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Research on the Impact of Industrial Intelligence on Labor Employment Structure

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ABSTRACT

Based on provincial panel data from 2006 to 2023 in China, this paper systematically investigates the skill stratification effect and regional heterogeneity of industrial intelligence on labor employment structure. It constructs an integrated analytical framework incorporating industrial intelligence level, urbanization, trade openness, industrial structure upgrading, and living costs, employing a fixed-effects model to unravel its mechanisms through three dimensions: substitution effect, creation effect, and productivity effect. The findings reveal that industrial intelligence significantly reduces demand for medium-skilled labor while markedly increasing demand for low-skilled labor, with a relatively modest impact on high-skilled labor. It elevates unemployment rates but concurrently fosters overall employment growth. Regional disparities are pronounced: eastern regions demonstrate positive employment effects from intelligence, whereas central and western regions confront structural unemployment risks due to delayed technological adaptation. Building on these conclusions, the paper proposes establishing a "pyramid-shaped" labor adaptation system, implementing a "flying geese-gradient" intelligent industrialization model, and refining an "incentive-buffer" policy toolkit to address employment challenges during intelligent transformation. Future research should deepen micro-level mechanism analysis, expand cross-national comparative perspectives, and dynamically assess long-term impacts. This study offers new insights into the relationship between technological change and labor markets, providing valuable references for policy formulation and practice.

KEYWORDS

Industrial intelligence; Labor force employment; Substitution effect; Creation effect; Skill stratification

1. INTRODUCTION

Industrial intelligence, as the core engine of the technological revolution, is reshaping the global economy through technologies such as artificial intelligence and big data, and has become a major competitive arena in international competition. Strategies like Germany's "Industry 4.0" and the United States' "Advanced Manufacturing Partnership Program" are competing to advance. In 2022, China installed 290,000 industrial robots, accounting for 56% of the global total, ranking first for nine consecutive years. As the "world factory" accounting for 28.5% of global manufacturing value-added, China is facing significant transformation pressures due to a substantial increase in labor costs and the decline of the demographic dividend caused by population aging. The "technology-employment paradox" brought about by industrial intelligence is becoming increasingly prominent, replacing a large number of low-skilled jobs and posing a risk of 235 million net unemployment globally by 2030. The unemployment risk for low-skilled workers in emerging economies like China is significantly higher than that in developed countries. It also gives rise to new high-skilled occupations and promotes employment model innovation. At the same time, it accompanies issues such as a decline in the proportion of manufacturing employment, structural unemployment and skill mismatch, and regional technological development imbalance. This study focuses on the multi-dimensional impact of industrial intelligence on the employment structure of workers at different skill levels. It uses a two-way fixed effects model by skill level and instrumental variable method to reveal the dynamic adjustment rules of the employment structure and verify the applicability of the technology polarization theory, providing scientific basis and practical guidance for governments, enterprises and workers. The aim is to solve the "technology-employment paradox" and help China achieve a balance between efficiency and fairness in the intelligent era.

2. LITERATURE REVIEW

Industrial intelligence, by altering the logic of production factor allocation, has given rise to a new employment ecosystem featuring human-machine collaboration, triggering the polarization and reorganization of the occupational structure and reshaping the labor market. Balancing technological innovation and the resilience of the employment market has become an era-defining issue. Its impact on the total employment, structure, and quality is not linear but exhibits complex characteristics such as substitution effects, creation effects, and structural differentiation. Scholars have conducted in-depth research on these aspects and regional heterogeneity. Scholars have also noted that with the advancement of strategies such as "Made in China 2025", the intelligent transformation of China's manufacturing industry has been remarkable, traditional low-skilled positions are facing the risk of replacement, the demand for high-skilled talents has surged, and new employment models such as flexible employment have also emerged.

2.1. The Dual Effects of Industrial Intelligence on Job Positions: Creation and Substitution Coexist

Some scholars have pointed out that in terms of the creation effect, industrial intelligence has given rise to new high-skilled positions such as AI algorithm engineers. Shen and Zhou (2024) found that industrial intelligence as a whole has a "creation effect", and when the density of robot installations reaches a critical value, it will deepen labor division, increase labor demand, and can also indirectly promote employment through collaborative aggregation and improving labor price distortion [1]. In terms of the substitution effect, industrial intelligence has a significant substitution effect on traditional repetitive and low-skilled positions. Arkadiusz and Michał (2019) pointed out that the widespread application of industrial robots has a prominent substitution effect on the labor force, and this effect becomes more significant as the penetration rate increases [2].

