The Impact of Artificial Intelligence Development on Firms' Educational Composition of Labor

Yanxing Shen [1,a]

[1] School of International Education, Jilin University of Finance and Economics, Changchun, Jilin 130117, China

[a] Shen_yx05@163.com

Abstract. As a strategic technology driving a new wave of scientific and technological revolution and industrial transformation, artificial intelligence (AI) is profoundly reshaping firms' factor allocation and labor demand structure. Using Chinese A-share listed firms in Shanghai and Shenzhen from 2014 to 2024 as the research sample, this study constructs firm-level AI development indicators through text analysis and machine learning methods, and empirically examines the effect of AI development on firms' labor structure from the perspective of educational composition, while further exploring its heterogeneity. The results show that, first, AI development significantly reshapes firms' educational composition of labor. For each one-unit increase in AI development, the share of low-educated labor decreases by 0.007 units, whereas the share of high-education labor increases by 0.006 units, revealing a typical pattern of "substituting for low-educated labor while complementing high-educated labor." Second, firms' technological innovation capability plays a significant mediating role between AI development and adjustments in labor educational structure. By enhancing firms' technological innovation capability, AI development reduces demand for low-educated labor and increases demand for high-education labor. Third, the effect of AI on labor educational structure exhibits significant regional and industrial heterogeneity. The substitution effect is stronger in developed regions, whereas the complementarity effect is more pronounced in less developed regions; moreover, the effect in high-technology industries is approximately 2.5 times as large as that in non-high-technology industries. This study reveals the micro-level logic of firms' labor allocation under the technological shock of AI, provides empirical evidence for understanding the application of skill-biased technological change theory in the AI era, and offers a scientific basis for governments to formulate differentiated talent policies, guide the smooth transformation of the labor market, and promote the coordinated development of technological progress and employment structure optimization.

Keywords: artificial intelligence, labor educational structure, technological innovation, firm labor demand, skill bias.

1. Introduction

The future is being defined by AI and the foundation of this is talent. Artificial Intelligence (AI) is a strategic technology that is impacting all sectors of the economy and society more deeply and extensively than ever before, revolutionizing modes of production and patterns of factor allocation, ushering a new wave of scientific and technological revolution and industrial transformation. The effect of AI on the labor market has been a major subject of study in recent years, spanning across various dimensions like employment, skills, wages, and policies (Zhou et al., 2025) [1]. National level China has always been proactively supporting AI development via forward-looking policy design. In 2017, the State Council released the New Generation Artificial Intelligence Development Plan, putting forward a "three-step" strategic plan, and clearly outlining the target to be "world class" in the overall performance of artificial intelligence theory, technology, and application by 2030. The "AI+" initiative is first mentioned in the Government Work Report in 2024, a policy shift from technological research and development to the deployment of applications. In 2025, the State Council released the Opinions on Deeply Implementing the "AI+" Initiative, which comprehensively set up the institutional framework for China's AI development and put forward a target: by 2030, the penetration rate of intelligent terminals, intelligent agents, and related applications will exceed 90%, bringing China into a new stage of intelligent economy and intelligent society. The Global Digital Economy White Paper (2024) released by the China Academy of Information and Communications Technology (CAICT) states that the scale of China's core AI industry has surpassed RMB 600 billion, the number of AI-related enterprises exceeds 4, 500, and the participation of AI in the real economy is accelerating. In the context of the fast pace of technological change and enduring policy backing, the dynamic adaptation of firms' educational structure to the development of AI is directly linked to employment quality, income distribution and the sustainability of economic and social development.

Since the reform and opening-up of China, traditional industries, such as manufacturing, have long been based on labor cost advantages to compete with other countries; traditionally, the employment structure of enterprises has been “shortage of high-end talents and surplus of low-end labor”. With the in-depth application of AI technologies, the production process of enterprises is transitioning from automation to intelligence. Autor et al. (2003) proposed a “task model”, which categorizes jobs into four groups, routine and non-routine jobs and cognitive and manual jobs, and highlighted the asymmetric effects of technological progress on the different types of jobs [4]. Acemoglu and Restrepo (2018) then systemically explained the labor market impact of automation via three channels: the displacement effect, the productivity effect, as well as the reinstatement effect [1]. Intelligent manufacturing, industrial robots replace a large number of repetitive positions, such as assembly line and quality inspection; intelligent customer service, automated office platforms replace a large number of information processing, data input jobs; intelligent R&D, machine learning, deep learning and so on constantly demand high education and quality manpower, such as algorithm engineers, data scientists. Maltseva and Nikitin (2025) [14] conducted a systematic analysis of 125 seminal studies between 2018 and 2023, revealing an increase in the impact boundary of AI from low-skill positions to high-skill ones, continually adding to the range of automated tasks and gradually moving into the realm of deep substitution for mental labor. According to the estimates of the McKinsey Global Institute, by 2030, there may be about 220 million jobs that will be impacted by AI in China, where the pressure of displacement of low-skilled workers will be significant and the shortage of high-skilled workers may reach 20 million (Bughin et al., 2018) [6]. This trend signifies a shift from a general macro-level assessment of the link between AI development and firms' educational makeup of labor to a more urgent micro-level question that needs to be explored.

