

Article

Artificial Intelligence Development and Worker Employment Quality: Evidence from China

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Abstract

With the continuous development of new technologies, these new technologies have a profound impact on the labor market. This paper uses micro-individual data from the China Family Panel Studies (CFPS) from 2016 to 2022 and provincial-level macro-data on artificial intelligence (AI), employing a two-way fixed-effects model to systematically examine the actual impact and underlying mechanisms of AI development on the employment quality of workers. The study shows a significant positive correlation between the level of regional artificial intelligence development and the employment quality of local workers. However, this overall effect at the regional level cannot directly prove the individual-level effect of enterprises or employees using artificial intelligence. Mechanism testing further confirms that the effect of the regional AI development on improving the employment quality of workers is mainly achieved through optimizing the industrial structure and promoting the intelligentization of workers' working mode. Heterogeneity analysis indicates that the regional artificial intelligence has a greater positive impact on employment quality for male workers, outside-system workers, and workers in the eastern region. Therefore, to achieve higher-quality employment for workers, it is necessary to promote the deep integration of AI with the real economy, build a multi-party collaborative education mechanism involving government, enterprises, and universities, and implement policies to promote digital inclusion and differentiated support.

Keywords: artificial intelligence; employment quality; industrial structure; work style

1. Introduction

Artificial intelligence (AI) has become a key driving force for a new round of technological revolution and industrial transformation. Its impact on the labor market presents a multifaceted and multi-layered structural reshaping effect, opening new development opportunities for high-quality employment in the new era. According to statistics from the International Federation of Robotics (IFR)'s "World Robotics Report 2025," China's stock of industrial robots in service exceeded 1 million in 2021, growing to 2.027 million units by 2024. The annual new installations in 2024 reached 295,000 units, accounting for 54% of global new installations, making it the core source of global industrial robot demand. According to the "Future Jobs Report 2025," by 2030, AI and information processing technologies will bring about a two-way shift in jobs: approximately 9 million jobs will face the risk of being replaced, while 11 million new jobs will be created; the share of work tasks entirely undertaken by humans will fall from 47% to 33%, reflecting the redistribution effect of work tasks driven by technology. The industrial application of artificial intelligence is no



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longer limited to local business operations and simple job automation, but is continuously advancing towards a new stage of human–machine collaboration that empowers the entire business chain and deeply integrates across industries. This technological transformation will have a different impact on workers than in the traditional era of automation in terms of wages, labor intensity, social security, and individual self-worth. However, existing research mainly focuses on the impact of artificial intelligence on the quantity and rate of employment, while the discussion on the quality of employment is still insufficient, and related research needs to be further expanded. This paper differs from the existing research in three respects: first, current studies largely examine the impact of robots on job quality within the manufacturing sector, failing to comprehensively reflect the agricultural and service industries. Second, existing research often focuses on specific demographic groups—such as young people, women, or migrant workers—whereas this paper addresses the entire workforce, offering broader applicability. Third, regarding mediating mechanisms, few studies have explored the impact of artificial intelligence on job quality through the lenses of industrial structure optimization and the smart transformation of work methods. This study closely aligns with the core thematic scope of *Sustainability* regarding social sustainability and inclusive long-term development and responds to the International Labor Organization (ILO)’s decent work initiative, as well as the United Nations Sustainable Development Goal 8, which advocates for productive employment, workplace equity, labor security, and human-centered working conditions for all workers. While existing sustainability research predominantly focuses on environmental and economic sustainability, social sustainability centered on labor well-being and high-quality employment has become an essential and indispensable dimension of balanced sustainable development. Focusing on the multifaceted impacts of artificial intelligence on labor employment quality, this study systematically examines changes in workers’ income levels, job stability, working conditions, and career development prospects driven by technological progress. It further clarifies how intelligent technology reshapes the realization of decent work in the digital era, addresses potential labor inequality and precarious employment risks brought about by technological transformation, and explores inclusive development paths for harmonizing technological innovation and labor welfare. Accordingly, this research enriches the social sustainability connotation of technological progress, provides empirical evidence for balancing technological upgrading and high-quality employment, and offers practical implications for promoting sustainable, inclusive, and people-centered labor market development in the digital economy.

Therefore, this paper empirically examines the impact of the regional AI development on employment quality using macro-level data on AI development and micro-level individual data from the China Family Panel Studies (CFPS). This article measures the regional artificial intelligence development by provincial-level AI patents. This indicator represents the supply of AI innovation in a region and is distinct from the adoption of AI technology by enterprises and the individual AI usage behavior of workers). Potential marginal contributions include the following: first, current research focuses on the impact of AI on employment scale and structure; this paper further focuses on employment quality, placing AI and employment quality within the same analytical framework to empirically test the impact of AI development on employment quality. Second, this paper focuses on individual workers, constructing a comprehensive employment quality index encompassing five aspects: worker income, working hours, job stability, job security, and work environment. It delves into the impact of AI development on employment quality and its sub-dimensions, further revealing the influencing mechanisms from the perspectives of industrial structure optimization and intelligent work methods, enriching the empirical evidence on how AI development empowers micro-level employment quality. Third, it

analyzes the impact of AI development on different worker groups, thus providing more precise empirical analysis for improving employment support systems for key groups and maintaining fairness in the employment market.

2. Literature Review

2.1. Artificial Intelligence

Research on artificial intelligence in academia originated in the 1950s. Constrained by early computing power, algorithm capabilities, and the scale of available data, the artificial intelligence industry gradually entered a period of stagnation after two waves of development. Entering the 21st century, the data dividend brought about by the mobile internet, the cost advantage of cloud computing, and technological breakthroughs in algorithms and related theories have led to the rapid development of artificial intelligence technology, resulting in multifaceted and multi-layered impacts on the labor market.

Currently, the impact of artificial intelligence on the labor market is mainly reflected in its influence on employment scale and employment structure. Regarding employment scale, the impact of artificial intelligence is mainly manifested as a substitution effect, a scale effect, and a creation effect, but the academic community has not yet reached a unified conclusion on the impact of artificial intelligence on employment scale. Regarding the substitution effect, Acemoglu and Restrepo (2020) used US labor market data to confirm, from industry and regional perspectives, that the application of industrial robots has a substitution effect on labor [1]. Aghion et al. (2019) verified from a French perspective that the application of robots will have a crowding-out effect, causing a decline in the overall employment level at the regional level [2]. Wang and Dong (2020) have found through enterprise data research that robot applications will replace some employees [3]. Regarding the scale effect, researchers have found through cross-national data that while the application of industrial robots reduces the number of workers, it also increases the demand for non-automated positions due to scale efficiency, thus promoting the growth of the overall number of jobs [4]. Regarding the creation effect, Wang et al. (2022) found that the impact of industrial robot applications on manufacturing employment has heterogeneity in the time dimension: in the short term, it mainly manifests as an employment substitution effect, while from a medium- to long-term perspective, the employment creation effect brought about by robots will gradually dominate [5].

In terms of employment structure, Acemoglu & Restrepo (2018) constructed a task analysis framework and found that the task substitution effect brought about by automation and the new task creation effect are engaged in a game together, determining the evolution direction of the labor market [6]. This theory lays an important theoretical foundation for analyzing the impact of artificial intelligence on the labor market [6]. Unlike the traditional view that automation mainly affects routine and repetitive jobs, Felten et al. (2018) explored occupational exposure to artificial intelligence by constructing a model [7]. They found that the impact of artificial intelligence is not limited to low-skilled jobs. Some high-skilled cognitive jobs also face technological shocks, which in turn restructure the skill demand structure of various occupations [7]. Zhou et al. (2021) analyzed the experience in China and found that artificial intelligence promotes the cross-industry reallocation of labor, reducing the proportion of employment in manufacturing while increasing the proportion of employment in the service industry [8]. At the same time, the impact of technological shocks on job opportunities and wage levels is not homogeneous and shows differentiated characteristics among different educational groups and different industries [8].