2.2. The Multi-Dimensional Impact of Industrial Intelligence on the Employment Structure

Industrial intelligence promotes the upgrading of the employment structure and contributes to the improvement of economic quality. Chen Xiao (2020) found that it mainly achieves the upgrading of the employment structure by increasing the demand for high-skilled labor and replacing middle-skilled labor, and the mediating effect of low-skilled labor was not verified [3].

The impact of industrial intelligence on the employment structure shows significant regional and industrial differences. Gong Sha (2021) empirically concluded that the regional development of industrial intelligence in China is uneven and presents a stepped characteristic, and there is a phenomenon of "employment polarization" [4]; Gao Mingyu (2024) further pointed out that intelligence can attract labor inflows, promote the polarization of the skill structure, promote the employment concentration of manufacturing in the east, accelerate the transformation of the service industry in the central and western regions, and support the construction of "intelligent adaptive" labor policies [5].

Industrial intelligence also affects wage gaps and the labor market. Li Hongbing et al. (2020) showed that industrial intelligence promotes employment growth, and this effect is more obvious in the central and western regions and among high-skilled groups, while it exacerbates the single-polarization of the employment structure and the "jump-like" flow of labor between industries, overall narrowing the wage gap in manufacturing but expanding the gap between middle and low-income groups [6].

In terms of labor demand and mobility, Shen Yang and Zhang Xiwu (2024) pointed out that industrial intelligence has a creative effect on the overall labor force, and the density of robots exceeding the threshold can deepen labor division and increase labor demand [7]; Liu Dongsheng (2023) found that it has range heterogeneity in labor mobility, facilitating the outflow of local registered labor from within the same county or district and suppressing the outflow across provinces, and overall promoting the transfer of labor from central cities to non-central cities [8].

2.3. The Multi-Dimensional Paths of Industrial Intelligence on the Employment Structure and the Policy Responses

Artificial intelligence, as an important application of industrial intelligence, has attracted significant attention in academic research regarding its employment impact. Bonney et al. (2024) found that in the short term, artificial intelligence mainly replaces tasks, and the lag effect may gradually influence the scale of employment [9]; Jia et al. (2024) proposed a four-dimensional analytical framework of penetration, collaboration, substitution, and creation, emphasizing that it stimulates a new occupational ecosystem through industrial activation [10].

Some studies focus on the transformation of employment structure and changes in labor demand and provide policy recommendations. Zhang Juanjuan et al. (2022) proposed that it is necessary to strengthen the training of employed personnel, optimize the talent cultivation mechanism of universities, and promote the development of intelligent industries and the transformation and upgrading of various industries [11].

The existing literature has revealed the complex impact of industrial intelligence on the employment structure from multiple dimensions: Ma Libo (2022) empirically found that the intelligentization of manufacturing industries enhances the employment of high-skilled labor and suppresses that of middle and low-skilled labor, with regional heterogeneity and single threshold effects [12]; Xu Siyu and Yang Yue (2022) indicated that intelligentization promotes employment overall but there are differences between industries, suppressing employment in the primary industry, increasing employment in the secondary and tertiary industries, and the creation effect on employment in the secondary industry weakens in regions with high wages and high intelligentization [13]; Wang Wen (2020) pointed out that it reduces the employment share of manufacturing industries and increases the employment share of knowledge and technology-intensive modern service industries, promoting the upgrading of industry employment structure [14].

2.4. literature Review

The current research has clearly demonstrated the impacts of industrial intelligence on aspects such as the upgrading of the employment structure, labor demand and mobility, wage gaps, etc., and has confirmed the existence of regional and industrial differences. However, there are still many shortcomings. The research mostly relies on static models and short-term data, making it difficult to capture long-term dynamic effects. It lacks analysis of differences among different educational groups and is limited to a domestic perspective, with insufficient attention paid to the imbalance in the distribution of educational dividends. The data also have problems such as being outdated, lacking micro-individual data, and insufficient data in emerging fields, resulting in general research conclusions that lack specificity, targetedness, and operability.

