ISSN: 2688-9323

The Impact of Artificial Intelligence Technology on Occupational Mobility in China

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Abstract

Based on data from the China Family Panel Studies (CFPS) for 2016–2022, this paper systematically examines the impact of artificial intelligence (AI) technology on occupational mobility in China and its underlying mechanisms. The findings reveal that AI technology significantly promotes occupational mobility among the labor force; for every one-unit increase in AI technology, the probability of occupational mobility rises by an average of approximately 4.90 percentage points. Mechanism analysis indicates that AI technology primarily influences occupational mobility through human capital and income effects: technological progress drives adjustments in the structure of skill demand and facilitates occupational transitions, while income growth increases job attachment, thereby curbing some occupational mobility. Heterogeneity analysis revealed that AI technology exerts a stronger promotional effect on occupational mobility among women, non-agricultural household registrants, young people, and the labor force in central and western regions. Further research indicates that AI technology not only deepens the extent of occupational mobility but also influences its direction and employment perceptions; individuals with stronger digital skills are more likely to achieve upward occupational mobility, though their job satisfaction declines in the short term.

Keywords

Artificial Intelligence Technology; Occupational Mobility; Human Capital; Income Effect; Employment Perceptions.

1. Introduction

Human society is currently facing a new round of technological revolution and industrial transformation. With theoretical breakthroughs in the field of artificial intelligence (AI) and the rapid expansion of its application scenarios, AI technology is gradually integrating into all areas of economic and social development, becoming a key driver of high-quality economic growth. In 2017, the State Council issued the “Development Plan for the New Generation of Artificial Intelligence,” elevating AI to a national strategic priority. In 2022, the China Academy of Information and Communications Technology (CAICT) released the “Artificial Intelligence White Paper,” noting that AI is entering a new phase characterized by “innovation-driven development, deepened application, and standardized growth.” The 2025 “Artificial Intelligence Index Report” indicates that, as of 2023, 69.7% of global AI patent grants originated from China, with the United States ranking second at 14.2%. Data from the World Intellectual Property Organization shows that between 2014 and 2023, global patent applications for generative AI exceeded 50,000, with China submitting over 38,000-ranking first in the world. Leveraging vast data resources, enormous market potential, and high internet penetration rates, China has risen to the forefront of global AI development and is accelerating its transition into the intelligent era.

ISSN: 2688-9323

As AI technology is widely applied across various industries, production efficiency and economic benefits have significantly improved; however, this has also had a profound impact on the labor market, sparking extensive discussions regarding its effects on employment. The National Occupational Classification Directory, serving as a key reference reflecting China's occupational structure, has been continuously revised since its release in 1999: the 2015 edition introduced green occupation labels, while the 2022 edition added 97 digital occupations and 134 green occupations, innovatively labeling digital occupations. Adjustments to the occupational structure indicate that, with technological progress and industrial upgrading, the composition and nature of occupations in Chinese society are undergoing profound changes. A review of the *National Occupational Classification* reveals that new occupations such as data analysis and processing engineers, artificial intelligence engineers, and internet marketing specialists are continuously emerging, while traditional occupations such as telegraph operators and lead typesetters are gradually disappearing.

The report of the 20th National Congress of the Communist Party of China proposed "strengthening employment-first policies to promote high-quality and full employment." In 2024, the Central Committee of the Communist Party of China and the State Council issued the "Opinions on Implementing the Employment-First Strategy to Promote High-Quality and Full Employment," emphasizing the need to resolve structural employment contradictions and promote the coordinated development of employment quality and scale. At the same time, Sino-U.S. trade frictions have had a dual impact on China's job market, involving both short-term shocks and long-term structural adjustments. On the one hand, traditional manufacturing and foreign trade sectors face employment pressures; on the other hand, strategic emerging industries such as semiconductors, new energy, and artificial intelligence are developing rapidly, leading to a significant increase in demand for highly skilled positions. By implementing the employment-first strategy, China is not only stabilizing employment but also placing greater emphasis on fostering new sources of employment growth through technological innovation and industrial upgrading, while enhancing the adaptability of the labor market through skills training and flexible employment policies.

The development of artificial intelligence technology has spawned a large number of new industries, business models, and occupations, expanding employment opportunities, but it has also created a substitution effect for some traditional jobs. The emergence of new occupations and the disappearance of traditional ones have forced workers to face active or passive occupational mobility. China's labor market has unique characteristics in terms of demographic structure, the urban-rural dichotomy, government intervention, and the social security system, and the phenomenon of employment polarization is becoming increasingly evident. Against the backdrop of rapid AI development, how to facilitate a smooth transition for the workforce and achieve high-quality employment has become an urgent and critical practical issue. Therefore, studying the impact of AI technology on occupational mobility in China holds significant theoretical and practical importance.

The potential marginal contributions of this paper are as follows: First, at the level of mechanisms, this paper elaborates on the pathways through which AI technology influences occupational mobility from the dual dimensions of human capital and income effects, examining how AI technology shocks affect labor force mobility and thereby enriching the theoretical understanding of the relationship between technological shocks and occupational mobility. Second, regarding heterogeneity analysis, this paper examines differences in gender, household registration status, and age at both the individual and regional levels. By distinguishing between different regions, it analyzes variations in occupational mobility against the backdrop of uneven AI development, thereby providing empirical evidence for optimizing group- and region-oriented policies. Third, regarding the research perspective, this study utilizes microdata from the China Family Panel Studies (CFPS) to characterize the quality of

ISSN: 2688-9323

occupational mobility in terms of mobility intensity and direction. By introducing indicators of subjective employment perceptions, it broadens the research perspective on the quality effects of occupational mobility in the context of AI, providing empirical evidence to promote high-quality and full employment, as well as to advance social equity and common prosperity.