The study of the labor-market impacts of AI has been a significant academic interest in recent years, shifting in focus from aggregate employment to the micro dynamics of the skill structure of the labor market, and from technology substitution to collaboration between humans and machines. Initial research focused on the replacement effect that automation had on routine occupations. Autor et al. (2003) were the first to formulate the “task model” of occupations, which categorizes jobs on the basis of routine, non-routine, cognitive and manual, and demonstrates asymmetric effects of technological change across jobs [4]. Acemoglu and Restrepo (2018) extended the “task framework” model, which was used to explain the labor market impacts of automation via displacement, productivity, and job-creation effects [1]. Maltseva and Nikitin (2025) noted that AI is taking on an increasing amount of cognitive work, leading to deep substitution of mental labor [14]. Theoretically, Jiang et al. (2025) built a multi-sector general equilibrium model and concluded that the capital effect and skill-structure effect of AI increase the share of the service sector and that it increases the gap in wages between high- and low-skilled labor; they also suggest that generative AI can accelerate the polarization of jobs. Empirically, Wang Linhui et al. (2020) concluded that AI leads to labor income inequality, which is manifested in the differential effects of AI on high-skilled and low-skilled workers. Yao Jiaquan et al. (2024) created AI indicators using the text in annual reports and confirmed the differential impact of AI on high and low-skilled labour. Based on the data of the labor force dynamics survey, Qi Jianhong and Fu Jingjing (2022) found that the substitution risk is higher for low-skilled workers. From the task-biased perspective, Bian Shu et al. (2025) identified both the task substitution and job creation effects of digital technological innovation which results in asymmetric labor demand. Zhang Dannan et al. (2025), based on 1.25 million job postings, constructed a “large language model exposure” index and found that highly exposed occupations are mostly highly educated white-collar jobs; greater exposure is associated with lower wage growth and wider within-occupation inequality. Babina et al. (2025), using U.S. firm-level data, found that AI investment shifts firms' labor force toward higher educational attainment, increases the share of Science, Technology, Engineering and Mathematics (STEM) workers, and flattens corporate hierarchies [5]. Overall, existing studies have largely reached a consensus that AI "substitutes for low-skilled labor while complementing high-skilled labor," but systematic evidence based on large-sample Chinese listed firms regarding the direct impact of AI on firms' educational composition of labor remains insufficient.

Against this backdrop, this study takes Chinese A-share listed firms in Shanghai and Shenzhen from 2014 to 2024 as the research sample, constructs firm-level AI development indicators using text analysis and machine learning methods, and empirically examines the impact of AI development on firms' labor structure from the perspective of educational composition. The marginal contributions of this paper are threefold. First, it reveals at the micro firm level the reshaping effect of AI on the educational composition of labor, thereby enriching the application of skill-biased technological change theory in the AI era. Second, by applying text analysis to listed firms' annual reports, it constructs a relatively rigorous measure of firm-level AI development, providing a methodological reference for subsequent research. Third, by introducing firms' technological innovation capability as a mediating variable, it systematically uncovers the internal mechanism through which AI development affects firms' educational composition of labor, offering micro-level evidence on the transmission path of the effect of "substituting for low-educated labor while complementing high-educated labor," and providing a new policy entry point for optimizing labor structure through the enhancement of firms' innovation capability. One limitation of this study is that it focuses on the dimension of educational composition and does not fully examine the heterogeneous effects of AI on other aspects of labor structure, such as skills, age, and gender. Future research may further expand the analytical scope.

2. Theoretical Analysis and Research Hypotheses

According to the theory of skill-biased technological change, technological progress does not affect all workers uniformly; rather, it exhibits a clear skill bias. Its core argument is that when new technologies are complementary to high-skilled labor, they increase both the marginal productivity and relative demand for such workers, while substituting for the routine and repetitive tasks typically performed by low-skilled labor (Li Junyu et al., 2025) [24]. As a core technology of the new wave of scientific and technological revolution, artificial intelligence (AI) essentially simulates, extends, and augments human intelligence, covering such fields as machine learning, deep learning, natural language processing, and computer vision. The development, application, and iteration of these technologies require substantial support from highly qualified talent with advanced education, professional expertise, and innovative capacity.

AI differs fundamentally from traditional automation. Traditional automation primarily substitutes for manual labor and simple repetitive work, whereas AI has begun to enter cognitive, judgment-based, and creative domains. Yet this "cognitive substitution" does not imply the complete replacement of humans; rather, it gives rise to a more advanced form of human–machine collaboration (Bughin and van Zeebroeck, 2025) [7]. At the firm level, the deployment of AI systems requires professional technicians for algorithm design, model training, parameter tuning, and system maintenance. The contextualized application of AI also requires interdisciplinary talent capable of integrating technological capabilities with industry-specific knowledge and business needs. Moreover, the development of AI-driven new products, services, and business models depends even more heavily on high-end talent with innovative capacity and strategic vision (Wang Sheng and Zhao Haoquan, 2025) [28]. From the perspective of firm behavior, the introduction of AI changes firms' decisions regarding factor allocation. According to production function theory, firms pursuing profit maximization adjust their input structure based on the marginal productivity and relative prices of production factors. By increasing the marginal productivity of high-educated labor, AI makes firms more inclined, under cost constraints, to hire more highly educated workers (Schaal, 2025) [15]. At the same time, highly educated workers possess stronger learning and adaptive capacities, enabling them to form dynamic complementarities with AI through continuous learning and skill upgrading. This synergy further strengthens firms' demand for high-educated labor (Wang Wentao and Xiu Bowen, 2025). In addition, competitive pressure induced by AI development compels firms to upgrade their human capital by actively recruiting and cultivating highly educated talent in order to build technological barriers and maintain competitive advantage (Wang et al., 2025) [17]. On this basis, this study proposes the following hypothesis:

H1: AI development significantly increases firms' demand for high-educated labor and thereby affects firms' labor structure.

From the perspective of substitutability, the impact of AI on low-educated labor is mainly manifested as a displacement effect. The effect of technological progress on different tasks depends on their codifiability, programmability, and automability (Jiang Wei et al., 2025) [21]. When a technology can perform a task at lower cost and with higher efficiency, it tends to replace the labor engaged in that task (Li et al., 2025) [11]. Owing to its strong capabilities in data processing, pattern recognition, and intelligent decision-making, AI can efficiently complete a large number of routine, repetitive, and rule-based tasks—precisely those that constitute the main work content of low-educated labor.