2.2. Employment Quality

Employment quality reflects the employment well-being of workers and is an important benchmark for measuring the development of people's livelihood and the high-quality development of the labor market. Currently, the measurement of employment quality is mainly carried out from subjective and objective, as well as macro and micro, aspects. From the subjective perspective, employment quality is the feeling and experience that workers gain in the process of working, and is mainly measured by the subjective satisfaction of workers [9,10]. From the objective perspective, employment quality focuses on the workers' salary level, contract status, career development, job stability, occupational safety and labor protection aspect [11–13]. From the micro perspective of employment quality, attention is paid to the measurement and evaluation of the individual employment quality of workers, focusing on the workers' salary level, labor intensity, social security and job satisfaction aspects. For example, Feng Xiliang and Wu Yunting (2026) focused on the youth group and constructed a comprehensive index of employment quality of young workers from the subjective and objective aspects of wage income, working hours, job stability, labor protection and job promotion satisfaction [14]. Zhang Guangsheng and Wang Ruonan (2023) constructed a comprehensive index of employment quality of migrant workers, which mainly involves five aspects: income, welfare, stability, intensity and career promotion [15]. Liu Cuihua et al. (2022) constructed an evaluation index system for the employment quality of young people, including three primary indicators: wages and benefits, labor protection and intensity, and job satisfaction, and 17 secondary indicators such as work income, labor contracts, and union membership [16]. From a macro perspective, employment quality focuses on the measurement and evaluation of regional employment quality, exploring the operation of the regional labor market and the efficiency of resource allocation. For example, Lai Desheng et al. (2011) evaluated the employment quality of various provinces in China by measuring six aspects: employment environment, employment ability, employment status, workers' remuneration, social protection, and labor relations [17]. Qi Yudong et al. (2020) mainly constructed a provincial-level employment quality evaluation index system for China from four primary indicators and 20 secondary indicators: employment environment, employment ability, workers' remuneration, and labor protection [18]. He Qin et al. (2024) constructed a high-quality employment index, involving six primary indicators such as employment environment and employment ability, including 14 secondary indicators such as economic development and education level, and 23 tertiary indicators such as per capita GDP [19].

Factors affecting employment quality can be divided into internal factors and external factors. Among them, internal factors mainly refer to factors related to the workers themselves, such as their education level, health level, social skills, digital literacy, career planning, and employment concepts. For example, Ding Shulei et al. (2024) found that over-education and under-education can affect the quality of youth employment [20]; Zhang Kai and Li Guoqing (2026) found that digital literacy can improve the quality of employment of rural youth workers by improving their cognitive level, expanding social networks and information access channels, and promoting non-agricultural employment [21]. External factors refer to factors other than personal factors, such as the development of the platform economy, flexible work, public employment services, and digital inclusive finance. For example, Lu Yang et al. (2026) found that the platform economy can promote high-quality employment of migrant workers by improving their access to information and human capital [22]; Liu Zishuo et al. (2026) found that the supply of public services can improve the quality of employment of female workers by alleviating information asymmetry and improving human capital [23]; and Liu Cuihua (2022) et al. found that flexible work can

improve the quality of employment of young people by improving their life satisfaction and mental health [16].

2.3. Artificial Intelligence and Employment Quality

Current research mainly focuses on the impact of artificial intelligence on a certain dimension of employment quality. In terms of wage income, scholars have explored the wage effect of artificial intelligence from multiple perspectives. For example, Wu Weijuan et al. (2026) found through survey data on platform workers nationwide that artificial intelligence can increase women's incomes, thereby narrowing the gender income gap on platforms [24]. Wang Yuxin and Yao Xumin (2026) revealed through policy quasi-experiments that artificial intelligence pilot zones have increased workers' income, but at the same time, they have also widened the urban–rural income gap [25]. Zhang Yi and Jiang Shan (2026) found that generative artificial intelligence has significantly reduced cognitive gig worker wages by 19.9% [26]. In terms of working hours, Zhou Guangsu et al. (2021) found that artificial intelligence exacerbates the risk of workers being replaced, making on-the-job workers face greater job replacement pressure [8]. In order to strengthen competitiveness, workers have to actively increase their work intensity and spend longer hours working [8]. At the same time, artificial intelligence can also replace workers in performing highly repetitive work tasks, thereby improving work efficiency and reducing their labor supply. For example, Noy and Zhang (2023) found through experiments that ChatGPT improved writing efficiency for relevant personnel, reduced time by 40%, and improved output quality by 18% [27]. In terms of job satisfaction, artificial intelligence is a double-edged sword. First, artificial intelligence can replace workers in performing trivial, tedious, and repetitive tasks, enabling workers to transform from operators to creators of systems, thereby improving their satisfaction [28]. Second, “machine replacement” will increase workers' perceived risk of unemployment, and the crowding-out effect of new technologies on labor will reduce workers' sense of self-worth, thereby reducing their job satisfaction [29].

A review of the literature reveals the following: first, employment quality is a comprehensive concept encompassing multiple dimensions, reflecting the overall employment status of workers. Second, current research largely focuses on the impact of artificial intelligence on employment scale and structure, lacking an examination of employment quality. Third, existing research on artificial intelligence and employment quality mostly focuses on a single, specific dimension of employment quality, thus failing to fully reflect the comprehensive impact of artificial intelligence development on workers' employment quality.

3. Theoretical Framework

3.1. The Impact of Artificial Intelligence on the Quality of Employment for Workers

As a key engine for a new round of technological innovation and industrial upgrading, artificial intelligence is reshaping the labor market and directly affecting the quality of employment for workers. On the one hand, the regional artificial intelligence technology can reduce the information collection and screening costs between enterprises and workers by processing massive job search and job data, weaken the information gap between enterprises and workers, improve the matching efficiency of labor supply and demand, and help workers find suitable jobs more quickly, enhancing the job matching degree and employment stability [30]. On the other hand, the regional artificial intelligence technology has spawned a large number of new industries, new business formats and new occupations, such as artificial intelligence engineers, blockchain engineers, cloud computing technicians, etc., which effectively expand the employment space, promote the improvement of labor productivity, and create higher income levels and broader career

development spaces for workers [1]. At the same time, the regional artificial intelligence technology empowers public service employment scenarios, promotes the transformation and upgrading of traditional public employment service models, helps to enhance the accuracy of employment service supply, strengthen the convenience of public employment services, and expand the coverage of public employment services [31]. The regional artificial intelligence technology helps workers obtain suitable jobs and improves the quality of employment for workers in multiple dimensions such as wage income, work efficiency and career development. Based on this, we propose Hypothesis 1 for this paper.

H1. *The level of the regional development of artificial intelligence can significantly improve the quality of employment for workers.*

3.2. The Mechanism and Effect of Artificial Intelligence in Improving the Quality of Employment for Workers

The improvement of the quality of employment for workers by the regional artificial intelligence also affects the optimization of industrial structure and the reshaping of workers' work methods. The development of the regional artificial intelligence has a profound impact on industrial structure. On the one hand, the development of regional artificial intelligence promotes the upgrading of the industrial structure of the service industry and the manufacturing industry. With the continuous development and diffusion of artificial intelligence technology, new business forms and models of platform economy, sharing economy and experience economy have expanded rapidly. Productive service industries such as smart logistics and financial technology have shown a trend of professional agglomeration and development. Life service industries such as smart healthcare and digital cultural tourism have moved towards a stage of quality and refinement, thereby increasing the proportion of the service industry and promoting the upgrading of industrial structure [32]. On the other hand, the regional artificial intelligence promotes the rational development of industrial structure. Artificial intelligence can help enterprises complete the collection of massive amounts of data through digital intelligence platforms and integrate fragmented supply and demand information, thereby accurately judging market trends and achieving precise matching between supply and demand. At the same time, enterprises can strengthen the level of collaboration and adaptation within the industrial chain and between upstream and downstream links by using artificial intelligence technology, thereby promoting the rationalization of industrial structure [33]. The upgrading and rationalization of industrial structure have spawned more high-tech, high-income jobs, and provided workers with more diversified employment options and broader career development paths [18,34].