This paper will build upon the existing research and introduce variables for different skill groups, focusing on the "sandwich" group with medium education levels. It aims to fill the research gaps, through comparative analysis, to reveal the differentiated impacts of industrial intelligence on different skilled labor forces, and then propose targeted policy recommendations. At the same time, it will track the employment changes triggered by the changes in skill structures and analyze the dynamic relationship between the two, providing support for policy formulation and employment market forecasting.

3. THEORETICAL ANALYSIS RESEARCH AND HYPOTHESES

China's industrial intelligence has been developing rapidly under the impetus of policy and technology integration, profoundly reshaping the employment structure. It not only replaces traditional repetitive jobs, resulting in a decline in their demand, but also gives rise to a large number of technical positions that require interdisciplinary knowledge and continuous learning abilities. At the same time, it promotes the transfer of employment opportunities to the upstream and downstream of the industrial chain and triggers regional employment differentiation. Its impact involves multiple factors. This article constructs a comprehensive theoretical framework and proposes that industrial intelligence acts on labor employment through three effects: substitution, creation, and productivity. It will also deconstruct its internal mechanism from these three dimensions.

3.1. Substitution Effect

Industrial intelligence reshapes the employment structure through multi-dimensional mechanisms such as task attribute matching and technology adaptation, presenting a distinct feature of skill stratification. Skilled labor with medium-level skills undertake routine repetitive tasks such as production assembly and inspection, which are highly compatible with intelligent technologies due to their high standardization and predictability. Enterprises tend to adopt technological substitution to improve efficiency and reduce costs. Labor-intensive industries, where medium-level skilled labor is concentrated, have seen a continuous decrease in job positions as intelligent equipment becomes more widespread.

Low-skilled labor has strong employment resilience: With their outstanding adaptability, they can quickly adjust their employment direction. Informal employment provides a buffer for them, and industrial intelligence drives the large-scale development of the service industry, creating a large number of basic service positions, which overall promotes an increase in demand for them.

The demand for high-skilled labor is significantly constrained by supply: High-skilled positions have strict requirements for professional capabilities, while the training costs and duration for relevant talents are high, and the supply cannot keep up with the pace of technological progress. The growth of new positions is also limited by technical directions and job requirements. The demand for them cannot increase rapidly. Therefore, this paper, referring to the research of Wang Hui and Wang Linhui (2022) [15], proposes a testable research hypothesis 1:

H1: The substitution effect of industrial intelligence will significantly reduce the demand for medium-skilled laborers, but will promote the demand for low-skilled laborers, and have no significant impact on the demand for high-skilled laborers.

3.2. Creation Effect

The impact of industrial intelligence on employment presents a dynamic balance mechanism of "destruction - compensation - upgrading", essentially representing the interactive process of employment structure reconfiguration triggered by technological innovation and market self-adaptation - it not only reduces traditional medium-skilled positions through automation, but also creates new employment opportunities through efficiency improvement, cost reduction, extension of the industrial chain, and the incubation of new business models.

Its creation effect is manifested in multiple dimensions: Firstly, it promotes enterprise expansion and the birth of new industries, giving rise to intelligent positions such as robot maintenance, data analysis, and AI training that require professional capabilities; Secondly, it drives the development of emerging industries such as the Internet of Things and cloud computing, which align with Schumpeter's theory that "technological innovation destroys old industries, creates new industries, and brings net employment growth". At the same time, industrial intelligence promotes industry structure upgrading. After traditional manufacturing undergoes transformation, the expansion of production efficiency brought about by increased production capacity and new business development can offset the job replacement effect; The economic growth driven by the improvement of total factor productivity will also further promote employment.

According to the Okun's Law, economic growth is negatively correlated with the unemployment rate: The economic growth brought about by industrial intelligence not only helps enterprises expand production and hire more employees, but also promotes the development of the service industry by reducing commodity prices and enhancing consumer purchasing power, thereby increasing employment. The employment market achieves dynamic adjustment through labor mobility and retraining, alleviating structural unemployment. Thus, this paper, referring to Wang Kaiwei's (2020) research [16], proposes a testable research hypothesis 2:

H2: Industrial intelligence can promote the growth of total employment, but it will increase the unemployment rate in the short term.