More specifically, in manufacturing, the application of AI has led to the gradual replacement of positions such as assembly-line work, quality inspection, and material handling by intelligent robots and automated equipment (Liu et al., 2025) [13]. In the service sector, the widespread use of intelligent customer service systems, self-service terminals, and smart checkout systems has reduced demand for positions such as front-desk receptionists and cashiers (Wang et al., 2025; Chen Lin and Gao Yuepeng, 2025) [17] [20]. In information processing, technologies such as optical character recognition and natural language processing can automatically perform document entry, information classification, and data verification, thereby replacing traditional clerical and data-entry jobs. As AI continues to evolve and its application scenarios expand, the scope of replaceable tasks is also widening, extending from low-skill manual labor to medium-skill cognitive work. From the perspective of production process reorganization, the introduction of AI not only directly replaces certain jobs but may also trigger profound changes in firms' modes of production organization. To fully exploit the efficiency gains of AI, firms often redesign production processes by integrating previously dispersed manual operations into automated and intelligent continuous workflows, thereby further reducing their reliance on low-educated labor. This restructuring effect is often path-dependent and difficult to reverse once established. Admittedly, AI development may also indirectly create employment opportunities for some low-education workers through a job-creation effect (Del Rio-Chanona et al., 2025) [8]. New industries and business forms enabled by AI may generate new jobs, while efficiency gains and output expansion brought about by AI may also increase aggregate employment (Gmyrek et al., 2025) [9]. However, existing studies suggest that, in the short run, the displacement effect dominates, and low-education workers face considerable difficulties in skill conversion and job adaptation, making it hard for them to transition quickly to newly created positions. On this basis, this study proposes Hypothesis 2:

H2: AI development significantly reduces firms' demand for low-educated labor and thereby affects firms' labor structure.

A deep deployment of AI can boost companies' technological innovation capacity in several ways, as it is a general-purpose technology. Firstly, AI is an innovation tool. It can greatly improve R&D efficiency and the success rate of innovation through algorithm optimization, data mining and intelligent decision making. Various research has demonstrated that AI reduces trial-and-error expenses during the R&D process, speeds up the recombination of knowledge, and technological integration, which helps to propel the increase in firms' innovation output (Agrawal et al., 2019) [2]. However, companies need to engage in organizational change and process reengineering when implementing AI systems. This adaptive adjustment in turn may drive businesses to boost R&D spending and re-allocate innovation resources, which is a way to improve businesses' innovation capability. Therefore, AI development can substantially enhance the technological innovation capacity of firms as measured by R&D intensity, number and quality of patent applications. Similarly, the influence of the technological innovation capability of firms on the educational structure of labour can be explained in two aspects: product innovation and process innovation. In the context of product innovation, R&D activities are very knowledge intensive. This means highly educated workers with professional knowledge and innovative thinking are important contributors to new product development, technological iterations as well as process improvement. This means that as more is invested in R&D, so will be the demand for highly skilled talent, which will grow endogenously. The main incentive effects induced by industrial technological progress are effects on the employment of highly educated workers, both through technology-investment expansion and through industrial-chain transmission effects (Liu et al., 2024) [12]. The technological innovation that increases total factor productivity, from the process innovation point of view, may be associated with the disappearance of routine and repetitive occupations and increase the use of automated equipment and intelligent systems, decreasing the demand for low-educated labor. The rise in TFP reduces the demand for low-skilled labor primarily due to the substitution of automation and intelligent systems for routine labor (Hang et al., 2024) [10]. On this basis, this study proposes Hypothesis 3:

H3: AI development enhances firms’ technological innovation capability, which in turn exerts a two-sided effect on firms’ labor structure.

3. Research Design

3.1. Variable Selection and Measurement

3.1.1 Core explanatory variable: AI development level (AI)

This study follows Yao Jiaquan et al. (2024) [30] in constructing a firm-level AI indicator. First, an AI seed-word set is established. By integrating prior academic studies with industry reports, including Ping An Securities’ Panoramic Map of the STAR Market AI Industry Chain and the China Business Industry Research Institute’s 2019 China Artificial Intelligence Industry Market Outlook Report, 52 AI-related terms are initially selected as seed words, including core terms such as “machine learning,” “deep learning,” “natural language processing,” and “computer vision.” Second, semantic expansion is conducted based on Word2Vec. Using the Word2Vec model (Skip-gram algorithm), listed firms’ annual reports and patent texts are used for training, and the semantic similarity between each seed word and other words is calculated. For each seed word, the top 30 semantically similar words are extracted. After deduplication, low-frequency-word filtering, and manual verification, an expanded dictionary containing 73 high-frequency AI keywords is ultimately obtained. Third, the firm-level AI indicator is constructed. Based on the above AI dictionary, full-text analysis is performed on listed firms’ annual reports, and the total frequency of AI keywords is counted. The firm-level AI application indicator is then measured as the natural logarithm of one plus the total keyword frequency.

3.1.2 Dependent variable: firm labor structure

Following Liu Wanting and Yang Yang (2025), this study constructs indicators of firm labor structure from two dimensions: educational structure and skill structure [25]. For educational structure, the number of employees with a bachelor’s degree or above is extracted from listed firms’ annual reports, and its proportion in total employment is used to measure the share of high-educated labor. Low-education labor is measured by the proportion of employees with a bachelor’s degree or below in total employment.

3.1.3 Control variables

Firm size (Size): measured by the natural logarithm of total assets at year-end, to control for the effect of firm size on digital technological innovation activity (Li Wenjing and Zheng Manni, 2016) [23].

Firm age (Age): measured by the natural logarithm of firm age, calculated as the observation year minus the founding year plus one, to control for the effect of lifecycle stage on innovation behavior (Qi Jianhong and Fu Jingjing, 2022) [26].

Ownership type (Soe): measured as a dummy variable equal to 1 if the firm's ultimate controller is state-owned, and 0 otherwise, to control for the influence of ownership differences on firms' innovation decisions (Wang Linhui et al., 2020) [27].

Leverage (Lev): measured by the ratio of total liabilities to total assets, to control for the constraining effect of financial leverage and debt-servicing capacity on innovation investment (Bian Shu et al., 2025) [19].

Profitability (Roa): measured by the ratio of net profit to average total assets, to control for the effect of profitability on firms' investment in innovation resources (Yao Jiaquan et al., 2024) [30].

Growth (Growth): measured by the sales revenue growth rate, calculated as current-year operating revenue divided by previous-year operating revenue minus one, to control for the driving effect of growth stage and market expansion capacity on innovation activity (Qi Jianhong and Fu Jingjing, 2022) [26].

Ownership concentration (Top1): measured by the shareholding ratio of the largest shareholder at year-end, to control for the governance effect of ownership structure on firms' innovation decisions (Li Wenjing and Zheng Manni, 2016) [23].