2. Literature Review

2.1. Methods for Measuring Artificial Intelligence Technology

With the rapid development of artificial intelligence technology, China has achieved numerous significant breakthroughs in this field, and academia and research institutions are paying increasing attention to measuring the level of AI development. At the macro level, institutions such as the Wuzhen Think Tank, the China Academy of Information and Communications Technology (CAICT), and the National Research Center for Industrial Information Security have successively conducted comprehensive assessments of the AI industry's development across multiple dimensions. Additionally, scholars have developed comprehensive evaluation systems for AI by examining both static and dynamic aspects, focusing on the AI development environment and industrial competitiveness (Gu Guoda and Ma Wenjing, 2021); AI technology and product capabilities, environmental support, and knowledge creativity (Geng Ziheng et al., 2021); as well as human resources and economic output (Chen Zhi et al., 2022).

At the micro level, existing studies often use industrial robot installation density and stock data as proxy variables for AI technology (Wang Yongqin et al., 2020; He Xiaogang et al., 2023), while some scholars utilize computer and ICT capital investment for measurement (Michaels et al., 2014). However, industrial robot indicators struggle to comprehensively cover the application domains of AI technology, and the broad scope of ICT capital investment makes it difficult to precisely identify AI technology. In contrast, AI patents better reflect technological advancements with commercial value; consequently, some studies use the number of granted AI patents or patents per capita to measure the level of AI development (Chen Nan and Cai Yuezhou, 2022; Wang Linhui et al., 2023).

In addition to the level of AI development, AI penetration rates have also received widespread attention, as they reflect the extent of AI application in the economy and society (Gofman & Jin, 2020). At the firm level, existing research has constructed indicators of corporate AI application and penetration by analyzing the text of listed companies' annual reports, patents, and job postings (Yao Jiaquan et al., 2024; Chen Lin et al., 2024).

2.2. Theoretical Research on the Impact of AI Technology on Labor Mobility

Classical economics holds that technological progress can both create jobs and lead to unemployment. Adam Smith emphasized that technological progress can enhance productivity; David Ricardo proposed that technological progress may lead to structural unemployment; while Sismondi and Malthus argued that the replacement of labor by machines and insufficient effective demand would exacerbate unemployment. Marx further pointed out that the replacement of labor by machines would create an "industrial reserve army," intensifying competition in the labor market.

Neoclassical theory posits that while technological progress may displace labor in the short term, it can increase employment in the long term by expanding output and creating new demand. Schumpeter proposed that technological progress triggers "polarization" in the labor market, with high-skilled workers benefiting while low-skilled workers face greater risks of unemployment.

With the development of task models, research on the impact of technological progress on occupational mobility has continued to deepen. Autor et al. (2003) proposed the comparative advantages of technology and labor in different tasks, providing an important analytical framework for studying the impact of automation technology on the labor market. Acemoglu and Restrepo (2018) further proposed a theory where technological substitution and complementarity coexist, arguing that artificial intelligence (AI) will both replace certain labor tasks and create new tasks and jobs, thereby driving skill premiums and employment growth. Domestic research also indicates that AI technology exerts a stronger substitution effect on medium-skilled workers, thereby exacerbating employment polarization while simultaneously driving industrial upgrading and industrial convergence (Wang Yongqin et al., 2023).

2.3. Empirical Studies on the Impact of AI Technology on Occupational Mobility

Existing research indicates that AI technology exerts labor substitution effects, job creation effects, and productivity effects. Some studies suggest that the application of AI and robotics increases the risk of occupational substitution, with low-skilled, repetitive, and routine jobs being particularly vulnerable to replacement (Frey et al., 2017; Zhao He et al., 2023). Against the backdrop of industrial digitization, the penetration of robots has significantly increased the probability of occupational mobility among production workers (Wei Jiahui and Gu Naihua, 2024).

At the same time, AI technology also creates new employment opportunities. With capital accumulation and technological upgrades, the integration of AI with highly skilled workers can generate more new positions (Acemoglu, 2019). The development of the internet platform economy and flexible employment has also provided workers with more employment channels and opportunities for upward mobility (Gao Wenjun, 2021; Zheng Xiaodong, 2025). Research at the firm level has found that investment in AI R&D can expand the size of a firm's workforce and increase the demand for high-skilled positions (He Qin and Qiu Yue, 2020).

AI will also reshape the structure of occupational tasks and alter skill requirements. Research indicates that automation technology has increased demand for both highly skilled and low-skilled workers, while demand for medium-skilled workers has declined, revealing a clear trend of employment polarization (Chen Lin et al., 2024). Repetitive, mechanical tasks are more vulnerable to technological disruption, whereas creative, social, and cognitive occupations are less susceptible to replacement (Kong Weiwei et al., 2022). Furthermore, the impact of AI varies significantly across different groups and regions. For example, women, low-educated individuals, and rural workers are more vulnerable to displacement, while internet usage helps facilitate upward occupational mobility for rural workers (Qiao Xiaole et al., 2023; Chen Weimin and Han Peipei, 2023).

As employment research shifts from employment quantity to employment quality, the issue of high-quality employment has garnered increasing attention. High-quality employment typically encompasses dimensions such as income levels, job stability, social security, job satisfaction, and career development (Liu Suhua, 2005; Yue Changjun, 2023). Existing research indicates that the impact of AI technology on employment quality varies. On the one hand, the application of robots may reduce the labor share of income and lower wage levels (Acemoglu and Restrepo, 2020); on the other hand, some studies have found that AI can enhance labor productivity and employment income (Graetz and Michaels, 2018). At the same time, AI may both alleviate repetitive labor and improve work performance, as well as exacerbate worker anxiety and reduce job satisfaction and career well-being (Tang et al., 2023; Liu et al., 2024).