3.3. Productivity Effect

The productivity effect of industrial intelligence reshapes the employment structure through skill-biased transformation. Skilled workers, with their cognitive flexibility and technological transformation advantages, can quickly master emerging skills such as digital twin operation and maintenance, forming a virtuous cycle of "technology empowerment - efficiency improvement - job creation". The skill premium drives enterprises to create high-end positions such as research and design, promoting the extension of the employment structure towards the high-skilled end.

Traditional low-skilled positions exhibit a coexistence of "substitution and compensation": Some low-skilled workers can adapt to new positions such as basic monitoring through standardized training, and industrial expansion also creates a small number of low-tech positions. However, automation replaces a much larger scale of assembly and quality inspection positions than new ones, resulting in a reduction in their employment capacity.

Luo Dongxia (2023) pointed out [17]: Technological iteration poses temporary skill mismatch for high-skilled groups, while low-skilled workers, due to insufficient training resources and limited conversion space, can only migrate to a few new positions. The asymmetry of skill conversion leads to an "expansion of high-end positions - compression of low-end positions" in the employment structure, and low-skilled groups mostly shift to informal employment.

There is significant regional heterogeneity in the employment reshaping of the productivity effect. Essentially, it is the result of the integration of technological innovation and regional development differences: The east relies on technological innovation and digital infrastructure to quickly create high-skilled positions; the central and western regions have insufficient technological accumulation and a high proportion of traditional industries, with a prominent pressure of low-skilled position loss. This disparity stems from differences in technological reserves, industrial transformation paths, and policy effectiveness across the eastern, central, and western regions — the eastern region's manufacturing has undergone high-end transformation and vocational education is well-developed, resulting in significant employment creation; in the central and western regions, industrial uptake is slower and labor mobility costs are high, limiting employment growth potential. Therefore, this paper, referring to the research of Liu Yang et al. (2023) [18], proposes a testable research hypothesis 3:

H3: The impact of industrial intelligence on employment has significant regional heterogeneity, and different regions have different employment effects due to factors such as technology, industry, and policy.

4. AN EMPIRICAL STUDY ON THE IMPACT OF INDUSTRIAL INTELLIGENCE LEVEL ON EMPLOYMENT STRUCTURE

4.1. Model Building

Based on the theoretical analysis conducted in the previous section, the main purpose of this part is to explore the impact of industrial intelligence on the employment of the Chinese labor force from an empirical perspective. The basic econometric model is set up using the formula of a multiple linear regression model as the reference standard.

This paper adopts a progressive research framework to systematically analyze the dual impact dimensions of industrial intelligence on the employment structure. Firstly, it starts from the macro level and conducts a quantitative assessment of the net effect of industrial intelligence technology on the overall employment scale and the unemployment rate level. Then, it delves into the micro employment structure, using the construction of a skill stratification index system to analyze the heterogeneous impact of industrial intelligence on the employment quality of different skill-endowed groups from multiple dimensions, thereby comprehensively revealing the penetration path and reconfiguration mechanism of technological innovation in the employment market. By controlling regional heterogeneity and time trends using province-year two-dimensional fixed effects, and incorporating urbanization, trade openness, industrial structure upgrading, and living costs as control variables, the paper systematically examines the multi-dimensional impact of industrial intelligence on the labor market. By integrating the skill level model, employment total volume model, and unemployment risk model, a system of five equations can be formed. This system of equations can be unifiedly expressed as:

$$Y_{it}^{k}=\alpha^{k}+\beta_1 RID_{\mathrm{it}}+\beta_2 URB_{\mathrm{it}}+\beta_3 TO_{\mathrm{it}}+\beta_4 ISU_{\mathrm{it}}+\beta_5 CL_{\mathrm{it}}+\mu_i+\lambda_t+\varepsilon_{it}^{k} \tag{1}$$

Among them, $Y_{it}^{k} \in \{LSL_{it}, MSL_{it}, HSL_{it}, EMPL_{it}, UNEMP_{it}\}$, representing different dimensions of employment indicators. The explained variable LSL_{it}refers to the proportion of low-skilled labor in the i province in the t year, MSL_{it} is the proportion of medium-skilled labor in the i province in the t year, HSL_{it} is the proportion of high-skilled labor in the i province in the t year, $EMPL_{it}$ is the number of employed people in the i province in the t year, which can reflect the overall scale of the labor market, and $UNEMP_{it}$ is the unemployment rate in the i province in the t year, used to measure the degree of labor idleness. X_{jit} is the vector of independent variables, which includes the core variable RID_{it} and the control variables URB_{it}, TO_{it}, ISU_{it}, and CL_{it}. β_j^k is the regression coefficient of the corresponding variable, reflecting the direction and intensity of the impact of industrial intelligence and control variables on different employment indicators. μ_i represents the fixed effect of the province, λ_t represents the fixed effect of the year, and ε_{it}^{k} represents the random disturbance term.