CEO duality (Dual): measured as a dummy variable equal to 1 if the chairman and general manager are held by the same person, and 0 otherwise, to control for the effect of leadership structure on the efficiency of strategic decision-making (Yao Jiaquan et al., 2024) [30].

3.1.4 Mechanism variable: firm technological innovation capability (TCE)

Drawing on Zheng Panpan and Zhuang Ziyin (2024) [32], this study constructs a measure of firm technological innovation capability based on annual report texts, using a combination of text analysis and machine learning. First, an initial seed-word set is constructed by selecting 45 digital-technology-related terms from official policy documents such as the Special Action Plan for Digital Empowerment of Small and Medium-sized Enterprises as the base vocabulary (Wu Fei et al., 2021) [29]. Second, the Word2Vec algorithm is applied to train financial texts, and the top 30 semantically similar words corresponding to each base term are extracted. After deduplication, filtering, and manual verification, an expanded vocabulary containing 99 keywords is obtained. Finally, these keywords are classified into three dimensions: digital product innovation, digital process innovation, and digital business model innovation. Firm technological innovation capability (TCE) is then measured by the percentage of the total frequency of keywords across these three dimensions in the total word count of the annual report text.

3.2. Model Specification

3.2.1 Baseline model

To examine the impact of AI on firms' educational composition of labor, this study constructs the following models:

$$Low_{\mathrm{it}} = \alpha_0 + \alpha_1 AI_{\mathrm{it}} + \alpha_2 Control_{\mathrm{it}} + \beta_{\mathrm{i}} + \omega_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{1}$$

$$High_{\mathrm{it}} = \alpha_0 + \alpha_1 AI_{\mathrm{it}} + \alpha_2 Control_{\mathrm{it}} + \beta_{\mathrm{i}} + \omega_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{2}$$

where i denotes the firm and t denotes time; Low_{it} represents the indicator of low-educated labor, and $High_{it}$ represents the indicator of high-educated labor; AI_{it} denotes the level of AI development, and Control_{it} denotes a set of control variables; β_i is the firm fixed effect; ω_t is the time fixed effect; and ε_{it} is the random error term.

3.2.2 Mediation model

Following Jiang Ting (2022) [22], the mediation effect is tested using the following model:

$$TCE_{it} = \chi_0 + \chi_1 AI_{it} + \chi_2 \text{Control}_{it} + \beta_i + \omega_t + \mu_{it} \tag{3}$$

Where TCE_{it} denotes the mediating variable; χ_1 is the regression coefficient of AI development on the mediating variable; and are random error terms. Based on the existing theory, the ε_{it} causal relationship between the mediating variable and the dependent variable is then further explained.

3.2.3 Data Sources and Descriptive Statistics

Given data validity and completeness, this study takes Chinese A-share listed firms in the Shanghai and Shenzhen stock markets as the research sample over the period 2014–2024. The choice of sample period is based mainly on two considerations. First, after 2019, the commercial application of AI technologies among Chinese listed firms entered a stage of scaled expansion, and the integration of deep learning with industry-specific scenarios continued to deepen, allowing the actual impact of AI on labor structure to be more effectively captured. Second, at the time of data collection, 2024 was the most recent year for which complete annual reports and financial data were available, thus ensuring the timeliness and practical relevance of the study. To ensure sample validity and the reliability of the findings, the initial sample is further screened as follows. First, listed firms in the financial industry are excluded, as their business attributes, regulatory requirements, and labor allocation characteristics differ substantially from those of non-financial firms, which may otherwise bias the estimates. Second, firms under ST, *ST, or delisting status are excluded, since such firms are in abnormal operating conditions and their financial data and labor structure decisions are not representative under normal conditions.

The annual report data of listed firms are collected from firms' disclosed annual reports, patent data are obtained from the IRPDB intellectual property database, and labor-related data, firm basic information, and financial data are drawn from the CSMAR database. Missing observations are supplemented using linear interpolation, adjacent mean imputation, and mean-value imputation. The descriptive statistics are reported in Table 1.

Table 1. Descriptive statistics

Variable type	Variable name	Observations	Mean	Std. dev.	Min	Max
Dependent variable	High-educated labor	38,515	0.324	0.238	0.000	10.060
	Low-educated labor	38,515	0.645	0.256	0.000	16.810
Core explanatory variable	AI development level	38,515	1.131	1.312	0.000	6.497
Control variable	Firm age	38,515	20.300	6.413	3.000	70.000
	Firm size	38,515	0.317	0.465	0.000	1.000
	Ownership type	38,515	0.344	11.94	-1.445	1881.000
	Leverage	38,515	0.028	0.284	-48.32	8.441
	Profitability	38,515	22.270	1.331	17.28	28.790
	Growth	38,515	33.390	15.00	0.290	100.000
	Ownership concentration	38,515	0.301	0.459	0.000	1.000
	CEO duality	38,515	0.419	0.405	0.009	63.970

4. Empirical Analysis

The multicollinearity analysis shows that the average variance inflation factor (VIF) is well below the critical threshold of 5, indicating no serious multicollinearity among the variables. Further, the LM test, F test, and Hausman test all suggest that the two-way fixed-effects model is the most appropriate specification for this study.

4.1. Baseline Regression Analysis

This study employs a two-way fixed-effects model to examine in depth the impact of AI development on firms' educational composition of labor. The regression results are reported in Table 2. Columns (1) and (2) present the results for the low-educated labor sample, while columns (3) and (4) report those for the high-educated labor sample. Columns (1) and (3) show the univariate regressions, whereas columns (2) and (4) include the control variables. Focusing on the core explanatory variable, in the low-educated labor sample, the regression coefficient of AI development level (AI) is significantly negative at the 1% level, with coefficients of -0.008 and -0.007 in columns (1) and (2), respectively, indicating that AI development significantly reduces demand for low-educated labor. By contrast, in the high-educated labor sample, the coefficient of AI development is significantly positive at the 1% level, with coefficients of 0.008 and 0.006 in columns (3) and (4), respectively, suggesting that AI development significantly increases demand for high-educated labor. These results indicate that AI development induces a clear skill-biased adjustment in firms' educational composition of labor, characterized by "substituting for low-educated labor while complementing high-educated labor," thereby supporting Hypotheses 1 and 2.