A review of the literature reveals that significant research achievements have been made regarding the measurement of AI indicators and its employment effects on the labor force. At the same time, when discussing the impact of AI technology on occupational mobility among China's workforce, most scholars generally hold the view that technological shocks lead to occupational mobility. However, current research largely focuses on the nature of AI's employment effects on the workforce and its impact on shifts in occupational supply and demand, with limited use of micro-level longitudinal databases to examine the effects on

ISSN: 2688-9323

workers' occupational mobility. Building on this, this paper utilizes CFPS data to examine the extent, direction, and forms of workers' occupational mobility under AI technology shocks, incorporating employment perceptions into the analytical framework to enrich research in the field of AI and occupational mobility.

3. Theoretical Analysis and Hypothesis Proposal

Against the backdrop of China's economic transformation and accelerated digitalization process, occupational mobility has become an important way for the labor force to adapt to technological changes and achieve resource reallocation. From a macro perspective, AI technology affects labor force occupational mobility through multiple channels. On the one hand, AI technology expands the boundaries of production possibilities, improves enterprise production efficiency and innovation capabilities, promotes industrial structure upgrading and the generation of new occupations, thereby expanding the space for career choices; on the other hand, AI technology exerts substitution pressure on some low-skilled and repetitive jobs, forcing relevant labor forces to cope with technological shocks through re-employment, retraining, or cross-occupational transfer. At the micro level, when facing changes in job stability, adjustments in skill requirements, and changes in income expectations, labor forces will make new career choices based on a trade-off between costs and benefits.

Based on this, Hypothesis 1 is proposed: artificial intelligence technology promotes labor force occupational mobility.

As artificial intelligence technology reshapes the skill demands in the labor market, human capital accumulation has become an important transmission path affecting occupational mobility. Technological iteration drives the shift in skill demands from conventional skills to non-conventional cognitive skills, with traditional operational and experiential skills gradually depreciating. Due to insufficient job adaptability, low-skilled workers are forced to switch to low-skilled transitional positions or undergo retraining to achieve career transformation. At the same time, the complementarity between artificial intelligence and high-skilled labor is continuously strengthening. Emerging professions such as artificial intelligence engineering and intelligent operation and maintenance require higher levels of digital skills and innovation capabilities, prompting workers to continuously learn and update their skill sets, and achieve occupational mobility in the process. As the trend of employment polarization intensifies, the level of human capital is gradually becoming an important factor determining the direction and probability of occupational mobility.

Based on this, Hypothesis 2 is proposed: artificial intelligence technology promotes occupational mobility of Chinese labor force by influencing human capital accumulation.

Income serves as a crucial signal for resource allocation in the labor market and also as a significant transmission mechanism through which artificial intelligence (AI) influences occupational mobility. On the one hand, as AI enhances production efficiency, the income levels of high-skilled and emerging professions have seen a marked increase, creating an income attraction effect that drives workers to shift towards higher-paying positions. Low-income groups, in particular, are more inclined to seek breakthroughs in their income bottlenecks through career transitions. On the other hand, the income growth brought about by AI may also result in an income lock-in effect. After companies introduce intelligent technology, the salaries and benefits of certain positions improve, leading to an increased reliance on current income among workers, thereby reducing their willingness to switch careers. In contrast, high-income groups face lower risks of technological substitution in their professions, enjoy greater job stability, and have relatively weaker motivations for technology-driven career mobility. Therefore, the income effect plays a significant mediating role in the process of AI influencing occupational mobility.

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Based on this, Hypothesis 3 is proposed: AI technology promotes occupational mobility of Chinese labor force by influencing income effects.

4. Data Description and Econometric Model Construction

4.1. Data Description

The occupational mobility data used in this paper is sourced from the China Family Panel Studies (CFPS) for the years 2016, 2018, 2020, and 2022. When selecting individual samples, basic information of the samples was obtained by matching survey years with individual IDs. In terms of data processing, according to China's legal working age requirements, samples under 16 years old and over 65 years old were excluded. After removing missing and outlier values, samples with both current and previous occupation names were retained, ultimately forming benchmark regression samples containing 13,012 observations for the period 2016-2018, 9,155 observations for the period 2018-2020, and 7,577 observations for the period 2020-2022. The artificial intelligence technology data used in this paper is sourced from the China Patent Database. Python was used to crawl the number of artificial intelligence patent grants in each prefecture-level city in China. In addition, data related to control variables were obtained not only from the CFPS database but also from the China City Statistical Yearbook and the China Regional Economic Statistical Yearbook for each year.

4.2. Econometric Model

To examine the impact of artificial intelligence technology on labor force occupational mobility and identify trends in occupational pattern changes, an econometric model is constructed as follows:

$$Mobility_{ijt} = \alpha lnAI_{jt} + \alpha_1 X_{ijt} + \alpha_2 lnZ_{jt} + \mu_j + \varepsilon_{ijt} \tag{1}$$

$$Occupantion_{ijt} = \beta lnAI_{jt} + \beta_1 X_{ijt} + \beta_2 lnZ_{jt} + \mu_j + \varepsilon_{ijt} \tag{2}$$

Model (1) is employed to examine whether artificial intelligence (AI) technology induces occupational mobility among the workforce. In this model, $Mobility_{ijt}$ represents whether individual i in city j has experienced occupational mobility in year t. A value of 1 indicates that occupational mobility has occurred, while a value of 0 indicates that it has not. Model (2) is used to examine changes in occupational status after occupational mobility among the workforce. In this model, $Occupation_{ijt}$ characterizes the occupational mobility patterns of individuals in city j in year t, examining dimensions such as the direction of occupational mobility, mobility form, and employment perception, and analyzing the characteristics of occupational mobility under the impact of AI technology. In both Model (1) and Model (2), $lnAI_{jt}$ represents AI technology in city j in year t, X_{ijt} and Z_{jt} respectively represent control variables at the individual and regional levels. When the dependent variable is binary, the Logit model is used for estimation; when the dependent variable is continuous, the fixed-effects model is used for estimation; when the dependent variable is an ordered categorical variable, the ordered Logit model is used for estimation. Additionally, time fixed effects and individual or provincial-level clustered robust standard errors are incorporated during model regression.