This model system, through the use of multi-dimensional dependent variable settings, can comprehensively capture the heterogeneous impacts of industrial intelligence on the skill structure of the workforce, the scale of employment, and the risk of unemployment, providing systematic quantitative basis for policy formulation.

4.2. Selection of Variables

The selection and definition of variables in this article are presented in Table 1. This study utilized provincial panel data from China from 2006 to 2023 for empirical research. The research data mainly originated from the official statistics of the National Ministry of Industry and Information Technology, as well as the authoritative publications "China Statistical Yearbook" and "China Labor Statistical Yearbook" over the years, and supplemented with industry data released by the International Federation of Robotics to ensure the authority and multi-dimensionality of the data sources.

Table 1. Variable selection and definition

types of variables	variable name	variable symbol	variable definition
Variable being explained	High-skilled labor	HSL	The proportion of individuals with a college degree or above in the total employment population
	Medium-skilled labor	MSL	The proportion of people with junior high school and high school education in the total employment population
	Low-skilled labor	LSL	The proportion of people with primary school or lower education levels in the employed population
	employment figure	EMPL	The number of people aged 16 and above who engage in labor and earn income
	unemployment rate	UNEMP	The proportion of unemployed people in the total labor force
Core independent variable	The level of industrial intelligence	RID	Installation density of industrial robots
Control variable	urbanization level	URB	The proportion of urban population in the total population
	trade openness	TO	The proportion of imports and exports in GDP
	Degree of industrial structure upgrading	ISU	The proportion of the added value of the tertiary industry in the GDP
	living cost	CL	The proportion of per capita consumption expenditure to disposable income

4.2.1. variable being explained

This study focuses on the dynamic changes in the labor force skill structure under technological innovation, and selects the employment population (EMPL) and the unemployment rate (UNEMP) as the core explanatory variables. The employment population (EMPL) is defined as the total population aged 16 and above who participate in social labor or business activities and receive remuneration, reflecting the basic scale of the labor market; the unemployment rate (UNEMP) is calculated as the percentage of unemployed people in the total labor force, measuring the changes in idle labor capacity.

Based on the research of Cao Yaru (2020) [19], this study measures the labor force skill level by education attainment, and combines the characteristics of the Chinese education system to divide the labor force into three skill levels: high-skilled laborers are those with college, undergraduate, and postgraduate education who are employed, whose employment proportion reflects the changes in the demand for knowledge-intensive positions, this group can benefit from the new jobs created by technological upgrading but also face the pressure of skill iteration; medium-skilled laborers are those with high school or junior high school education who are employed in traditional manufacturing and service industries, which are vulnerable to the effect of automation substitution, job compression and structural transformation are the research focus; low-skilled laborers are those with primary school or lower education, the positions they are involved in are sensitive to automation substitution, and at the same time, a complex situation of coexistence of substitution and creation may be formed due to the emergence of new low-skilled service positions.

To align with the classification of educational qualifications by the Ministry of Education, this study adopts the method of Chen Zongsheng and Zhao Yuan (2021) [20] to adjust and merge the classification of educational attainment: high school includes secondary vocational education, and college includes higher vocational education. This classification is both in line with the hierarchical characteristics of the Chinese education system and can capture the polarization phenomenon of positions caused by technological progress. Through panel data empirical analysis, it can systematically reveal the impact mechanism of industrial intelligence on the employment scale, structure transformation and regional differences of different skill laborers, providing quantitative basis for policy formulation.