Regarding the control variables, firm size (Size) has a significantly negative effect on low-educated labor and a significantly positive effect on high-educated labor, suggesting that larger firms are more inclined to employ highly educated workers. Leverage (Lev) exerts a significantly positive effect on low-educated labor but a significantly negative effect on high-educated labor, indicating that firms with higher debt burdens are more likely to rely on low-educated labor in order to contain labor costs. The coefficient of ownership concentration (Top1) shows the same directional pattern as firm size, further confirming that corporate governance structure shapes labor allocation in differentiated ways. Firm age (Age) is significantly positive only in the high-educated labor sample, implying that older firms enjoy an advantage in talent accumulation. Other control variables, including CEO duality (Dual), growth (Growth), profitability (Roa), and ownership type (Soe), are not statistically significant, but are still included in the model as important controls to mitigate omitted-variable bias.

Overall, AI development significantly reshapes firms' educational composition of labor through a substitution effect on low-educated labor and a complementary effect on high-educated labor. This finding provides empirical evidence for understanding employment restructuring under the technological shock of AI.

Table 2. Baseline regressions

	(1) low-educated	(2) low-educated	(3) high-educated	(4) high-educated
AI	-0.008***	-0.007***	0.008***	0.006***
	(-8.060)	(-7.360)	(8.540)	(7.400)
Age		0.003		-0.004**
		(1.540)		(-2.500)
Dual		-0.002		0.001
		(-1.120)		(0.580)
Growth		-0.001		0.001
		(-0.340)		(0.930)
Roa		0.016		0.009
		(1.340)		(0.810)
Size		-0.011***		0.016***
		(-5.120)		(8.280)
Top1		-0.001***		0.001***
		(-3.680)		(5.360)
Soe		-0.002		-0.001
		(-0.450)		(-0.400)
Lev		0.035***		-0.041***
		(4.660)		(-6.270)
Constant	0.653***	0.846***	0.315***	0.043
	(534.510)	(14.350)	(287.640)	(0.830)
Observations	37,905	37,905	37,905	37,905
R-squared	0.880	0.881	0.909	0.910
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.

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

4.2. Robustness Tests

To ensure the reliability of the results, this study conducts multiple robustness tests. First, industry-by-year fixed effects are added to control for unobservable industry-level factors varying over time that might otherwise affect the estimates, thereby allowing cleaner identification of the causal effect of AI development on firms' educational composition of labor. As shown in columns (1) and (2) of Table 3, after including industry-by-year fixed effects, the coefficient of AI development remains significantly negative for low-educated labor and significantly positive for high-educated labor. The core findings therefore remain substantively unchanged.

Table 3. Robustness test 1

	(1) low-educated	(2) high-educated
AI	-0.007***	0.007***
	(-4.65)	(4.92)
Age	0.004	-0.006**
	(1.04)	(-1.99)
Dual	-0.002	0.001
	(-0.64)	(0.28)
Growth	-0.000	0.001
	(-0.16)	(0.44)
Roa	0.016	0.009
	(1.01)	(0.64)
Size	-0.012***	0.017***
	(-3.03)	(4.75)
Top1	-0.001**	0.001***
	(-2.18)	(2.89)
Soe	-0.003	0.000
	(-0.47)	(0.06)
Lev	0.030**	-0.035***
	(2.47)	(-3.25)
Constant	0.846***	0.059
	(7.82)	(0.62)
Observations	37,868	37,868
R-squared	0.883	0.912
Firm FE	YES	YES
Year FE	YES	YES
IndxYear FE	YES	YES

Note: Standard errors are reported in parentheses.
p < 0.1, ** p < 0.05, *** p < 0.01.

Second, the sample period is adjusted. To avoid potential interference from economic fluctuations or policy shocks in specific periods, the sample interval is further modified to test the robustness of the estimated effect of AI development on firms' educational composition of labor. Specifically, given that after 2019 the commercial application of AI among Chinese listed firms entered a stage of scaled expansion and the integration of deep learning with industry scenarios deepened steadily, this study excludes the 2014–2018 observations and re-estimates the model using only the 2019–2024 subsample. Columns (1) and (2) of Table 4 report the results. In the low-educated labor sample, the coefficient of AI development is -0.007 and remains significantly negative at the 1% level; in the high-educated labor sample, the coefficient is 0.006 and remains significantly positive at the 1% level. The sign, significance level, and magnitude of the coefficients are all highly consistent with the full-sample results, indicating that the baseline findings are robust to changes in the sample period.

Table 4. Robustness test 2

	(1) low-educated	(2) high-educated
AI	-0.007***	0.006***
	(-3.840)	(4.040)
Age	-0.001	-0.002
	(-0.260)	(-0.430)
Dual	-0.001	0.005
	(-0.190)	(1.590)
Growth	-0.003	0.005**
	(-1.020)	(2.400)
Roa	0.005	0.020
	(0.230)	(1.090)
Size	-0.020***	0.023***
	(-4.970)	(6.350)
Top1	0.000	0.000
	(0.04)	(0.780)
Soe	-0.011	0.009
	(-1.000)	(0.930)
Lev	0.024*	-0.039***
	(1.770)	(-3.120)
Constant	1.137***	-0.189*
	(9.280)	(-1.700)
Observations	16,242	16,242
R-squared	0.879	0.910
Firm FE	YES	YES
Year FE	YES	YES

Note: Standard errors are reported in parentheses.
p < 0.1, ** p < 0.05, *** p < 0.01.

4.3. Endogeneity Test

Because firms within the same industry may face similar market environments and be affected by comparable industrial policies, their employment and talent allocation decisions may generate spillover effects on peer firms. As a result, AI development and changes in firms' educational composition of labor may be jointly determined, giving rise to peer effects and reverse causality, and thus to endogeneity concerns. To address this issue, this study uses the one-period lag of AI development as an instrumental variable (IV).