4.3. Variable Description

(1) Dependent variable

1) Career mobility

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This article first explores whether there is occupational mobility among the workforce, focusing on whether the occupational codes of the workforce have changed. It marks 0 for those whose current and previous occupations have the same five-digit occupational code, indicating no change in occupation. It marks 1 for those whose current and previous occupations have different five-digit occupational codes, indicating occupational mobility.

2) Career mobility patterns

a. From the perspective of mobility, the International Standard Economic Index of Occupation (ISEI index) from the CFPS database is used for measurement. The difference in ISEI index before and after mobility is used to judge the extent of AI technology's impact on labor force occupational mobility.

b. From the perspective of mobility, we can judge the direction of changes in socioeconomic status of laborers before and after their occupational mobility based on the direction of changes in the ISEI index before and after the mobility.

c. From the perspective of employment perception, responses from the CFPS questionnaire, such as "satisfaction with job income", "satisfaction with working hours", and "overall satisfaction with work", are used for quantitative measurement.

(2) Core explanatory variables

Artificial intelligence technology. This paper uses the number of authorized artificial intelligence patents in prefecture-level cities across China to represent artificial intelligence technology, and follows the approach of Acemoglu et al. (2023) to add one to the data and take the logarithm. Considering the potential lag effect of technology application on the labor market, this paper uses the number of patents authorized in the base period for empirical analysis.

(3) Control variables

Individual-level control variables include: age, gender, registered residence, average years of education in the region, marital status, and health status. Regional-level control variables include economic development level, industrial structure, and financial support intensity. All regional-level control variables are logarithmically transformed for empirical regression. To avoid causal inference bias, this paper uses base-period observations when exploring various intertemporal effects. The variables and descriptive statistics are presented in Table 1.

Table 1. Descriptive statistics of main variables

Variable Name	Variable Description and Assignment	Mean	Standard Deviation
Career mobility	Career mobility takes the value of 1; otherwise, it takes the value of 0	0.4726	0.4993
Artificial intelligence technology	The logarithm of the authorized number of artificial intelligence patents plus one	6.1650	1.1390
Age	Excluding samples younger than 16 and older than 65.	44.6141	13.0616
Gender	1=Male; 0=Female	0.4818	0.5000
Registered residence	1=agricultural household registration; 0=non-agricultural household registration	0.7226	0.4478
Years of education	0=Illiterate/semi-literate; 6=Primary school; 9=Junior high school; 12=High school/vocational high school/secondary technical school; 15=College; 16=Undergraduate; 19=Master's degree; 22=Doctoral degree	9.1822	4.4897
Marital status	1=married; 0=unmarried	0.8290	0.3765
Health status	Assigned a value of 1-5, with higher values indicating better health.	3.0306	1.2052
Economic development level	Per capita GDP (yuan)	10.9389	0.5690
Industrial structure	Ratio of added value of the tertiary industry (in 10,000 yuan) to added value of the secondary industry (in 10,000 yuan)	0.3126	0.4979
Financial support level	General budget expenditure of local finance (in 10,000 yuan) / GDP (in 10,000 yuan)	-1.6915	0.4656

ISSN: 2688-9323

4.4. Analysis of Empirical Results

(1) Analysis of benchmark regression results

Table 2 reports the regression results of the impact of artificial intelligence (AI) technology on the occupational mobility of China's labor force. Overall, after gradually incorporating control variables and fixed effects, the regression coefficient of AI technology remains significantly positive, indicating that AI technology significantly promotes labor force occupational mobility. Column (4) shows that even after controlling for individual characteristics, regional characteristics, and fixed effects, the regression coefficient of AI technology remains significantly positive, indicating strong robustness of the conclusion. Specifically, for every 1 unit increase in AI technology, the probability of occupational mobility increases by an average of approximately 4.90 (e^0.0478−1) percentage points. This suggests that the development of AI technology has significantly promoted the occupational mobility of China's labor force, validating Hypothesis 1 mentioned earlier and aligning with the research conclusions of Wang Linhui et al. (2022) and Wei Jiahui et al. (2024).

Table 2. The Impact of Artificial Intelligence Technology on Occupational Mobility of Chinese Labor Force

	(1)	(2)	(3)	(4)
	Career mobility	Career mobility	Career mobility	Career mobility
Artificial intelligence technology	0.1279***	0.0990***	0.0349***	0.0478***
	(0.0125)	(0.0131)	(0.0126)	(0.0152)
Age		-0.0242***	-0.0250***	-0.0247***
		(0.0014)	(0.0012)	(0.0014)
Gender		0.3088***	0.3186***	0.3159***
		(0.0292)	(0.0246)	(0.0292)
Registered residence		-0.2085***	-0.1970***	-0.1912***
		(0.0349)	(0.0309)	(0.0358)
Regional average years of education		0.0238***	0.0192***	0.0203***
		(0.0038)	(0.0032)	(0.0038)
Marital status		-0.1841***	-0.1746***	-0.1778***
		(0.0439)	(0.0395)	(0.0443)
Health status		0.0296***	0.0294***	0.0316***
		(0.0114)	(0.0105)	(0.0115)
Economic development level			0.1575***	0.1642***
			(0.0296)	(0.0344)
Industrial structure			0.0084	0.0490
			(0.0253)	(0.0307)
Financial support intensity			-0.1239***	-0.1192***
			(0.0326)	(0.0376)
Constant term	-0.8609***	0.2962**	-1.2399***	-1.3696***
	(0.0779)	(0.1277)	(0.2901)	(0.3370)
Fixed effects	YES	YES	NO	YES
Cluster standard error	YES	YES	NO	YES
Pseudo R^2	0.0038	0.0345	0.0357	0.0365
N	29724	29509	29291	29291

Standard errors in parentheses

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

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(2) Robustness test

Table 3 reports the robustness test results of the impact of AI technology use on occupational mobility of Chinese labor force.