As the application of artificial intelligence technology in enterprises continues to deepen, the focus has shifted from the initial stage of mechanically completing repetitive, high-intensity tasks to human-machine collaboration, and the way and content of workers' work have also changed. On the one hand, enterprises use deep learning and large-scale modeling and other machine learning algorithms to conduct pattern recognition, and use big data analysis to optimize business processes, thereby empowering employees to improve work efficiency and service quality [35]. For example, artificial intelligence technology undertakes standardized teaching tasks such as knowledge answering and homework correction, which, while reducing the burden of repetitive tasks on teachers, promotes the iterative reconstruction of traditional teaching models, thereby effectively improving teachers' sense of professional gain and job satisfaction. On the other hand, human-machine collaboration enables workers and machines to realize greater self-worth in the process of collaboration [36]. Workers are transitioning from performing single

tasks to performing multiple tasks simultaneously, and from completing standardized, procedural tasks to engaging in highly flexible, multifaceted work. This, in turn, prompts workers to continuously improve their digital literacy, professional skills, and other human capital, gaining greater bargaining power in the labor market and thus enhancing their employment quality. Based on this, this paper proposes hypotheses 2 and 3. And theoretical logic is shown in Figure 1.

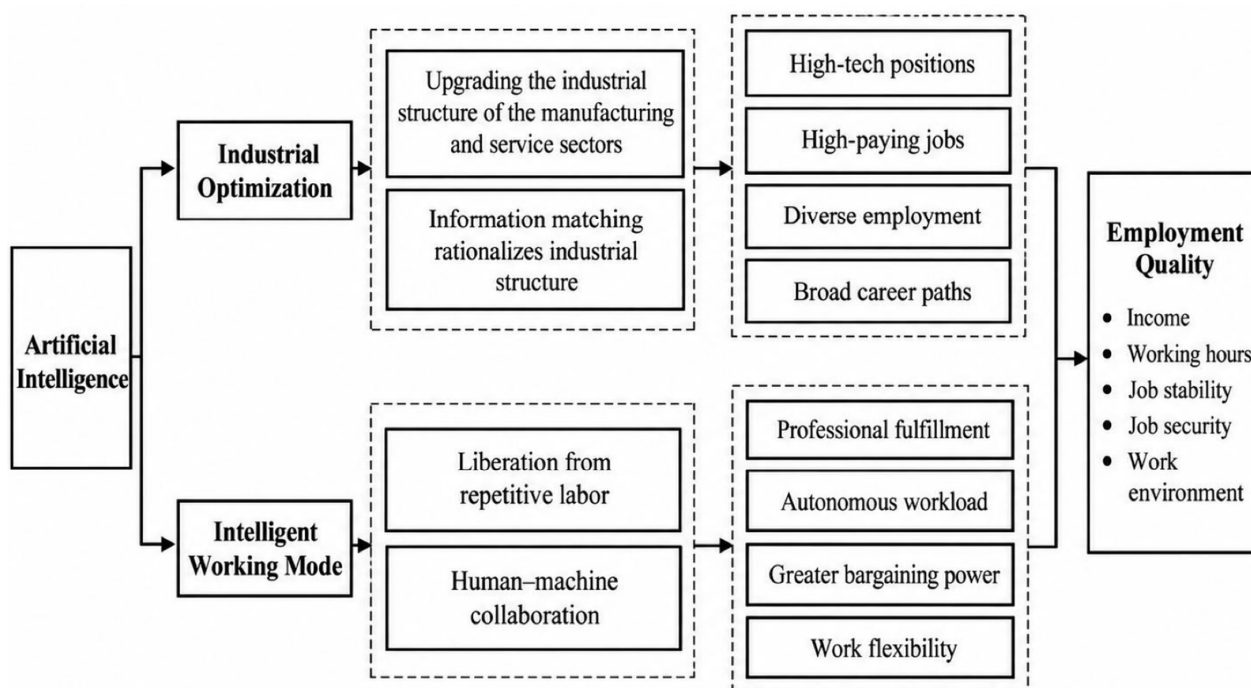


Figure 1. Theoretical Framework.

H2. *The level of the regional artificial intelligence development improves the quality of workers' employment through industrial structure optimization.*

H3. *The level of the regional artificial intelligence development improves the quality of workers' employment by reshaping work methods.*

4. Research Design

4.1. Data Source

The main data used in this paper include the following. First, macro-level data on the development level of artificial intelligence and economic indicators. Among them, artificial intelligence patent data comes from the Patsnap patent database. The key words include "artificial intelligence", "machine intelligence", "machine learning", "deep learning", "neural network", "reinforcement learning", "computer vision", "image recognition", "natural language processing", "knowledge graph", "pattern recognition", and "generative AI". Among the 27 sample provinces, the total numbers of artificial intelligence patent applications in 2016, 2018, 2020, and 2022 were 214,375, 306,400, 393,164, and 436,792, respectively, showing a continuous upward trend. Economic indicator data comes from the China Statistical Yearbook. Some missing values are supplemented by statistical yearbooks and statistical bulletins of various provinces and cities. Second, micro-level data on individual workers, which comes from the China Family Panel Studies (CFPS) database. The database covers 25 provinces, municipalities and autonomous regions. The sample information includes the employment quality indicators of workers required for the study, such as wage income, working hours and workplace, as well as information on working

with the Internet. According to the needs of the study, the CFPS data is processed as follows: based on the study of Liu Beiyu and Li Xiang (2025) [34], the focus is on workers aged 18 to 60; the geographical information of the respondents is matched to the provincial level according to their region, and matched with the calculated provincial artificial intelligence development level; individual labor data with missing employment quality indicators are removed. To avoid bias in the estimation results, continuous variables were winsorized at the 1st and 99th percentiles. The final observed value is 16,324, and the effective number of independent workers is 6567, among which 3872 workers have valid observations for two periods, 2200 for three periods, and 495 for four periods; consequently, this study employs an unbalanced individual panel. The numbers of valid observations for the years 2016, 2018, 2020, and 2022 are 2338, 4903, 4681, and 4402, respectively. With these samples, 9263 were male and 7061 were female, demonstrating a balanced gender distribution. In terms of age, 8279 were young workers aged 35 and under, and 8045 were middle-aged workers aged 35 and over, highlighting the breadth and representativeness of the research sample.

4.2. Variable Description

4.2.1. Explanatory Variable: Level of the Regional Artificial Intelligence Development (AI)

The explanatory variable in this paper is the level of the regional artificial intelligence application. Although the application of artificial intelligence in the industrial field can reflect the level of regional intelligence to a certain extent, it is difficult to fully reveal its impact on other industries and social wage income. Therefore, this paper draws on the patent identification strategy of Acemoglu and Restrepo (2020) [1] and Wang Linhui et al. (2023) [36], and uses related words such as “automatic”, “digital control” and “unmanned” to search and screen artificial intelligence patents; then, the number of patents is aggregated to the provincial level, and the number of artificial intelligence patents per 10,000 employees in the province is calculated, which is used as a measure of the level of artificial intelligence development.

4.2.2. Explained Variable: Employment Quality (EQ)

According to Zhang J (2025), the explained variable in this paper is employment quality, which mainly includes wage income, work intensity, job stability, labor protection, and work environment [37]. Wage income is measured by the worker’s monthly wage income; regarding work intensity, according to Yao et al., (2026), a value of 1 is assigned if the worker’s weekly working hours do not exceed 50 h, otherwise a value of 0 is assigned, indicating overtime work [38]; job stability is measured by whether a labor contract has been signed, and a value of 1 is assigned if a labor contract has been signed, otherwise a value of 0 is assigned, indicating job instability; labor protection is measured by whether the worker has the five social insurances and one housing fund (pension insurance, medical insurance, unemployment insurance, work injury insurance, maternity insurance, and housing provident fund), with 1 point awarded for each item, and the total score being a measure of work welfare. The workplace is coded as followed according to Liu et al. (2022): offices are assigned a value of 1; residences, other indoor workplaces, workshops, workplaces within vehicles, and outdoor workplaces are assigned a value of 0 [16]. Then, referring to other methods, the five indicators are used to calculate the comprehensive employment quality index using the entropy weighting method.