Table 5 reports the two-stage least squares (2SLS) estimates. For the low-educated labor sample, column (1) presents the first-stage results, where the lagged IV is significantly and positively associated with current AI development at the 1% level, with a coefficient of 0.436, satisfying the relevance requirement for a valid instrument. Column (2) reports the second-stage results, showing that the estimated coefficient on AI development is significantly negative at the 5% level, with a value of -0.270, indicating that AI development significantly reduces demand for low-educated labor. The core conclusion therefore remains robust. For the high-educated labor sample, column (3) presents the first-stage results, again showing that the lagged IV is significantly and positively associated with current AI development at the 1% level, with a coefficient of 0.436, confirming instrument relevance. Column (4) reports the second-stage results, in which the estimated coefficient on AI development is significantly positive at the 5% level, with a value of 0.324, indicating that AI development significantly increases demand for high-educated labor. The core findings thus remain robust.

After addressing endogeneity using the instrumental-variable approach, the absolute value of the coefficient on the core explanatory variable becomes larger than in the baseline regressions (from -0.007 to -0.270 in the low-education sample, and from 0.006 to 0.324 in the highly educated sample), suggesting that endogeneity leads to an underestimation of the effect of AI development. Furthermore, the Kleibergen–Paap rk LM statistics are 164.344 and 152.363, respectively, both rejecting the null hypothesis of underidentification. The Cragg–Donald Wald F statistics are 240.206 and 215.432, respectively, both exceeding the Stock–Yogo critical values at the 10% significance level, indicating that the instrument does not suffer from weak identification and can be regarded as validly exogenous.

Table 5. Endogeneity test

	low		high	
	(1) First stage	(2) Second stage	(1) First stage	(2) Second stage
AI		-0.270** (-2.315)		0.324** (2.134)
IV	0.000*** (4.153)		0.436*** (4.133)	
Kleibergen-Paaprk LM statistic		164.344		152.363
Cragg-Donald Wald F statistic		240.206		215.432
Controls	Control	Control	Control	Control
Observations	37,905	37,905	37,905	37,905
R-squared	0.803	0.803	0.372	0.783
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
p < 0.1, ** p < 0.05, *** p < 0.01.

4.4. Mechanism Analysis

To test the mediating role of firms' technological innovation capability in the relationship between AI development and the adjustment of firms' educational composition of labor, this study adopts a two-step approach. In the first step, the effect of AI development on firms' technological innovation capability is examined. Column (2), which includes the full set of control variables, Table 6 shows that the regression coefficient of AI is 0.156 and remains significantly positive at the 1% level. Its magnitude is larger than that in the specification without controls, indicating that the promoting effect of AI development on firms' technological innovation capability is robust and even more pronounced. This result suggests that the application of AI can significantly enhance firms' technological innovation capability, as reflected in higher R&D investment, more patent applications, and improved quality of innovation output. Prior research shows that product innovation tends to increase demand for high-educated labor, whereas process innovation generates a significant substitution effect on low-educated labor (Arenas-Díaz et al., 2020) [3]. Hang et al. (2024) further construct a unified analytical framework and show that R&D innovation stimulates demand for both high- and low-skilled labor, while total factor productivity growth reduces only demand for low-skilled labor, confirming the coexistence of the "labor-friendly effect" of product innovation and the "labor-saving effect" of process innovation [10].

With respect to the effect of technological innovation on high-educated labor, increased R&D investment implies endogenous expansion in firms' demand for high-skilled talent. Liu et al. (2024) find that industrial technological progress mainly exerts an incentive effect on highly educated workers and non-production departments, through both technology-investment expansion and industrial-chain transmission effects [12]. Evidence from the perspective of digital transformation further confirms that both business-model transformation and manufacturing-process transformation significantly increase firms' demand for high-educated labor (Zhang Guiping et al., 2025). Tong et al. (2025) also show that R&D investment indirectly improves firms' innovation performance by raising the relative wages of high-skilled labor, thereby confirming the demand-enhancing effect of R&D investment on highly educated talent [16]. As for low-educated labor, the substitution effect of process innovation and automation is more pronounced. Growth in total factor productivity reduces demand for low-educated labor, mainly because automated equipment and intelligent systems substitute for routine and repetitive tasks (Hang et al., 2024). Empirical evidence from Liu et al. (2024) similarly indicates that industrial technological progress significantly suppresses demand for low-education workers and production departments, through job-substitution and destruction effects. Zhang Guiping et al. (2025) further find that, in the short run, digital transformation of manufacturing processes directly replaces low-educated labor, while in the long run the scale-expansion effect may partially increase demand for such labor, although the overall substitution effect still dominates.

Table 6. Mechanism analysis

	(1) TCE	(2) TCE
AI	0.088***	0.156***
	(4.560)	(8.320)
Age		0.012**
		(2.150)
Dual		-0.005
		(-0.870)
Growth		0.008
		(1.120)
Roa		0.182***
		(4560)
Size		0.234***
		(12.340)
Top1		-0.001*
		(-1.850)
Soe		0.008
		(0.620)
Lev		-0.045**
		(-2.430)
Constant	-0.653***	-3.452***
	(-13.210)	(-8.670)
Observations	37,905	37,905
R-squared	0.880	0.750
Firm FE	YES	YES
Year FE	YES	YES

Note: Standard errors are reported in parentheses.
p < 0.1, ** p < 0.05, *** p < 0.01.

4.5. Heterogeneity Analysis

4.5.1 Regional heterogeneity

Based on the regression results in Table 7, this study further examines the regional heterogeneity in the effect of AI development on firms' educational composition of labor. Following the existing literature, the sample is divided into developed and less developed regions according to regional economic development levels, and grouped regressions are conducted. Columns (2)–(4) of Table 7 report the grouped regression results for the low-educated labor sample in developed and less developed regions, while columns (6)–(8) report those for the high-educated labor sample.

For the low-educated labor sample, the coefficient of AI development is significantly negative at the 1% level in both developed and less developed regions, indicating that the substitution effect of AI on low-educated labor is pervasive and does not fundamentally vary by regional development level. In terms of magnitude, the coefficients are -0.008 and -0.006, respectively, suggesting that the substitution effect is slightly stronger in developed regions. This difference may stem from the fact that developed regions exhibit a higher degree of industrial digitalization and richer AI application scenarios, allowing the substitution process to proceed more deeply, whereas in less developed regions, traditional industries account for a larger share and AI penetration remains at an earlier stage, resulting in a relatively weaker substitution effect.