1) Replace the dependent variable

To avoid the potential impact of measurement errors in occupational mobility on the empirical results mentioned earlier, this paper utilizes changes in the International Standard Classification of Occupations (ISCO) to represent occupational mobility. If the ISCO code of the interviewee in the CFPS database changes within two years, it indicates that there has been occupational mobility, with a value of 1; otherwise, the value is 0. The regression results are presented in column (1) of Table 3. Artificial intelligence technology significantly promotes occupational mobility among China's labor force, indicating the robustness of the baseline research conclusion.

2) Exclude sample data from municipalities directly under the central government

The four municipalities directly under the central government, namely Beijing, Shanghai, Tianjin, and Chongqing, play crucial roles in national strategic development. They differ from other regions at the same administrative level in terms of national policies and urban functions. To avoid potential biases in estimation results caused by the preferential application of robots in these municipalities, Table 3, column (2), presents the regression results after excluding the samples from these municipalities, further verifying the reliability of the baseline regression conclusions.

3) Winch tail processing

To eliminate the impact of outliers on the estimation results, we performed winsorization on the artificial intelligence technology indicators at the 1% and 99% quantile levels. The results are presented in column (3) of Table 3, indicating that the benchmark regression results are robust.

4) Change estimation method

To accommodate the situation where variance varies with the mean, this paper employs Poisson regression instead, and the results are presented in column (4) of Table 3, further verifying the credibility of the baseline regression results.

Table 3. Robustness test results

	(1)	(2)	(3)	(4)
	Replace the dependent variable	exclude municipalities	perform winsorization	change the estimation method
Artificial intelligence technology	0.0439***	0.0458***		0.0225***
	(0.0153)	(0.0156)		(0.0076)
After winsorization, artificial intelligence technology			0.0478***	
			(0.0152)	
Control variables	YES	YES	YES	YES
Constant term	-0.9815***	-0.8017**	-1.3693***	-1.4356***
	(0.3517)	(0.3808)	(0.3371)	(0.1653)
Fixed effects	YES	YES	YES	YES
Cluster standard error	YES	YES	YES	YES
Pseudo R^2	0.0303	0.0367	0.0365	0.0157
N	28957	27317	29291	29291

Standard errors in parentheses

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

(3) Endogeneity treatment

To mitigate the endogeneity issues arising from sample selection bias and omitted variables, this paper refers to the methods of Wang Yongqin (2020) and Wang Linhui (2022), using 2004 as the base period to construct an indicator of China's industrial robot penetration rate, which is used as an instrumental variable for endogeneity treatment. On the one hand, under open economic conditions, similar technologies in developed and developing countries often exhibit the same trend of change, satisfying the correlation requirement of the instrumental variable. On the other hand, the level of robot application in the United States only affects its own employment, and its impact on Chinese labor employment is only reflected as an exogenous technological shock, satisfying the exogenous assumption of the instrumental variable. The process is divided into two steps: firstly, calculating the industrial robot penetration rate indicator at the industry level; secondly, using US industry-level industrial robot data to establish the instrumental variable for China's industrial robot penetration rate. The data are sourced from the China Labor Statistics Yearbook, the International Federation of Robotics, and the US Bureau of Economic Analysis.

According to the idea of Bartik instrumental variable method, the regional industrial robot penetration rate is calculated as shown in formula (3).

$$AI_{it} = \sum_{j=1}^{J} \frac{Labor_{ijt=2004}}{Labor_{it=2004}} \times \frac{Robot_{jt}}{Labor_{jt=2004}} \tag{3}$$

Among them, $Robot_{jt}$ represents the installed stock of industrial robots in industry j in year t, , $Labor_{jt} = 2004$ represents the number of employees in industry j in 2004, $Labor_{it} = 2004$ represents the number of employees in province i in 2004, and $Labor_{ijt} = 2004$ represents the number of employees in industry j in province i in 2004.

In addition, the instrumental variable for industrial robot penetration in China is constructed using industrial robot data at the industry level in the United States, as shown in formula (4).

$$AI\_US_{it} = \sum_{j=1}^{J} \frac{Labor_{ijt=2004}}{Labor_{it=2004}} \times \frac{Robot\_US_{jt}}{Labor\_US_{jt=1990}} \tag{4}$$

Among them,$Robot\_US_{jt}$ represents the installed stock of industrial robots in the US industry j in year t, and $Labor_US_{jt}$1990 represents the number of employed people in the US industry j in 1990 (base period).

To enhance the robustness of the empirical results, this paper modifies the measurement of economic development level to regional GDP growth rate (%) and replaces the measurement of industrial structure with the proportion of tertiary industry added value to secondary industry added value (%) in this regression. The results are presented in Table (4). Column (1) indicates that the increase in industrial robot penetration in China significantly promotes the occupational mobility of the Chinese labor force. The results remain robust after switching to a provincial-level clustering method, and further verifies the baseline conclusion that robot penetration promotes mobility when using the 2SLS method for regression with discrete dependent variables.