4.2.2. Core explanatory variable

This study selects the installation density of industrial robots as the core indicator for measuring the level of industrial intelligence. With the strong support provided by the new generation of information technology, industrial robots are gradually evolving beyond their traditional role as mere tools, and are developing into intelligent production units with perception, decision-making, motion control, and collaborative interaction capabilities. Driven by the dual factors of technological evolution and industrial upgrading, industrial robots have been widely and deeply integrated into the entire manufacturing process. They can act as independent operation units to complete repetitive process operations, or can be implemented flexibly for complex production tasks through the human-machine collaboration model. Given the crucial role of industrial robots in the intelligent transformation of production systems, their installation density can objectively reflect the degree of automation penetration in the regional industrial system, the progress of technological iteration, and the efficiency of human-machine collaboration. It provides a key observation dimension with theoretical significance and practical value for quantitatively assessing the level of industrial intelligence. This paper refers to the methods of Kang Qian (2022) [21] and Lu Tingting (2022) [22], based on the 13-43 industry codes published by the International Federation of Robotics (IFR) for China's various industries, and then collects the percentage of employment in each province of the industry in the total national employment from the "China Labor Statistical Yearbook". The calculation method for the installation density of industrial robots is to multiply this percentage by the total number of robot installations in each industry across all sectors.

The calculation formula for the installation density of industrial robots is as follows:

$$RID_{ijt} = \frac{E_{ijt}}{E_{total}} \times N_{jt} \tag{2}$$

In the formula, RID_{ijt} represents the industrial robot installation density in the j industry of province i in the t year, while E_{ijt} refers to the number of employed people in the j industry of province i in the t year, E_{total} represents the total employment scale of this industry across the country, and N_{jt} is the installation quantity of industrial robots in the j industry nationwide in the t year.

This formula precisely quantifies the installation density of industrial robots by constructing a double-layer nested structure. In the horizontal dimension, it standardizes the mapping based on the data statistics of the International Federation of Robotics to ensure that the statistical standards of technical equipment are fully compatible with the industrial classification system. In the vertical dimension, the proportion of the employment of each sub-sector in each province to the total national employment is taken as the weight coefficient, and the total installation volume of industrial robots at the national level is dynamically allocated to regional-industry units. Thus, a three-dimensional intelligent level measurement matrix including regions, industries, and time is formed. This method innovatively integrates the cutting-edge technology monitoring data of industrial alliances and the employment structure information from statistical yearbooks. By relying on cross-validation of multiple data sources, it effectively reduces the systematic errors of a single data source, providing a representative and precise quantitative tool for analyzing the spatio-temporal heterogeneity impact of industrial intelligence on the employment market.

4.2.3. Control variable

To avoid endogeneity issues caused by the omission of key variables and to obtain more accurate estimation results, referring to the research by Ma Riguang et al. (2024) [23], this paper selects the following four key control variables: The urbanization level is measured by the proportion of urban population in the total population of each province, which serves as the core of spatial agglomeration effect and factor mobility. The evolution of this variable profoundly changes the employment carrying capacity of the labor market. Trade openness is measured by the proportion of total exports and imports to GDP of each province, which reflects the degree of regional participation in international division of labor. Changes in this variable may have an impact on the total employment and skill structure through international trade channels. The degree of industrial structure upgrading is measured by the proportion of the added value of the tertiary industry in GDP of each province, which reflects the process of economic structure transformation and also indicates the allocation efficiency of production factors to high value-added fields, which is closely related to the employment market. The cost of living is measured by the proportion of per capita household consumption expenditure of urban residents to disposable income of each province, which comprehensively reflects the consumption capacity and living cost pressure of residents in the region. Changes in this variable may indirectly affect the employment structure through the demand effect.

4.3. Empirical Result Analysis

4.3.1. Empirical benchmark results

This paper explores the impact of industrial intelligentization development on the employment structure of the Chinese labor force, and constructs a regression model. This model includes variables such as the level of industrial intelligentization, the level of urbanization, the degree of trade openness, the degree of industrial structure upgrading, and living costs. A fixed effect model is used to control individual and time factors, in order to analyze the impact of each variable on the labor force employment structure. All models are selected to estimate the fixed effect model through the Hausman test to ensure the reasonable model setting and the robustness of the estimation results. The empirical benchmark results are shown in Table 2:

