table 2 Benchmark regression results of AI technology level and residents' income level.

	(1)	(2)	(3)
	Inc	*Inc*	*Inc*
AI	0.4489*** (0.0076)	0.0918*** (0.0146)	0.0546*** (0.0153)
Edu			-0.075 (0.0626)
Logi			0.1636*** (0.0172)
GDP			-0.1290 (0.3791)
Urban			0.2735 (0.2977)
Province FE	N	Y	Y
Year FE	N	Y	Y
N	496	496	496
R^2	0.8754	0.9896	0.9914

4.2. Robustness Checks

To verify the reliability of the benchmark results, the following robustness checks were performed:

1) Considering that municipalities directly under the central government receive greater policy support than other provinces, and that their artificial intelligence technology development level and residents' income level are relatively higher, a robustness check was conducted by removing the samples from the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing to more comprehensively examine the reliability of the conclusions. Column (1) in Table 3 shows the regression results after removing the municipalities directly under the central government. *AI* is significant at the 5% level, indicating that the positive impact of artificial intelligence technology on residents' income is not limited to the municipalities directly under the central government with high development levels.

2) Considering that the impact of artificial intelligence technology on residents' income was relatively weak in the early stages of its development, to avoid interference from early data, this paper removed the samples from 2008-2009 and re-performed the regression analysis. Column (2) in Table 3 shows the regression results after removing the early data. *AI* is significant at the 1% level. In the baseline regression without removing the early data, the t-statistic is 3.57, while in the regression results after removing the early data, the t-statistic is 4.13. Therefore, after the development of artificial intelligence technology, its impact on residents' income is more significant.

Table 3 Robustness checks results of AI technology level and residents' income level.

	(1)	(2)
	Inc	*Inc*
AI	0.0378** (0.0151)	0.0684*** (0.0166)
Edu	-0.3412 (0.0609)	-0.0139 (0.0716)
Logi	0.2102*** (0.0187)	0.1420*** (0.0182)
GDP	-0.0860 (0.3849)	-0.0013 (0.4078)
Urban	2.8339*** (0.4109)	0.2532 (0.3481)
Province FE	Y	Y
Year FE	Y	Y
N	432	434
R^2	0.9924	0.9914

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4.3. Heterogeneity Analysis

The impact of different levels of artificial intelligence technology development on residents' labour income in different regions is influenced by factors such as policy and economic development level. Therefore, this paper conducts the following heterogeneity analysis:

1) Based on the division of the eastern, central, western and northeastern regions by the National Bureau of Statistics of China, the sample was divided into four major regions and regression analysis was performed separately. Table 4 lists the regression results (1) to (4), among which only the central region is significant. The central region is mainly supported by manufacturing and agricultural production. Artificial intelligence technology plays a role in improving efficiency and supplementing production capacity, and has a significant effect on the transformation of industries in the central region. It can directly drive employment expansion and productivity improvement, and therefore has a significant promoting effect on residents' income.

2) Regions with different levels of economic development have varying abilities to translate the optimization of artificial intelligence technology into actual development benefits and improve residents' income levels. Therefore, this paper uses the median income level as the dividing line to divide the sample into high-income and low-income regions for further heterogeneity analysis. Column (5) in Table 4 shows the regression results for high-income regions, which are significant at the 10% level, while column (6) shows the regression results for low-income regions, which are significant at the 1% level. In low-income regions, the application of artificial intelligence technology can address shortcomings in production efficiency and broaden employment channels, resulting in a highly significant positive increase in residents' income.