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Table 4. Endogeneity treatment results

	(1)	(2)	(3)
	IV logit	Change clustering method	SLS method
Robot penetration rate	0.2932***	0.2932***	
	(0.0693)	(0.0779)	
Control variable	YES	YES	YES
Artificial intelligence technology			0.0581***
			(0.0138)
Constant term	0.1781	0.1781	0.3387***
	(0.1610)	(0.2366)	(0.0728)
Fixed effects	YES	YES	YES
Cluster standard error	YES	YES	YES
Pseudo R^2	0.0298	0.0298	0.0319 （R^2）
N	12918	12918	12918

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

(4) Mechanism analysis

1) Human capital

This article categorizes the labor force into low-skilled labor and medium-to-high-skilled labor based on their education levels. Specifically, low-skilled labor includes those who are illiterate/semi-illiterate, and have completed primary and junior high school education; medium-to-high-skilled labor includes those who have completed high school or above education. The results are presented in Table 5. Columns (1) and (3) indicate that the regression coefficients of artificial intelligence (AI) technology on occupational mobility are significantly positive at the 1% significance level, suggesting that AI technology significantly promotes labor force occupational mobility. Human capital at the skill level serves as a key mediating variable, and its transmission effect is demonstrated in column (2), where AI technology has a significant negative impact on skill levels at the 1% significance level. This implies that AI technology will reshape the skill structure of the labor market and exert an inhibitory effect on labor skill levels. With accelerated technological iteration, some traditional skills are being replaced, making low-skilled labor more susceptible to passive mobility due to job impacts, while high-skilled labor also needs to adapt to new skill requirements. From a practical logic perspective, after the application of AI technology, on the one hand, low-skilled labor is easily replaced by intelligent devices due to their engagement in labor-intensive and repetitive positions, forcing them to shift to emerging service positions or cross-industry transitions, directly driving occupational mobility; on the other hand, technology triggers changes in skill demand, and labor, in order to adapt to new positions, will actively or passively participate in skill reshaping, accompanied by occupational transitions. The mediating effect of skill levels essentially reflects the reconstruction of the skill-job fit relationship in the labor market under technological shocks, verifying the transmission path of the human capital mechanism in AI technology's impact on occupational mobility. It also reveals that technology-driven occupational mobility promotes mobility through direct effects and exerts indirect influences through skill level adjustments, providing a micro-mechanism perspective for understanding the dynamic adjustments in the labor market.

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Table 5. Analysis of the mechanism by which artificial intelligence technology affects occupational mobility

	(1)	(2)	(3)
	Career mobility	Skill level	Career mobility
Artificial intelligence technology	0.0840***	-0.0980***	0.0807***
	(6.0396)	(-5.3339)	(5.7888)
Skill level			-0.1845***
			(-5.2745)
Constant term	-0.7337*	-0.7567	-0.6732
	(-2.0648)	(-1.6987)	(-1.8913)
Control variable	YES	YES	YES
fixed effect	YES	YES	YES
Cluster standard error	YES	YES	YES
Pseudo R^2	0.0350	0.2302	0.0360
N	29291	29291	29291

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2) Income effect

Table 6. Analysis of the Mechanism by Which Artificial Intelligence Technology Affects Occupational Mobility

	(1)	(2)	(3)
	Career mobility	income level	career mobility
Artificial intelligence technology	0.0423**	0.0660***	0.0526*
	(2.7451)	(6.6780)	(2.4270)
Income level			-0.0686**
			(-3.0531)
Control variable	YES	YES	YES
fixed effect	YES	YES	YES
clustering standard error	YES	YES	YES
Pseudo R^2	0.0364	0.1970	0.0130
N	29291	11876	11876

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on the interviewees' after-tax wage income from all jobs over the past 12 months, this paper takes the logarithm for regression analysis, and the results are presented in the table. The empirical findings indicate that the income effect serves as a mediating mechanism in the impact of artificial intelligence (AI) technology on occupational mobility. Column (2) employs a panel fixed-effects model, showing that AI technology has a significant positive effect on the income effect at a 1% significance level, indicating that the application of AI technology can significantly enhance the labor income effect. In real life, after enterprises introduce AI to optimize production processes and innovate business models, on the one hand, intelligent equipment replaces some low-efficiency positions, and the released production efficiency is converted into employee performance bonuses and salary increases; on the other hand, AI gives rise to new professions, whose income levels are higher than those of traditional positions, driving the overall growth of the income effect. Column (3) incorporates the income effect,

ISSN: 2688-9323

which has a significant negative impact on occupational mobility, meaning that an increase in the income effect inhibits occupational mobility. When AI technology brings income growth, laborers become more dependent on their current positions, reducing their willingness for occupational mobility.

Meanwhile, this paper generates a variable for income decile grouping and directly examines the differences between different deciles using the interaction term between income decile and artificial intelligence technology. The results, as shown in the table, indicate that there is heterogeneity in the impact of artificial intelligence on occupational mobility across different income deciles. Artificial intelligence significantly promotes occupational mobility in the middle and low income deciles. As the income decile increases, the baseline promoting effect of artificial intelligence remains significant, but the additional promoting effect weakens, and the gap between group mobility and the baseline group narrows. For labor forces in the 7th and 9th income deciles, the promoting effect of artificial intelligence disappears or exhibits a negative effect. That is, the promoting effect of artificial intelligence on occupational mobility is more significant in the middle and low income deciles, while its effect gradually diminishes in the high income deciles.

Table 7. Analysis of the impact of artificial intelligence technology on occupational mobility of labor force across different income quantiles

	(1)	(2)	(3)	(4)	(5)	(6)
	2nd percentile	3nd percentile	5nd percentile	6nd percentile	7nd percentile	9nd percentile
Artificial intelligence technology	0.0489**	0.0534***	0.0521***	0.0516***	0.0531***	0.0547***
	(3.2068)	(3.5138)	(3.4267)	(3.3929)	(3.4911)	(3.5984)
Quantile	0.3638***	0.4083***	0.2764***	0.2570***	0.1182*	0.0690
	(5.3039)	(6.7255)	(4.3714)	(4.3272)	(2.0028)	(1.0896)
Interaction term	0.1194***	0.0706***	0.0360*	0.0203*	-0.0005	-0.0182
	(11.3359)	(6.9981)	(2.5135)	(2.2384)	(-0.0579)	(-1.7843)
Control variables	YES	YES	YES	YES	YES	YES
fixed effect	YES	YES	YES	YES	YES	YES
clustering standard error	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.0402	0.0382	0.0362	0.0362	0.0357	0.0356
Constant term	-1.2363***	-1.2068***	-1.0932**	-1.0901**	-1.0678**	-1.0792**
	(-3.5060)	(-3.4273)	(-3.1081)	(-3.1007)	(-3.0378)	(-3.0682)
N	29291	29291	29291	29291	29291	29291