For the high-educated labor sample, the coefficient of AI development is significantly positive at the 1% level in both developed and less developed regions, with coefficients of 0.006 and 0.008, respectively, indicating that the complementary effect of AI on high-educated labor is also broadly present. Notably, the coefficient is slightly larger in less developed regions. One possible explanation is that the initial stock of high-educated labor is relatively smaller in less developed regions, making the marginal effect more sensitive. Another is that firms in these regions, during digital transformation, may face a stronger "catch-up" demand for highly educated talent, while policy support and resource allocation may be more strongly tilted toward high-end talent, thereby amplifying the complementary effect.

Overall, the effect of AI development on firms' educational composition of labor—namely, "substituting for low-educated labor while complementing high-educated labor"—is significant in both developed and less developed regions, indicating strong regional generalizability. At the same time, the strength of the effect differs across regions: the substitution effect is stronger in developed regions, whereas the complementary effect is more pronounced in less developed regions. This finding reveals clear regional heterogeneity in the labor-market effects of AI and provides empirical support for differentiated regional talent policies and industrial transformation strategies.

Table 7. Heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	low-educated	low-educated	low-educated	low-educated	high-educated	high-educated	high-educated	high-educated
	(developed)		(less developed)		(developed)		(less developed)	
AI	-0.008***	-0.008***	-0.008***	-0.006***	0.006***	0.005***	0.010***	0.008***
	(-6.850)	(-6.500)	(-4.180)	(-3.510)	(6.130)	(5.350)	(5.750)	(5.050)
Age		0.002		0.011***		-0.004**		-0.007**
		(1.140)		(2.860)		(-2.310)		(-2.490)
Dual		0.001		-0.009**		-0.001		0.006**
		(0.400)		(-2.400)		(-0.280)		(2.000)
Growth		-0.001		0.001		0.001		0.001
		(-0.650)		(0.270)		(0.620)		(0.290)
Roa		0.023		0.008		-0.000		0.020
		(1.560)		(0.350)		(-0.010)		(1.030)
Size		-0.007***		-0.016***		0.013***		0.017***
		(-2.590)		(-3.860)		(5.520)		(4.790)
Top1		-0.000**		-0.000*		0.001***		0.000*
		(-2.560)		(-1.730)		(4.990)		(1.680)
Soe		-0.003		-0.003		-0.000		-0.005
		(-0.640)		(-0.320)		(-0.010)		(-0.700)
Lev		0.016*		0.061***		-0.027***		-0.058***
		(1.800)		(4.730)		(-3.450)		(-4.860)
Constant	0.643***	0.753***	0.680***	0.805***	0.324***	0.122**	0.291***	0.061
	(409.130)	(11.200)	(391.320)	(6.600)	(236.880)	(2.050)	(183.62)	(0.610)
Observations	27,477	27,477	10,385	10,385	27,477	27,477	10,385	10,385
R-squared	0.885	0.885	0.869	0.870	0.915	0.916	0.892	0.894
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2 Industry heterogeneity

To further explore industry heterogeneity in the impact of AI development on firms' educational composition of labor, this study divides the sample into high-technology and non-high-technology industries according to the Classification of High-Tech Industries (Manufacturing) (2017) issued by the National Bureau of Statistics, and then conducts grouped regressions (See Table 8**)**.

For the low-educated labor sample, the coefficient of AI development is significantly negative at the 1% level in both high-technology and non-high-technology industries, with coefficients of -0.010 and -0.004, respectively, indicating that the substitution effect of AI on low-educated labor is significant in both groups, but much stronger in high-technology industries. This difference may reflect the higher technology intensity and stronger R&D demand in high-technology industries, where AI applications are broader and deeper. To maintain technological leadership, firms in these industries are more likely to adopt AI systems to replace traditional manual operations, resulting in a stronger displacement effect on low-educated labor. By contrast, non-high-technology industries are still dominated by traditional production and routine services, where AI applications remain largely at the pilot or auxiliary stage, and the substitution effect is therefore relatively weaker.

For the high-educated labor sample, the coefficient of AI development is also significantly positive at the 1% level in both high-technology and non-high-technology industries, with coefficients of 0.010 and 0.004, respectively, indicating clear industry heterogeneity in the complementary effect as well. The stronger complementary effect in high-technology industries may arise because, first, their core competitiveness depends on continuous technological innovation, while the development, deployment, and upgrading of AI technologies rely heavily on highly educated talent with professional expertise and innovative capacity, generating deep complementarities between the two. Second, competition is more intense in high-technology industries, prompting firms to recruit more highly educated talent to build technological barriers and seize the initiative in innovation, thereby supporting the contextualized application and industrial commercialization of AI. Although non-high-technology industries also display objective demand for highly educated workers, the strength of this complementarity remains more limited because of lower levels of technological application and earlier stages of industrial transformation.

Overall, compared with non-high-technology industries, the reshaping effect of AI on firms' educational composition of labor is more pronounced in high-technology industries, as reflected in both a stronger substitution effect on low-educated labor and a stronger complementary effect on high-educated labor. This finding highlights the moderating role of industry technology intensity in shaping the labor-market effects of AI and provides empirical support for differentiated policy design and more precise human-capital adaptation strategies across industries. For high-technology industries, greater attention should be given to the cultivation and accumulation of high-end talent to sustain continued AI innovation and deeper application. For non-high-technology industries, digital transformation should be accompanied by stronger skills training and job-transition support for low-education workers in order to mitigate the employment shocks induced by technological substitution.