The entropy weighting method measurement process is as follows:

The first step is standardization of indicator data.

Standardization of positive indicators:

$$X_{ij} = \frac{X_{ij} - \min_1(X_{1j}, X_{2j} \dots X_{nj})}{\max_1(X_{1j}, X_{2j} \dots X_{nj}) - \min_1(X_{1j}, X_{2j} \dots X_{nj})}$$

Standardization of negative indicators:

$$X_{ij} = \frac{\max_1(X_{1j}, X_{2j} \dots X_{nj}) - X_{ij}}{\max_1(X_{1j}, X_{2j} \dots X_{nj}) - \min_1(X_{1j}, X_{2j} \dots X_{nj})}$$

where X_{ij} represents the j -th indicator data of the i -th youth individual.

The second step is to calculate the proportion of the i -th individual value of the j -th indicator to the total value of that indicator,

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^n X_{ij}}$$

The third step is to calculate the entropy value of the j -th indicator,

$$S_j = -k \sum_{i=1}^n (Q_{ij} * \ln(Q_{ij}))$$

The fourth step is to calculate the redundancy of information entropy,

$$d_j = 1 - S_j$$

The fifth step is to calculate the weight of indicator j ,

$$w_j = d_j / \sum_{j=1}^m d_j$$

The sixth step is to calculate the total entropy weight of employment quality,

$$Score_i = \sum_{j=1}^m w_j X_{ij}$$

The current entropy weight index employs a set of fixed weights across waves: wage income 0.0085 (0.85%), working hours 0.2951 (29.51%), employment stability 0.2665 (26.65%), labor protection 0.3512 (35.12%), and workplace 0.0788 (7.88%), with the weights summing to 1.

4.2.3. Control Variables

To account for potential biases in the estimation results due to omitted variables, this paper selects and includes control variables that influence the level of artificial intelligence development and the quality of employment at the individual, family, and regional levels, thereby constraining the model. At the individual level, variables include age square, place of residence, self-reported health, and marital status. At the family level, family size (number of children) and family economic status (logarithm of total monthly family income) are selected. At the regional level, variables include consumption ratio (the ratio of household consumption expenditure to GDP) and financial development (ratio of the sum of outstanding deposits and loans of financial institutions to GDP).

4.2.4. Mechanism Variables

1. Industrial structure optimization: Industrial structure is an important foundational condition for changes in employment structure and employment quality. This paper refers to the approach of Hu Ningning et al. (2026) [31] and divides industrial optimization into two aspects: industrial upgrading and industrial rationalization. Industrial upgrading is measured by the ratio of the output value of the tertiary industry to that of the secondary industry; industrial rationalization is measured by the deviation of industrial structure. The smaller the deviation, the more rational the industrial structure.
2. Intelligent working mode: Workers' engagement in digitalized work methods, referring to the approach of Liu Beiyu and Li Xiang (2025) [34], is measured based on the "frequency of using the Internet for work" in the questionnaire. Adopting the measurement method from Zhang J (2025), the questionnaires of CFPS2016 and CFPS2018 asked about the "frequency of using the Internet for work", and assigned a value ranging from 1 to 5; the questionnaires of CFPS2020 and CFPS2022 asked about the importance of the Internet to work, and assigned a value from 1 to 5 [37]. The larger the value, the more intelligent technology the worker uses in the work process.

Table 1 provides the definition of the variables and their statistical analysis.

Table 1. Variable definition and descriptive statistical analysis.

Variable	Name	Definition	Mean	SD	Min	Max
Explained variable	Employment quality	The comprehensive employment quality index is obtained by using the entropy weight method to comprehensively consider dimensions such as wages, working hours, stability, labor protection, and workplace	0.532	0.341	0.000	0.999
Explanatory variable	The regional artificial intelligence (standardized)	Measured by the number of AI patent applications per 10,000 employees in the province and perform Z-score standardization	0.000	1.000	−3.611	1.968
Control Variables	Age ²	Age ²	1489.548	810.804	324.000	1225.000
	Marriage	Married = 1, no = 0	0.774	0.418	0.000	1.000
	Residence	Urban = 1, rural = 0	0.653	0.476	0.000	1.000
	Self-assessment of health	Health, 1—5, the higher the score, the healthier.	3.297	1.034	1.000	5.000
	Family size	The number of children	3.888	1.940	1.000	15.000
	Family economic situation	Take the logarithm of the total monthly household income	8.651	0.887	0.000	12.940
	Consumption ratio	Measured by the ratio of household consumption expenditure to GDP	0.391	0.058	0.175	0.689
	Financial development	Ratio of the sum of outstanding deposits and loans of financial institutions to GDP	3.535	0.742	2.227	6.204
Mechanism variables	Intelligent working mode	2016/2018 represents the working frequency of the Internet, with values ranging from 1 to 5. 2020/2022 represents the significance of the network to work, with values ranging from 1 to 5	3.643	1.575	1.000	5.000
	Rationalization of industrial structure	Structural deviation degree	0.184	0.099	0.020	0.521
	The upgrading of the industrial structure	Output value of the tertiary industry/output value of the secondary industry	1.308	0.204	0.756	3.132

4.3. Model Setting

This paper establishes the following benchmark econometric model to reveal the impact of artificial intelligence on the quality of employment for workers. The model is defined as follows:

$$EQ_{ipt} = \alpha + \beta AI_{pt} + \gamma X_{ipt} + \mu_i + \lambda_t + \varepsilon_{ipt}$$

where EQ_{ipt} represents the employment quality of individual i in province p and year t ; AI_{pt} represents the level of the regional artificial intelligence development at the province level; X_{ipt} represents a set of control variables, including variables at the individual, family, and city levels; μ_i represents the individual fixed effect; λ_t represents the year fixed effect, used to control for macroeconomic fluctuations, institutional adjustments, and common time shocks; and ε_{ipt} is a random disturbance term. The core coefficient β measures the impact of artificial intelligence development on the employment quality of workers.

To further explore the direct impact of the level of the regional artificial intelligence development on the quality of employment, and the indirect impact of industrial structure optimization and intelligent work methods as mediating variables on the impact of the level of artificial intelligence development on the quality of employment, this paper conducts a mediation analysis [39], and the mediation model is as follows:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_{it}$$

$$EQ_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \mu_{it}$$

$$EQ_{it} = (\gamma_0 + \gamma_2 \beta_0) + (\gamma_1 + \gamma_2 \beta_1) AI_{it} + (\gamma_3 + \gamma_2 \beta_2) X_{it} + \mu_{it}$$

where M_{it} is the mediating variable; AI_{it} is the explanatory variable representing the level of artificial intelligence development; X_{it} is the control variable; and μ_{it} is the random error term. i represents the individual; t represents the year. β_1 represents the impact of the level of the regional artificial intelligence development on the mediating variable. γ_1 represents the direct impact of the level of artificial intelligence development on employment quality. $\gamma_2 \beta_1$ represents the indirect impact of the level of artificial intelligence development on employment quality through the mediating variable M_{it} . $(\gamma_1 + \gamma_2 \beta_1)$ represents the total effect of the level of the regional artificial intelligence development on employment quality.

5. Empirical Results and Analysis

5.1. Benchmark Regression

To examine the impact of the level of the regional artificial intelligence (AI) development level on the quality of workers' employment, this study conducts a regression analysis—controlling for individual and time fixed effects—by progressively introducing variables representing individual, household, and regional characteristics; the results are presented in Table 2. Column (1) includes only the regional AI development level; Column (2) adds control variables for individual characteristics to the model in Column (1); and Columns (3) and (4) further incorporate control variables for household and regional characteristics, respectively. The regression coefficients for the regional AI development level are positive and statistically significant at the 5% level across all four columns, indicating that the impact of AI development on workers remains robust regardless of whether individual, household, or regional variables are included. Column (4), which controls for individual and time fixed effects as well as variables at the individual, household, and regional levels, offers a more nuanced reflection of the impact of the regional AI development on employment quality; consequently, the results in Column (4) are the most accurate. For every one-unit increase in the level of the regional AI development level, the quality of workers' employment improves by 0.025 units. The regional average overall effect driven by regional

AI innovation may play a role through industrial spillovers, changes in industrial structure, and shifts in the labor market environment, rather than necessarily through the direct use of AI by enterprises or individual workers. The findings are consistent with H1.