Table 2. Empirical benchmark results

	LSL	MSL	HSL	EMPL	UNEMP
RID	0.003***	-0.006***	0.005	0.027***	0.009***
	(-4.130)	(-3.492)	(-0.673)	(-21.114)	(-5.726)
URB	-0.934***	0.479***	0.458***	41.964***	-0.028***
	(-17.502)	(-8.445)	(-13.851)	(-7.637)	(-3.178)
TO	0.141***	0.036	-0.178***	11.513***	0.009**
	(-6.518)	(-1.583)	(-13.292)	(-5.177)	(-2.555)
ISU	0.189***	-0.499***	0.309***	18.612***	-0.006
	(-3.463)	(-8.626)	(-9.147)	(-3.317)	(-0.623)
CL	-0.099	0.279***	-0.174***	-22.641***	-0.055***
	(-1.624)	(-4.324)	(-4.621)	(-3.614)	(-5.556)
Hausman test	fixed effect	fixed effect	fixed effect	fixed effect	fixed effect
R^2	0.593	0.269	0.844	0.77	0.125
Obs	540	540	540	540	540

Note: The values in parentheses are t-values. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

The empirical research results show that industrial intelligence has a differentiating effect on the demand structure of labor: the industrial intelligence level (RID) significantly increases the employment proportion of low-skilled labor (LSL), reduces the proportion of medium-skilled labor (MSL), shows a positive trend for high-skilled labor (HSL) but the statistical significance is not significant, and the employment scale is highly synchronized with industrial intelligence, supporting the theory of skill-biased technological progress. The employment market presents a polarization feature of "low-skilled retention - medium-skilled contraction - high-skilled release".

The control variables have multiple dimensions of influence: the improvement of urbanization level aggravates the demand for high and medium-skilled labor and suppresses the demand for low-skilled labor; the expansion of trade openness increases the demand for high and medium-skilled labor and reduces high-skilled positions, and has no significant impact on medium-skilled labor; the upgrading of industrial structure "low-end concentration" and "high-end ascent" coexist, reducing the demand for medium-skilled labor, increasing low-skilled positions and strengthening the demand for high-skilled labor; the increase in living costs positively stimulates the demand for medium-skilled labor and suppresses the demand for high-skilled labor.

The impact of different factors on the number of employed people varies: industrial intelligence (improving efficiency and creating jobs), urbanization (industrial agglomeration expansion), trade openness (expanding international markets), and industrial structure upgrading (cultivating emerging industries) all promote employment growth; although the increase in living costs is often regarded as an employment suppression factor, in this study, overall employment increases, which may be because enterprises adjust the employment scale to cope with cost pressure.

In terms of the unemployment rate dimension, industrial intelligence, urbanization, trade openness, and living costs can all reduce the unemployment rate, while the impact of industrial structure upgrading is limited: the former play roles through optimizing positions, transferring labor force, expanding the market, and regulating supply elasticity, while the latter, due to the friction in job conversion during the transformation, has an insignificant effect on reducing unemployment, reflecting the differences in the paths of employment quantity regulation and quality improvement of different factors.

The empirical results of this study show that the development of industrial intelligence has an impact on the employment structure of the Chinese labor force, leading to the emergence of a "polarization" trend in employment. Industrial intelligence significantly reduces the demand for medium-skilled labor, increases the demand for low-skilled labor, but has little impact on the demand for high-skilled labor. Urbanization, trade openness, industrial structure upgrading, and living costs have also had an impact on the employment structure of the labor force. These findings provide new evidence for understanding the effects of different factors on the employment structure of the labor force and offer references for policy formulation.

4.3.2. Endogeneity handling

When discussing the impact of industrial intelligence on the employment structure, endogenous bias has become a very crucial issue. There might be a bidirectional causal relationship between the level of industrial intelligence and the employment variable. That is to say, industrial intelligence may have an impact on the employment structure, and changes in the employment structure may also have an effect on the level of industrial intelligence. Such endogenous bias may cause deviations in the estimation results and affect the reliability of the research conclusions. To overcome this bias, this study, following the approach of Sun Zao and Hou Yulin (2019), uses the lagged one-period industrial intelligence level (LRID) as an instrumental variable for two-stage least squares estimation [24]. The lagged one-period LRID has a strong correlation with the endogenous variable. The density of industrial robots is a key indicator for measuring the level of industrial intelligence. The lagged one-period LRID retains a high correlation with the current technological level and can better reflect the trend of changes in the level of industrial intelligence. Moreover, the lagged one-period LRID has its own exogeneity. With the help of time isolation, the lagged one-period LRID avoids directly affecting the current employment decision and effectively conforms to the core assumption of the instrumental variable. The lagged one-period LRID reflects the level of industrial intelligence in the past period, while the current employment decision is mainly influenced by many factors such as the current economic environment and policy factors, and has no direct correlation with the level of industrial intelligence in the past period. Comparatively, if the lagged one-period LRID is not used as an instrumental variable but the current RID is directly used, then there may be a situation where the RID is directly affected by the current employment decision. For example, enterprises may adjust the density of industrial robots based on the current employment demand, resulting in a two-way causal relationship between RID and the employment variable, which aggravates the endogenous bias. Using the lagged one-period LRID as an instrumental variable retains a strong correlation with the endogenous variable and avoids directly affecting the current employment decision through time isolation, effectively overcoming the endogenous bias between the level of industrial intelligence and the employment variable, and improving the reliability and rigor of the estimation results.