Table 4 Heterogeneity analysis results of AI technology level and residents' income level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Inc	*Inc*	*Inc*	*Inc*	*Inc*	*Inc*
AI	-0.052 (0.0339)	0.1930*** (0.0402)	0.0237 (0.0151)	0.0466 (0.0299)	0.0576* (0.0343)	0.0468*** (0.0172)
Edu	-0.2298 (0.1475)	-1.0592*** (0.1991)	-0.0765 (0.0591)	1.8294*** (0.2612)	-0.1012 (0.1269)	-0.2236** (0.1119)
Logi	0.1623*** (0.0272)	-0.1102** (0.0533)	0.3256*** (0.0336)	-0.0393 (0.0383)	0.1751*** (0.0282)	0.1571*** (0.0223)
GDP	-1.1417 (0.8440)	-0.5936 (0.5790)	0.1407 (0.4855)	1.3607* (0.6635)	0.4710 (0.5083)	-0.1922 (0.5690)
Urban	-0.5538 (0.4328)	7.3452*** (1.7285)	3.2068*** (0.5758)	-1.1847 (1.2843)	-0.1291 (0.4651)	3.7256*** (0.5959)
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	160	96	192	48	248	246
R^2	0.9929	0.9893	0.9955	0.9949	0.9826	0.9889

5. Conclusions and Policy Recommendations

This paper uses a two-way fixed effects model to empirically examine the impact of AI technology on residents' labour income. The baseline regression results show that, after introducing province and year effects and a series of control variables, AI technology has a significant positive impact on residents' labour income. After robustness checks by separately removing samples from municipalities and earlier data, AI technology still has a significant positive impact on residents' labour income, indicating that the baseline regression results are stable and reliable. Finally, heterogeneity tests were conducted according to region and income level, showing that the impact of AI technology on residents' labour income is significant in central and low-income regions.

In conclusion, AI technology can promote the increase of residents' labour income. The empirical research in this paper has the following policy implications:

1) AI technology can significantly boost residents' labour income. Therefore, the government needs to formulate corresponding policies to regulate, promote, and constrain its development, ensuring that the benefits of AI development reach all sectors of society while the technology itself develops rapidly.

2) In the central region, AI technology has a significant impact on residents' labour income. Continued efforts should be made to strengthen the popularization of AI technology and further

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enhance its contribution to income growth. In the eastern region, the impact is insignificant and even negative. The distribution mechanism should be optimized to stabilize residents' income. In the western and northeastern regions, the effect is not significant. The shortcomings in the application of artificial intelligence should be addressed to enhance its ability to drive income growth.

3) In low-income areas, AI technology has a significant impact on residents' income. Increased policy and resource allocation should be provided to low-income areas to leverage AI technology and narrow the income gap, promoting coordinated income growth across different regions.

References

[1] Ernst, E., Merola, R. and Samaan, D. (2019) Economics of artificial intelligence: Implications for the future of work. IZA Journal of Labor Policy, 9, 1-35.

[2] Frank, M.R., Autor, D., Bessen, J.E. et al. (2019) Toward understanding the impact of artificial intelligence on labor. Proceedings of the National Academy of Sciences, 116, 6531-6539.

[3] Acemoglu, D. (2025) The simple macroeconomics of AI. Economic Policy, 40, 13-58.

[4] Skare, M., Gavurova, B. and Burić, S.B. (2024) Artificial intelligence and wealth inequality: A comprehensive empirical exploration of socioeconomic implications. Technology in society, 79, 102719.

[5] Wang, Y. (2025) The Impact of Artificial Intelligence on the Urban-Rural Income Gap in China. Proceedings of the 2025 4th International Conference on Public Service, Economic Management and Sustainable Development (PESD 2025), 41.

[6] Liu, F. and Liang, C. (2025) Analyzing wealth distribution effects of artificial intelligence: A dynamic stochastic general equilibrium approach. Heliyon, 11.

[7] Wu, Y., Lin, Z., Zhang, Q. et al. (2024) Artificial intelligence, wage dynamics, and inequality: Empirical evidence from Chinese listed firms. International Review of Economics & Finance, 96, 103739.

[8] Czarnitzki, D., Fernández, G.P. and Rammer, C. (2023) Artificial intelligence and firm-level productivity. Journal of Economic Behavior & Organization, 211, 188-205.

[9] Acemoglu, D., Autor, D., Hazell, J. et al. (2022) Artificial intelligence and jobs: Evidence from online vacancies. Journal of Labor Economics, 40, S293-S340.

[10] Wang, S., Wang, Y. and Li, C. (2024) AI-driven capital-skill complementarity: Implications for skill premiums and labor mobility. Finance Research Letters, 68, 106044.