Table 2. Benchmark Regression.

	(1) EQ	(2) EQ	(3) EQ	(4) EQ
AI	0.030 ** (0.011)	0.026 ** (0.012)	0.025 ** (0.011)	0.025 ** (0.011)
Wild-cluster p (9999 reps)	0.003	0.009	0.012	0.014
Age ²		−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)
Marriage		0.010 (0.011)	0.010 (0.012)	0.009 (0.012)
Residence		0.031 ** (0.013)	0.029 ** (0.014)	0.029 * (0.014)
Health		0.003 (0.003)	0.003 (0.003)	0.003 (0.003)
Family size			−0.003 (0.004)	−0.003 (0.004)
Family economic situation			0.007 (0.005)	0.007 (0.005)
Consumption ratio				−0.035 (0.089)
Financial development				−0.016 (0.018)
Constant	0.256 ** (0.102)	0.538 *** (0.111)	0.503 *** (0.133)	0.577 *** (0.173)
Individual fixation effect	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES
N	16,324	16,324	16,324	16,324
R ²	0.772	0.773	0.773	0.773

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.

5.2. Robustness Test

Furthermore, to identify whether the baseline regression results are robust, this paper examines them from five aspects: replacing the core explanatory variables, changing the measurement method of the explained variable, adding more stringent fixed effects, adjusting the estimation model, and performing tail reduction. Table 3 shows the robustness test results.

First, the core explanatory variables were replaced. One approach involved using the stock of AI enterprises in a region as a proxy for the regional industrialization and marketization of AI. Column (1) of Table 3 shows that the results were significantly positive at the 10% level for both per capita patent applications and the stock of regional AI enterprises. Another approach used robot installation density as a proxy for the level of AI development. Column (2) of Table 3 indicates that, following this substitution, the regression coefficient for the level of AI development remained significantly positive at the 5% level.

Table 3. Robustness test.

	(1) AI-Firm Stock	(2) Robot Density	(3) Equal- Weighted EQ	(4) CRITIC EQ	(5) Excluding 2020	(6) 2020 Only
AI/ Alternative AI measure	0.035 * (0.018)	0.002 ** (0.007)	0.023 ** (0.009)	0.007 *** (0.004)	0.017 *** (0.008)	0.016 *** (0.004)
Control variables	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	16,214	16,317	16,324	16,324	9395	4681
R ²	0.773	0.773	0.765	0.788	0.805	0.132

Notes: The values in parentheses represent robust standard errors, with *, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.

Second, the measurement method of the explained variable was changed. Considering the error caused by the measurement method of the employment quality index, this paper uses the equal weighted average method and CRITIC method to recalculate employment quality and then performs regression again. Columns (3) and (4) of Table 3 show that, after recalculating employment quality using these methods, the regression coefficient for the level of AI development remained significantly positive at the 10% and 1% level.

Third, the sample range was changed. The public health emergency that broke out at the end of 2019 affected the labor market. First, the 2020 samples were removed. Column (5) of Table 3 shows that, after excluding the 2020 sample, the coefficient of the core explanatory variable remains significantly positive at the 1% level, consistent with the baseline regression results. The second step is to retain only the 2020 samples. Column (6) of Table 3 shows that the coefficient of the core explanatory variable remains significantly positive at the 1% level.

As can be seen, regardless of whether the core explanatory variable is changed, the measurement method of the explained variable is altered, or samples are excluded, the regression coefficient of the level of artificial intelligence development is significantly positive at the 10%, 5% and 1% level, indicating that the conclusion that the level of artificial intelligence development promotes the improvement of the quality of employment for workers is robust.

5.3. Endogeneity Test

Although the baseline model has controlled for individual characteristics, family characteristics, regional economic environment, and fixed effects of year and individual, mitigating the bias of omitted variables to some extent, potential endogeneity issues may still exist between the level of AI development and the quality of employment. On the one hand, regions with higher employment quality typically have more complete industrial systems, higher levels of human capital accumulation, and stronger technology absorption capabilities. These factors may, in turn, promote AI development, leading to an inverse causal relationship between AI and employment quality. On the other hand, factors that are difficult to observe, such as regional governance capabilities, innovation environment, and the tendency of enterprises to digitally transform, may simultaneously affect the level of the regional AI development and the quality of employment, thus causing the bias of omitted variables. Therefore, this paper further employs the instrumental variable method and the Oster test to examine the reliability of the baseline conclusions.

First, drawing on the construction logic of the Bartik (Shift-Share) instrumental variable according to Zhang X.L. et al. (2026) [40], this paper employs an interaction

term—combining a region’s historical AI patent application base with national AI patent application trends—as an instrumental variable for the region’s level of AI development. Regarding relevance, the historical AI patent base reflects a region’s accumulated AI innovation, industrial infrastructure, and capacity for technology absorption, while national AI patent application trends capture the macro-level expansionary shock of AI technological innovation. When a national wave of AI innovation surges, regions with a stronger historical patent base can more rapidly capitalize on technological dividends to boost local AI development; thus, the interaction term is significantly correlated with the endogenous core explanatory variable, satisfying the relevance condition. Regarding exogeneity, the overall trend of national AI patent applications is driven by nationwide technological breakthroughs and top-level policies, remaining unaffected by labor market conditions in any single region. Furthermore, the historical AI patent application base relies on data predating the sample period—representing a predetermined regional endowment—and is therefore immune to reverse causality from contemporaneous labor market outcomes, such as local employment quality, observed during the sample period. This interaction term captures the differential exposure of regions with varying historical technological endowments to a common national technological shock; theoretically, it influences workers’ employment quality only indirectly by altering the region’s level of AI development, thereby satisfying the exogeneity requirement for an instrumental variable. After controlling for individual fixed effects, year fixed effects, and variables such as regional economic development level and urbanization level, the digital infrastructure supply level does not directly determine workers’ wages, labor security, and job stability, thus satisfying the exogeneity requirement of instrumental variables. The test results are shown in Table 4. Column (1) shows the first-stage regression results of the instrumental variable. The regression coefficient of the instrumental variable on the core explanatory variable is significantly positive at the 1% level, indicating that the supply of digital infrastructure can effectively explain the regional differences in artificial intelligence development. Column (2) shows the second-stage regression results. The coefficient of the impact of the level of artificial intelligence development on employment quality is positive and significant at the 1% level, which demonstrates that the conclusion of the baseline regression remains valid.

Table 4. Endogeneity test.

	IV Stage1 AI	IV Stage2 EQ
Historical AI Patent Application Baseline × National AI Patent Application Trends	0.910 *** (0.056)	
AI		0.017 *** (0.005)
Kleibergen–Paap rk Wald F		261.150
Kleibergen–Paap rk LM		4.790
K-P rk LM test <i>p</i> -value		0.029
Control variables	YES	YES
Individual FE	YES	YES
Year FE	YES	YES
N	16,324	16,324
R ²	0.979	0.773

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.

Second, considering that even with the addition of many control variables, the model may still be affected by unobservable factors, this paper further uses the Oster (2019) method to examine the impact of omitted variable bias on the research conclusions [41]. Table 5 shows that after adding control variables, the coefficient of the artificial intelligence variable increased from 0.007 to 0.012, and the model R^2 increased from 0.032 to 0.878. When the true effect is assumed to be 0, the explanatory strength δ required by the unobserved variable relative to the observed variable is 3.006, which is significantly higher than the empirical judgment standard 1 usually used in the Oster method. This means that only when the influence of unobserved factors on the relationship between artificial intelligence and employment quality exceeds that of observed factors by about three times can the positive influence of artificial intelligence be completely offset. Therefore, the endogeneity problem caused by the omission of unobservable variables has a small impact and will not affect the main conclusions drawn from the baseline regression.