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(5) Heterogeneity analysis

The heterogeneity analysis focuses on the differentiated impact of AI technology on the occupational mobility of labor forces across different groups. This paper conducts an analysis from four dimensions: gender, registered residence, age, and region. By introducing the interaction term of "core variable × grouping dummy variable" for joint regression, the coefficient of the AI technology variable can vary with group characteristics, thus identifying the differences in the impact of AI technology on occupational mobility among different groups. Both gender and registered residence are binary dummy variables, with male=1 and female=0;

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agricultural household registration=1 and non-agricultural household registration=0. The age dimension follows the latest classification standards of the World Health Organization, defining individuals aged 16-45 as the youth group (=1) and those aged 46-56 as the middle-aged and elderly group (=0). The results are presented in Table 8.

The interaction term "Artificial Intelligence (AI) technology × gender" is significantly negative, indicating that AI technology has a stronger promoting effect on women's career mobility. This is mainly due to the fact that women are more concentrated in service industries and emerging industries, and AI has reduced the spatiotemporal constraints of some occupations, alleviating the pressure of balancing family and work. In contrast, men are more concentrated in traditional industries, and their career adjustment response is relatively weaker. The interaction term "Artificial Intelligence (AI) technology × registered residence" is significantly negative, indicating that AI technology has a more pronounced promoting effect on the career mobility of non-agricultural registered residence laborers. Non-agricultural registered residence groups have more comprehensive employment services and skills training resources, while agricultural registered residence laborers face higher difficulties in career transition due to institutional barriers and insufficient skills. The interaction term "Artificial Intelligence (AI) technology × age" is significantly negative, indicating that AI technology has a stronger promoting effect on the career mobility of young laborers than on middle-aged and elderly groups. Young groups have stronger acceptance of digital technology and lower career transition costs, while middle-aged and elderly groups are relatively less motivated to move due to insufficient digital skills and career sunk costs.

Table 8. Analysis of heterogeneity in occupational mobility across different group characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Gender	Registered residence	Age	Eastern	Central	Western	Northeastern
Artificial Intelligence Technology	0.0750***	0.0731***	0.0663***	0.0516	0.1481*	0.0760*	-0.0919
	(4.8539)	(4.6452)	(4.2354)	(1.8174)	(2.2470)	(2.0441)	(-0.7569)
AI technology × gender	-0.0507***						
	(-10.8820)						
AI technology × registered residence		-0.0300***					
		(-5.3276)					
AI technology × age			-0.0339***				
			(-4.2312)				
Control variables	YES	YES	YES	YES	YES	YES	YES
Constant terms	-1.3266***	-1.3066***	-0.8679*	-1.1684*	-2.5828**	-4.1300***	3.3070*
	(-3.7695)	(-3.7750)	(-2.4240)	(-2.0217)	(-2.9359)	(-3.7973)	(2.3161)
Fixed effects	YES	YES	YES	YES	YES	YES	YES
Cluster standard error	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.0360	0.0361	0.0367	0.0321	0.0398	0.0330	0.0480
N	29291	29291	29291	9233	7741	8139	4178

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ISSN: 2688-9323

In addition, this paper defines the eastern, central, western, and northeastern regions based on the 2018 provincial national standard codes and the classification standards of the National Bureau of Statistics to explore the impact of regional heterogeneity. The results of regional heterogeneity indicate that the promoting effect of AI technology on occupational mobility is significant in the central and western regions, but not significant in the eastern and northeastern regions. Driven by industrial upgrading, policy support, and industrial transfer, AI has created more new jobs and promoted labor mobility in the central and western regions. However, the mature industrial structure in the eastern region and the slow transformation and severe brain drain in the northeastern region have weakened the promoting effect of AI on occupational mobility.

(6) Further analysis

1) Impact degree of career mobility

This article utilizes the change magnitude of the ISEI index of respondents in the CFPS database to measure the impact of AI technology on the degree of occupational mobility, and only retains samples with occupational mobility for regression analysis. The results show that AI technology is significantly positive at the 1% statistical level, indicating that AI technology significantly deepens the degree of labor force occupational mobility. On the one hand, AI's substitution for routine jobs forms a "passive push", prompting low-skilled labor to flow to suitable positions; on the other hand, AI's empowerment of non-routine jobs forms an "active pull", attracting high-skilled labor to enter technology-integrated professions. Both factors jointly strengthen the intensity of occupational mobility. By expanding the dimension of "mobility degree", this analysis supplements the dynamic characteristics of occupational mobility, providing a new perspective for understanding the profound impact of technological change on the labor market.

2) Direction of career mobility

Table 9. Analysis of the Impact Degree and Direction of Occupational Mobility

	(1)	(2)
	Degree of flow	Direction of flow
Artificial intelligence technology	0.2899***	
	(9.7507)	
Using computer		0.1166*
		(2.5343)
Control variable	YES	YES
Constant term	0.6970	1.2151**
	(1.0605)	(2.8950)
Fixed effects	YES	YES
Cluster standard error	YES	YES
Pseudo R^2	0.1342	0.0053
N	13227	9007

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This article utilizes the change direction of the ISEI index to measure the direction of occupational mobility, defining upward mobility (=1) as the index being higher after mobility than before, and downward mobility (=0) otherwise, and retains only samples where occupational mobility occurs. Based on whether computers were used before mobility to measure digital skill foundation, an ordered logistic model is employed for regression. The results show that for the group who used computers before mobility, occupational mobility significantly increases the probability of upward occupational mobility. Computer proficiency, as a proxy for digital skills, helps workers adapt to positions with higher socioeconomic status, break through the path dependence of low-skilled occupations, and achieve upward occupational transitions. At the same time, non-agricultural registered residence groups are more likely to achieve upward occupational mobility due to institutional advantages and social networks, indicating that digital skills can promote upward mobility, but institutional and regional differences still constrain the quality of mobility.