Table 8. Heterogeneity test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	low-educated	low-educated	low-educated	low-educated	high-educated	high-educated	high-educated	high-educated
	Non high-tech		high-tech		Non high-tech		high-tech	
AI	-0.004***	-0.004***	-0.010***	-0.009***	0.004***	0.004***	0.010***	0.007***
	(-2.910)	(-2.950)	(-7.720)	(-6.590)	(3.580)	(3.470)	(7.780)	(6.220)
Age		0.006***		-0.001		-0.006***		-0.001
		(2.990)		(-0.500)		(-3.290)		(-0.490)
Dual		0.004		-0.006**		-0.004*		0.003
		(1.410)		(-2.100)		(-1.740)		(1.400)
Growth		0.004		-0.004*		-0.005**		0.006***
		(1.520)		(-1.740)		(-2.180)		(2.900)
Roa		0.036**		-0.000		-0.001		0.023
		(1.990)		(-0.020)		(-0.060)		(1.530)
Size		-0.003		-0.018***		0.007***		0.023***
		(-0.980)		(-6.120)		(2.660)		(8.960)
Top1		-0.000		-0.001***		0.000**		0.001***
		(-1.340)		(-3.580)		(2.120)		(4.650)
Soe		-0.015**		0.013**		0.007		-0.013**
		(-2.400)		(2.160)		(1.480)		(-2.510)
Lev		0.060***		0.018*		-0.069***		-0.026***
		(5.680)		(1.840)		(-7.680)		(-2.930)
Constant	0.658***	0.598***	0.650***	1.093***	0.306***	0.290***	0.321***	-0.186**
	(339.620)	(7.630)	(427.02)	(12.600)	(194.060)	(4.440)	(227.010)	(-2.390)
Observations	15,387	15,387	22,309	22,309	15,387	15,387	22,309	22,309
R-squared	0.870	0.871	0.890	0.891	0.912	0.913	0.912	0.914
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.

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

5. Conclusions and Policy Implications

Based on panel data for Chinese A-share listed firms in Shanghai and Shenzhen from 2014 to 2024, this study employs a two-way fixed-effects model to examine in depth the relationship between AI development and firms’ educational composition of labor, as well as the underlying mechanism. The main conclusions are as follows.

First, AI development significantly reshapes firms’ educational composition of labor. The baseline regression results show that a one-unit increase in AI development reduces the share of low-educated labor by 0.007 units and increases the share of high-educated labor by 0.006 units, exhibiting a clear pattern of “substituting for low-educated labor while complementing high-educated labor.” This core finding remains robust after multiple robustness tests. Second, the effect of AI on firms’ educational composition of labor displays significant regional and industrial heterogeneity. From the regional perspective, both the substitution effect and the complementary effect are significant in developed and less developed regions, but their intensities differ: the substitution effect is stronger in developed regions, whereas the complementary effect is more pronounced in less developed regions. From the industrial perspective, the effect of AI is significantly stronger in high-technology industries than in non-high-technology industries. Specifically, in high-technology industries, both the substitution effect on low-educated labor and the complementary effect on high-educated labor are about 2.5 times as large as those in non-high-technology industries, highlighting the moderating role of industry technology intensity in shaping the labor-market effects of AI.

Based on these findings, this study proposes the following policy implications.

First, a stratified and targeted talent development system should be established to adapt to the restructuring of firms’ educational composition of labor induced by AI. In response to the typical pattern of “substituting for low-educated labor while complementing high-educated labor,” the government should coordinate efforts on both the demand side and the supply side. On the demand side, it should guide firms to optimize their talent recruitment mechanisms and provide tax incentives or fiscal subsidies to firms that actively recruit highly educated workers and offer employee skill training, thereby encouraging firms to improve their labor structure. On the supply side, a multi-tiered talent development system should be established. For low-educated labor, a lifelong learning system and reemployment training mechanism should be developed, with a focus on digital skill upgrading and job-transition training. Through industry–education integration and school–enterprise cooperation, workers in traditional jobs can be helped to acquire new skills for working alongside AI, thereby alleviating the employment shock caused by technological substitution. For high-educated labor, the cultivation and reserve of high-end talent should be strengthened. Universities should be encouraged to establish more interdisciplinary programs related to AI, while firms and research institutes should be supported in building joint training mechanisms to foster a group of internationally competitive leading talents in such core fields as machine learning, deep learning, and computer vision.

Second, greater emphasis should be placed on strengthening firms’ technological innovation capability in order to smooth the transmission channel through which AI optimizes labor structure. The government should increase support for scientific and technological innovation and reduce the cost of innovation through policy instruments such as additional tax deductions for R&D expenses, innovation vouchers, and special technology subsidies, thereby incentivizing firms to increase R&D investment. At the same time, firms should be encouraged to establish industry–university–research collaboration mechanisms with universities and research institutes to accelerate the commercialization of scientific and technological achievements and enhance their innovation capability. For technology-intensive industries, policy support should focus on breakthroughs in key core technologies and on promoting deeper integration between AI and industry. For traditional industries, firms should be guided to pursue technological upgrading and process improvement while also paying attention to the optimization of labor structure, so as to achieve coordinated development between technological progress and employment restructuring.

Third, differentiated guidance strategies tailored to regional and industrial conditions should be implemented in order to address more precisely the regional and industrial heterogeneity of AI’s labor-market effects. In developed regions, where the substitution effect is stronger, greater emphasis should be placed on building public training centers and skill-upgrading platforms to provide low-education workers affected by technological substitution with smoother employment transition channels. At the same time, an unemployment early-warning mechanism should be explored so that reemployment training resources can be deployed in advance. In less developed regions, where the complementary effect is more pronounced, efforts should be made to attract high-end talent by offering such policy support as talent apartments, research start-up funding, and education guarantees for children, thereby encouraging highly educated workers to move to central and western regions. Meanwhile, the local talent development environment should be improved to create favorable career prospects and innovation ecosystems for high-end talent, thus narrowing regional talent disparities. With respect to industrial heterogeneity, high-technology industries should focus on the leading role of top talent and encourage firms to increase investment in AI basic research and frontier technologies, while using equity incentives and project-based profit sharing to stimulate the innovation vitality of highly educated workers. Non-high-technology industries, by contrast, should pay greater attention to upgrading the skills of low-education workers while promoting digital transformation. Through government-purchased training services and firm-level training subsidies, workers in traditional industries can be supported in achieving skill upgrading and job transition, thereby ensuring the coordinated development of technological progress and employment stability.

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