Table 5. Oster test.

Explained Variable	R^2_max	Test Methods	Judgment Criteria	Actual Estimation Results	Whether It Passes
Employment Quality	1.000	Method 1	[0.008, 0.037]	β_1^* has the same sign as the benchmark regression coefficient, and the coefficient range does not include 0.	YES
		Method 2	$\delta > 1$	$\delta = 3.006$	YES

Note: In the Oster test, R_max is set to 1 to assess the impact of omitted variable bias on the core conclusions. β_1^* is corrected hypothetical coefficient.

5.4. Heterogeneity Analysis

The baseline regression results revealed that the development of artificial intelligence has improved the quality of employment for workers. However, different worker groups differ in various aspects such as job skills, professional experience, and regional technological application conditions. Therefore, the impact of artificial intelligence on the quality of employment may be heterogeneous across different groups. Accordingly, this paper explores the heterogeneity of the impact of the level of artificial intelligence development on employment quality from three aspects: gender, nature of the employer, and region.

First, this paper performs grouped regression analysis on workers of different genders. Columns (1) and (2) of Table 6 show that the level of the regional artificial intelligence development has a significant positive impact on men, whereas its impact on women is not significant. A possible reason is that male workers have a relatively higher employment rate in positions that are highly complementary to artificial intelligence, such as manufacturing, IT operations and maintenance, intelligent system debugging, and supply chain optimization.

Secondly, from the nature of the employer, this paper divides the work into within the system and outside the system. Employment within “state-owned enterprises, public institutions, government departments/Party and state agencies and non-governmental non-enterprise organizations/associations/industry bodies/foundations/village or neighborhood committees” is classified as employment within the system; all other employment falls outside the system. Columns (3) and (4) of Table 6 show that the regional artificial intelligence has a significant positive impact on workers outside the formal institutional system, whereas its impact on workers within the formal institutional system is not significant. The possible reason is that the informal sector encompasses a vast number of routine cognitive tasks, assembly-line operations, and standardized service roles—such

as customer support, financial accounting, production jobs, and platform-based gig work. These tasks are highly codifiable, making them particularly susceptible to displacement or transformation by artificial intelligence. On one hand, AI empowerment can boost the earnings and productivity of high-skilled workers in this sector; on the other, the threat of displacement erodes the bargaining power of low-skilled workers, exacerbating issues like extended working hours and employment instability.

Table 6. Heterogeneity analysis.

	(1) Male	(2) Female	(3) Outside System	(4) Inside System	(5) Eastern Region	(6) Non-Eastern Regions
AI	0.027 ** (0.011)	0.023 (0.017)	0.030 ** (0.011)	0.013 (0.020)	0.063 ** (0.026)	0.046 (0.055)
Control variables	YES	YES	YES	YES	YES	YES
Individual fixation effect	YES	YES	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES	YES	YES
N	9253	7049	10,535	3916	5604	10,262
R ²	0.762	0.793	0.751	0.742	0.771	0.781

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.

Finally, based on the National Bureau of Statistics' (1986) classification of provinces, autonomous regions, and municipalities in China, this paper divides the sample regions into eastern and non-eastern regions (including the central and the western regions) to further explore the impact of the level of the regional artificial intelligence development on the employment quality of workers in different regions. Columns (5) and (6) of Table 6 show that the level of artificial intelligence development has a significant positive impact on the eastern region, but no significant impact on non-central regions. A possible reason is that enterprises in the eastern region have achieved a high level of digital transformation, with intelligent technologies deeply integrated into production and operational processes; in contrast, while the central and western regions do generate AI-related innovations, most traditional enterprises there have yet to complete their intelligent upgrades.

6. Further Analysis

6.1. Mechanism Testing

The baseline regression in the previous analysis shows that the development level of the regional artificial intelligence significantly improves the employment quality of workers, but the mechanism by which artificial intelligence affects employment quality still needs further investigation. This article examines the mechanism from two aspects, industrial structure optimization and intelligent working mode, and investigates the channels through which artificial intelligence promotes the improvement of the employment quality of workers. The regression results are shown in Tables 7 and 8.

Columns (1) and (2) of Table 7 show that the regression results of the regional artificial intelligence on the rationalization of industrial structure are significantly positive at the 10% level, indicating that the improvement of the development level of artificial intelligence can improve the degree of rationalization of industrial structure. After industrial structure rationalization is used as an intermediary mechanism, the impact of artificial intelligence on employment quality is significant at the 1% level, while the impact of industrial structure rationalization on employment quality is not significant. A Sobel test is conducted to further examine this mediating channel. The indirect effect of industrial rationalization was 0.0006,

with a Z-value of 1.917 ($p = 0.0553$), which was significant at the 10% level. Therefore, although the single path in the stepwise regression did not pass the significance test, the indirect effect formed by the product of the coefficients of the two paths is still significantly different from 0, indicating that the mediating effect of industrial rationalization is valid. Columns (3) and (4) of Table 7 show that the regression results of the regional artificial intelligence on the upgrading of industrial structure are significantly positive at the 5% level, indicating that the improvement of the development level of the regional artificial intelligence can increase the degree of upgrading of industrial structure. With the upgrading of industrial structure as an intermediary mechanism, the impact of artificial intelligence on the upgrading of industrial structure and employment quality is significant at the 5% and 1% levels respectively. A Sobel test is conducted below to further examine this mediating channel. The indirect effect of industrial upgrading is 0.0076, and the Sobel Z-value is 1.752 ($p = 0.0798$), which is significant at the 10% level. This indicates that the development of the regional artificial intelligence can further improve the quality of employment by promoting the evolution of industrial structure to a higher level, and the mediating effect of industrial upgrading is valid.

Table 7. Mechanism analysis: Industrial structure optimization.

	(1)	(2)	(3)	(4)
	Industrial Rationalization	EQ	Industrial Upgrading	EQ
AI	0.044 * (0.025)	0.024 *** (0.008)	0.100 ** (0.042)	0.028 *** (0.006)
Industrial rationalization		0.032 (0.112)		
Industrial upgrading				0.072 ** (0.033)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	107	16,324	107	16,324
R ²	0.930	0.148	0.919	0.773

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating p -values less than 0.10, 0.05, and 0.01, respectively.

Table 8. Mechanism analysis: intelligent working mode.

	(1)	(2)
	Intelligent Working Mode	EQ
AI	0.100 ** (0.039)	0.022 ** (0.009)
Intelligent working mode		0.017 ** (0.007)
Control variables	YES	YES
Constant	2.008 * (1.140)	0.669 *** (0.218)
Individual FE	YES	YES
Year FE	YES	YES
Observations	12,534	12,534
R-squared	0.645	0.778

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating p -values less than 0.10, 0.05, and 0.01, respectively.

Columns (1) and (2) of Table 8 show that artificial intelligence positively influences the intelligent working mode at the 5% significance level, indicating that advancements in artificial intelligence can enhance the intelligent working mode. When intelligent working mode is introduced as a mediating mechanism, the effects of artificial intelligence on both the intelligence of work methods and employment quality remain significant at the 5% level. A Sobel test is conducted below to further examine this mediating channel, which is in Table 9. The indirect effect of intelligent work mode was 0.0036, with a Sobel Z-value of 3.741 ($p = 0.0002$), which was significant at the 1% level. This result indicates that the development of the regional artificial intelligence can further improve the quality of employment by increasing the level of intelligent work mode, demonstrating that intelligent work mode plays a significant mediating role in the impact of the regional artificial intelligence on employment quality.

Table 9. Sobel mediation effect test results.

Variables	Indirect Effects ($a \times b$)	Sobel Z-Value	p-Value	Mediation Effect
Intelligent working mode	0.0036 ***	3.741	0.0002	YES
Industrial rationalization	0.0006 *	1.917	0.0553	YES
Industrial upgrading	0.0076 *	1.752	0.0798	YES

Notes: Standard errors clustered at the provincial level. The values in parentheses represent robust standard errors, with *, **, and *** indicating p -values less than 0.10, 0.05, and 0.01, respectively.