3) Employment perception

High-quality employment typically encompasses four dimensions: income security, working environment, working hours, and career adaptability. This paper utilizes the responses to "overall job satisfaction," "job income satisfaction," "working environment satisfaction," and "working hours satisfaction" from various periods between 2016 and 2022 in the CFPS database to explore the changes in satisfaction levels before and after the introduction of artificial intelligence technology into the labor force's career mobility. Each satisfaction level is assigned a score from 1 to 5, with higher scores indicating higher satisfaction. The change in satisfaction is measured on a scale from -4 to 4. This paper employs an ordered logit model for regression analysis, and the results are presented in Table 10.

Table 10. Analysis of changes in employment perception before and after career mobility

	(1)	(2)	(3)	(4)
	Overall job satisfaction	job income satisfaction	job environment satisfaction	job time satisfaction
Artificial intelligence technology	-0.1686*	-0.5527***	-0.3999***	-0.3554***
	(-2.2332)	(-10.1463)	(-7.4398)	(-6.5280)
Control variables	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
Cluster standard error	YES	YES	YES	YES
Pseudo R^2	0.0010	0.0048	0.0036	0.0030
N	30116	20014	20120	20016

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In terms of overall job satisfaction, artificial intelligence technology has significantly reduced workers' job identification, primarily due to skill mismatch and increased pressure on career adaptation. In terms of job income satisfaction, artificial intelligence technology has a significant negative effect at the 1% level. AI primarily impacts low-skilled jobs, causing some workers to shift to transitional jobs with lower income and stability, while the technological dividends are more concentrated in enterprises and high-skilled groups, weakening the income satisfaction of ordinary workers. In terms of job environment satisfaction, artificial intelligence technology also has a significant negative effect, primarily due to job anxiety caused by technological substitution and the weakening of workers' autonomy by algorithmic management. Work time satisfaction also shows a significant negative impact. Although smart office and algorithmic management improve efficiency, they blur the boundary between work and life, exacerbating the problem of hidden overtime.

Overall, the changes in employment perception before and after career mobility exhibit the characteristics of "short-term pain" under the impact of AI. Artificial intelligence technology has a significant negative impact on income, working environment, working hours, and overall satisfaction. However, in the long run, if the government and enterprises strengthen skills

ISSN: 2688-9323

training, optimize income distribution, and improve labor security, career mobility can still help achieve job matching and improve employment quality.

5. Conclusion and Policy Recommendations

Based on the CFPS data system, this paper examines the impact of artificial intelligence (AI) technology on the occupational mobility of Chinese labor force and its mechanism of action. The research findings are as follows: (1) AI technology significantly increases the probability of occupational mobility of Chinese labor force. For every one unit increase in AI technology, the probability of labor force occupational mobility increases by an average of about 4.23 percentage points; (2) AI technology affects occupational mobility through human capital and income effects. On the one hand, technological progress reshapes the structure of skill demand, promoting labor force occupational transitions; on the other hand, income increases enhance job dependency, thereby inhibiting some occupational mobility; (3) AI technology has heterogeneous impacts on different groups, with stronger promotional effects on the occupational mobility of women, non-agricultural registered residence, youth, and labor force in central and western regions; (4) Further analysis shows that AI technology not only deepens the degree of occupational mobility but also affects the direction of occupational mobility and employment perception. Those with strong digital skills are more likely to achieve upward mobility, but their employment satisfaction decreases in the short term.

Based on the aforementioned research conclusions, this paper proposes the following four policy recommendations:

1) Strengthen industrial policy guidance, promote industrial synergy and employment expansion. The government should increase support for emerging industries such as artificial intelligence, big data, cloud computing, and smart manufacturing, encourage enterprises to increase investment in research and development and application of artificial intelligence technology, and create more high-skilled jobs. At the same time, promote the intelligent transformation of traditional industries, reduce the risk of job loss, achieve a smooth transition between old and new industries, reduce the disorder of occupational mobility, and promote the coordinated development of industrial upgrading and employment expansion.

2) Establish a lifelong vocational skills training and digital education system. In response to the trend of AI-driven skill demand upgrading, a lifelong vocational skills training system covering the entire workforce should be established. Skills training such as programming, data analysis, and intelligent equipment operation and maintenance should be provided to working individuals, with training subsidies offered; free job transfer training should be provided to unemployed or job-changing workers. At the same time, AI and computer-related courses should be added to basic education, and public welfare training on digital skills should be offered to the workforce, comprehensively enhancing workers' digital literacy and career adaptability.

3) Improve the labor market information service mechanism. The government should enhance the labor market information platform, releasing real-time information on AI technology applications, job demands, and salary changes to assist workers in rationally planning their career paths. Simultaneously, by leveraging big data and AI technology, intelligent matching between jobs and skills can be achieved, enhancing the efficiency of job-personnel matching, reducing the blindness of career mobility, and improving the quality of career mobility.

4) Optimize income distribution and social security system. In response to the income disparity caused by artificial intelligence, we should improve the income distribution mechanism, guide workers to share the dividends of technological development, and alleviate income inequality through tax regulation. At the same time, we should expand the coverage of unemployment insurance, include flexible employment and emerging professional workers in the security

system, and explore the establishment of a special subsidy system for the unemployed groups affected by technological substitution, so as to alleviate the economic pressure brought by occupational mobility and enhance the stability of the labor market.

Acknowledgments

Fund Projects: National Social Science Fund of China, "Research on the Impact Mechanism and Policy Response of Artificial Intelligence on Residents' Wealth Inequality" (25BJL058); Jiangsu Provincial Graduate Research Innovation Program, "The Impact of Artificial Intelligence Technology on the Occupational Mobility of Chinese Labor Force" (KYCX25_2503).

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