6.2. The Multidimensional Impact of Artificial Intelligence on Employment Quality

The previous paper examined the significant positive impact of the regional artificial intelligence development on the comprehensive index of employment quality. This paper further explores the impact of the promotion effect of the regional artificial intelligence development on different dimensions of employment quality. Table 10 shows the regression results of artificial intelligence on workers' wages, working hours, job stability, labor protection, and workplace. Column (1) shows that the effect of the regional artificial intelligence on workers' income is significantly positive at 1%. This is because the application of artificial intelligence enables enterprises to improve their total factor productivity, eliminate low-paying jobs, create high-paying skill jobs, and improve employees' wage levels. Column (2) shows that the impact of the regional artificial intelligence on working hours is significantly negative at the 10% level, indicating that the development of the regional artificial intelligence can reduce workers' working hours. This is because artificial intelligence can replace high-intensity, highly repetitive tasks, thereby improving workers' work efficiency and reducing their working hours [42]. Column (3) shows that the impact of the regional artificial intelligence on job stability is significantly positive at the 5% level, indicating that the development of artificial intelligence improves workers' job stability. This is because the regional artificial intelligence can optimize job search matching, reduce the search costs for enterprises and workers, and promote the formation of long-term and stable labor relations between enterprises and workers [43]. Column (4) shows that the regional artificial intelligence has a positive impact on labor protection, and this impact is significant at the 5% level, indicating that artificial intelligence can improve the level of labor protection for workers. This is because the application of artificial intelligence has led to the upgrading of corporate human capital and the expansion of corporate scale, increasing the demand for highly skilled personnel and making companies more willing to pay social insurance in compliance with regulations [44]. Column (5) shows that the regional artificial intelligence has a positive impact on the workplace, and this impact is significant at the 1% level, indicating that the development level of the regional artificial intelligence has improved the workplace environment for workers. This is because the

application of artificial intelligence technology allows workers to reduce high-risk and high-intensity tasks, improve the physical environment of the workplace, and thereby improve physical and mental health [45].

Table 10. The impact of the level of artificial intelligence development on employment quality in multiple dimensions.

	(1) Income	(2) Work Time	(3) Work Stability	(4) Work Security	(5) Work Place
AI	0.271 *** (0.096)	−0.027 * (0.013)	0.019 ** (0.009)	0.112 *** (0.041)	0.152 *** (0.052)
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	16,324	16,324	16,324	16,324	16,324
R ²	0.546	0.646	0.709	0.797	0.670

Notes: The values in parentheses represent robust standard errors, with *, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.

7. Conclusions and Policy Implications

7.1. Conclusions

This paper constructs an AI development level index and a comprehensive employment quality index based on provincial-level AI patent data and CFPS data from 2016 to 2022. Using a fixed-effects model, it systematically explores the impact and mechanism of the regional AI development level on employment quality. The study finds that, first, the regional AI development level significantly improves employment quality, a conclusion that remains valid even after robustness tests including replacing core explanatory variables, changing the measurement method of the explained variable and changing the samples. Second, the regional AI development level promotes employment quality improvement by optimizing industrial structure and driving the transformation of workers' work methods towards intelligence. Third, the regional AI development level has a greater effect on improving employment quality for men and the workers outside the system, as well as workers in the eastern regions. Finally, the regional AI development level has different effects on different dimensions of employment quality, improving workers' wages, labor protection, job stability, and workplace conditions, while reducing workers' labor supply time.

7.2. Policy Recommendations

Based on the above research findings, this paper proposes the following policy recommendations:

First, promote the deep integration of artificial intelligence (AI) with the real economy. Continuously promote the application of AI technology in the real economy, increase efforts to cultivate the AI industry, support the development of innovative enterprises in the AI field, improve the innovation ecosystem of the industrial chain, and solidify the industrial foundation for AI-enabled employment quality improvement.

Second, build a multi-party collaborative talent cultivation mechanism. Facing the skill-upgrading demands brought about by AI, a lifelong learning system should be jointly built through government–enterprise–university platforms to accurately match job requirements, break down barriers to skill transformation, and achieve efficient connection between workers' skill enhancement and employment positions.

Finally, implement policies to promote digital inclusion and differentiated support, enhance the digital literacy of disadvantaged groups, and help them share the benefits of intelligent transformation. For women, further improve the supporting systems for flexible employment, such as flexible work arrangements and remote work from home; for middle-aged individuals, strengthen their digital skills training, provide public employment services, and offer diversified employment options in conjunction with new employment forms such as the platform economy.

7.3. Limitations

This study has three limitations. First, the core explanatory variable in this study is the level of the regional AI development represented by provincial patent data. This indicator reflects the region's AI innovation supply capacity but cannot characterize the actual application of AI at the individual job level, and it has the limitation of failing to identify the heterogeneity of AI application among individuals within the province. The estimated regional average effect cannot be mechanically interpreted as an individual-level causal effect used by artificial intelligence. Future research can rely on enterprise surveys or individual digital work questionnaire data to further identify the micro-level impact of AI applications in workplace scenarios. Second, this study covers the period from 2016 to 2022. The launch of ChatGPT at the end of 2022 propelled generative AI into large-scale application. This technology has achieved leaps in efficiency, cost savings, and creativity stimulation, and its impact on the quality of employment presents new characteristics that require further investigation. Third, the core explanatory variable in this study is the level of AI development represented by provincial patent data. This indicator reflects the region's AI innovation supply capacity but cannot characterize the actual application of AI at the individual job level, and it has the limitation of failing to identify the heterogeneity of AI application among individuals within the province. Due to the limited availability of micro-enterprise AI usage survey data, this paper identifies the average effect of regional technological innovation, rather than the individual effect brought about by workers' direct use of AI. Future research can rely on enterprise surveys or individual digital work questionnaire data to further identify the micro-level impact of AI applications in workplace scenarios. Third, future research should examine both the quantity and quality of employment, including factors such as job loss, employment probability, number of positions, wages, working hours, job stability, and labor protections. Fourth, this study draws on pooled cross-sectional CFPS data from four survey waves: 2016, 2018, 2020 and 2022. Wording and response categories for several individual-level items are slightly adjusted between the 2016–2018 and 2020–2022 waves. Although we harmonized variable coding across all waves following official CFPS guidelines, formal configural measurement invariance tests are not performed in the present study for “intelligent working mode”. Strict measurement equivalence of latent constructs across survey years cannot be guaranteed. Subtle questionnaire revisions may generate measurement discrepancies across waves and potentially bias coefficient estimates, which represents an inherent limitation of secondary multi-wave survey data. Future dedicated primary surveys with standardized scales would help improve cross-period measurement comparability.

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References

1. Acemoglu, D.; Restrepo, P. Robots and jobs: Evidence from US labor markets. *J. Political Econ.* **2020**, *128*, 2188–2244. [[CrossRef](#)]
2. Aghion, P.; Antonin, C.; Bunel, S. Artificial intelligence, growth and employment: The role of policy. *Econ. Stat. Stat.* **2019**, *510–511–512*, 150–164.
3. Wang, Y.Q.; Dong, W. How is the rise of robots affecting China’s labor market?—Evidence from listed manufacturing companies. *Econ. Res.* **2020**, *55*, 159–175.
4. Autor, D.; Salomons, A. *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
5. Wang, X.J.; Zhu, X.A.; Wang, Y. Research on the impact of industrial robot application on employment in manufacturing. *Quant. Econ. Technol. Econ. Res.* **2022**, *39*, 88–106.
6. Acemoglu, D.; Restrepo, P. The race between man and machine: Implications of technology for growth, factor shares, and employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [[CrossRef](#)]
7. Felten, E.W.; Raj, M.; Seamans, R. A method to link advances in artificial intelligence to occupational abilities. *AEA Pap. Proc.* **2018**, *108*, 54–57. [[CrossRef](#)]
8. Zhou, G.S.; Li, L.X.; Meng, L.S. The Impact of Intelligentization on China’s Labor Market: An Analysis Based on Employment Breadth and Intensity. *Financ. Res.* **2021**, *6*, 39–58.
9. Xiao, Y.C.; Zhang, Z.G.; Fang, H.L. Can digital literacy improve the quality of rural labor employment? Empirical evidence based on CFPS. *Chin. Econ. Issues* **2026**, 182–196. [[CrossRef](#)]
10. Zhao, J.G.; Ren, G.Y.; Wang, J.J. Research on the impact and patterns of digital embedding on the employment quality of migrant workers. *Res. Financ. Econ. Issues* **2023**, 101–113.
11. Zhang, F.; Yu, F. The impact of age at first childbirth on female employment quality—An empirical study based on CFPS data. *Chin. Popul. Sci.* **2025**, *39*, 45–60.
12. Ding, S.L.; Liu, C.H. A Study on the Impact of Internet Use on Employment Quality in the Digital Economy Era—Based on the Perspective of Social Networks. *Econ. Manag. Res.* **2022**, *43*, 97–114.
13. Yang, Z.Y.; Yang, J. A Study on Social Capital and Employment Quality of New Generation Migrant Workers—Based on the Perspective of Personal Relationship Resources and Information Resources. *Youth Stud.* **2021**, *10*, 14.
14. Feng, X.L.; Wu, Y.T. Research on the impact and mechanism of digital skills on the employment quality of young people. *J. China Labor Relat. Inst.* **2026**, *40*, 54–70.
15. Zhang, G.S.; Wang, R.N. How can the development of the digital economy empower high-quality employment for migrant workers? *China Rural Econ.* **2023**, *1*, 58–76.
16. Liu, C.H.; Qi, Y.D.; Ding, S.L. How does flexible work affect the quality of youth employment in the digital economy era? *Macro Qual. Res.* **2022**, *10*, 43–60.
17. Lai, D.S.; Su, L.F.; Meng, D.H.; Li, C.A. Measurement and evaluation of employment quality in various regions of China. *Econ. Theory Econ. Manag.* **2011**, *11*, 88–99.
18. Qi, Y.D.; Liu, C.H.; Ding, S.L. Development of digital economy, optimization of employment structure and improvement of employment quality. *Econ. Dyn.* **2020**, *11*, 17–35.
19. He, Q.; Qiu, Y.; Xu, G. Artificial intelligence, fiscal expenditure structure bias and high-quality employment. *Econ. Manag. Res.* **2024**, *45*, 70–86.
20. Ding, S.L.; Wang, J.P.; Liu, C.H. The impact of educational mismatch on the quality of youth employment: Theory and empirical evidence. *Chin. Youth Stud.* **2024**, *9*, 101–110+119.
21. Zhang, K.; Li, G.Q. The impact of digital literacy on the employment quality of rural youth. *East China Econ. Manag.* **2026**, *40*, 1–12.
22. Lu, Y.; Tang, M.H.; Yuan, R.Y.; Feng, P.C. Has the platform economy promoted high-quality employment for migrant workers? *Agric. Technol. Econ.* **2026**, *3*, 87–103.

23. Liu, Z.S.; Yang, Z.A.; Fu, Z.G. Can the supply of public services improve the employment quality of women? A micro-examination based on the perspective of career advancement. *J. Northeast. Univ.* **2026**, *28*, 69–79.
24. Wu, W.J.; Huang, X.; Dong, Z.Q.; Li, S.Y. Gender income gap in artificial intelligence technology and platform economy. *Econ. Theory Econ. Manag.* **2026**, *46*, 117–136.
25. Wang, Y.X.; Yao, X.M. National New Generation Artificial Intelligence Innovation and Development Pilot Zones and Urban-Rural Income Gap. *J. Yunnan Univ. Finance Econ.* **2026**, *42*, 53–63.
26. Zhang, Y.; Jiang, S. The impact of generative artificial intelligence on gig wages. *Econ. Q.* **2026**, *26*, 852–873.
27. Noy, S.; Zhang, W. Experimental evidence on the productivity effects of generative artificial intelligence. *Science* **2023**, *381*, 187–192. [[CrossRef](#)] [[PubMed](#)]
28. Wu, W.; Yang, Y.; Yang, L.; Su, L.; Chen, Z. The inverted U-Shaped relationship between AI and job satisfaction: Empirical evidence from china's CLDS microdata. *Emerg. Mark. Finance Trade* **2026**, *62*, 2554–2569. [[CrossRef](#)]
29. Chuang, Y.T.; Chiang, H.L.; Lin, A.P. Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being. *Int. J. Inf. Manag.* **2025**, *83*, 102887. [[CrossRef](#)]
30. Chen, Z.; Cheng, C.P.; Chen, A.Q. Research on Artificial Intelligence Promoting High-Quality Employment in China. *Econ. Issues* **2022**, *9*, 41–51.
31. Hu, N.N.; Hou, G.Y.; Wang, Q.K. How digitalization affects the quality of residents' employment: Based on micro-survey data of Chinese households. *Explor. Econ. Issues* **2026**, *5*, 175–190.
32. Shi, D.; Ye, Y.L. Artificial Intelligence, Employment Structure and High-Quality Development. *Contemp. Finance Econ.* **2023**, *2*, 3–14.
33. Wei, L.L.; Hou, Y.Q. Research on the impact of digital economy on green development of Chinese cities. *Quant. Econ. Technol. Econ. Res.* **2022**, *39*, 60–79.
34. Liu, B.Y.; Li, X. "Machines Helping People" or "Machines Replacing People"—From the Perspective of Service Industry Intelligence and Employment Quality. *J. Shanxi Univ. Finance Econ.* **2025**, *47*, 81–95.
35. Chao, X.J.; Shen, L.; Xue, Z.X. Recalculation of the Development Level of China's Provincial Digital Economy Based on Morphological Attributes. *Econ. Issues* **2023**, *522*, 23–34.
36. Wang, L.H.; Qian, Y.Y.; Song, D.L.; Dong, Z.Q. Job switching effect of robot application and characteristics of employment-sensitive groups: Empirical evidence from the micro-individual level. *Econ. Res.* **2023**, *58*, 69–85.
37. Zhang, J. Unveiling the mechanism of digital literacy on job quality: Micro evidence from China. *Cities* **2025**, *166*, 10628. [[CrossRef](#)]
38. Yao, S.; Wang, Y.; An, L. How People-Centered New-Type Urbanization Promotes Secure Housing: Evidence from the Home-Buying Decisions of the Agricultural-to-Urban Migrant Population. *Reform Econ. Syst.* **2026**, 15–29.
39. Wen, Z.; Zhang, L.; Hou, J.; Liu, H.Y. Testing and application of the mediating effects. *Acta Psychol. Sin.* **2004**, *36*, 614–620.
40. Zhang, X.; Chen, A.; Lü, H. How Does Technological Containment Affect Firm Total Factor Productivity? *Reform* **2026**, 149–169.
41. Oster, E. Unobservable Selection and Coefficient Stability: Theory and Evidence. *J. Bus. Econ. Stat.* **2019**, *37*, 187–204. [[CrossRef](#)]
42. Shen, K.; Shi, X.F. The impact of urban artificial intelligence development on individual labor participation and working hours: A finding based on the density of artificial intelligence technology. *China Popul. Sci.* **2025**, *39*, 45–61.
43. Fang, T. The Artificial Intelligence Revolution and the Profound Reshaping of the Global Labor Market: Mechanisms, Challenges and Governance Paths. *J. China Inst. Labor Relat.* **2026**, *40*, 56–65.
44. Song, J.X.; Jin, G.; Wu, C.H.; Fan, L.L. Digital transformation and corporate social insurance contributions. *J. Shanghai Univ. Finance Econ.* **2025**, *27*, 93–107.
45. Sheng, D.; Lü, L. Intelligent Manufacturing and Workers' Health: An Investigation Based on Individual Micro-Data. *Financ. Res.* **2025**, *51*, 20–33+124.

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