The results of the instrumental variable regression are shown in Table 3. The results show heterogeneity in different skill groups. In the low-skilled group, the lagged LRID has a significant positive impact on employment, meaning that industrial intelligence may create new employment opportunities through job optimization and technology adaptation, even after controlling for the fixed effects of the city, this conclusion remains robust, highlighting the employment compensation mechanism for low-skilled labor due to technological progress. The middle-skilled group shows a significant negative impact, confirming the "employment polarization" phenomenon, that is, technological progress has a substitution effect on middle-skilled positions, and the application of the instrumental variable method makes this effect clearer in the original model. The high-skilled group does not show a significant impact, which may be because high-skilled positions and technological progress have a high degree of complementarity, or the instrumental variable has an insufficiently direct effect on the employment of high-skilled groups, and the adjustment effect of technology-skill matching needs to be analyzed.

At the employment total level, the lagged one-period industrial intelligence level (LRID) has a significant impact on the total employment number and the unemployment rate. From the coefficient direction, industrial intelligence creates new jobs and reduces the unemployment level through optimizing the employment structure, even after controlling for endogeneity, this conclusion still holds, verifying the employment creation hypothesis of technological progress. The control variables exhibit a restructuring effect in different models: Urbanization, through industrial agglomeration, prompts the transfer of low-educated employment to the service sector; Trade openness increases the demand for low-skilled labor in the global value chain; Industrial structure upgrading presents the characteristics of both "low-end retention" and "high-end ascent"; And the cost of living, by adjusting the elasticity of labor supply, brings complex influences to the labor market. This study effectively identifies the net employment effect of industrial intelligence using the instrumental variable method, points out the multi-faceted impact mechanism of technological progress on the labor market, and provides a differentiated intervention basis based on skill structure for policy formulation.

Table 3. Regression results of instrumental variable approach

	LSL	MSL	HSL	EMPL	UNEMP
URB	-0.841***	0.377***	0.468***	48.066***	-0.020**
	(-14.693)	(-6.215)	(-12.989)	(-7.919)	(-2.129)
TO	0.136***	0.055**	-0.192***	11.350***	0.009**
	(-5.684)	(-2.188)	(-12.773)	(-4.478)	(-2.253)
ISU	0.132**	-0.436***	0.302***	15.912***	-0.011
	(-2.321)	(-7.251)	(-8.452)	(-2.640)	(-1.187)
CL	-0.134**	0.301***	-0.160***	-22.117***	-0.059***
	(-2.164)	(-4.600)	(-4.135)	(-3.381)	(-5.676)
LRID	0.002***	-0.004***	0.003	0.030***	0.005***
	(-3.840)	(-3.304)	(-0.544)	(-19.948)	(-5.771)
_cons	70.391***	35.465***	-6.388*	-1424.561**	8.925***
	(-11.625)	(-5.530)	(-1.678)	(-2.219)	(-8.771)
N	510	510	510	510	510
R^2	0.523	0.277	0.832	0.764	0.143
F	104.201	36.45	471.894	307.369	15.904

Note: The values in parentheses are t-values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3.3. Robustness test

(1) Change the dependent variable. In the robustness test section, this paper initiates a sensitivity analysis of the dependent variable, using a combination of theoretical guidance and statistical verification to enhance the reliability of the conclusion. Given that the impact of industrial intelligence on the employment structure has industry heterogeneity, this paper refers to the measures of Zhao He (2023), replacing the total employment number in the base model with the total number of employment in the secondary industry [25]. The total number of employment in the secondary industry is represented by SIE. This adjustment has the following theoretical logic: The technological innovation and production mode transformation brought about by industrial intelligence mainly affect the secondary industry, which is also the industrial sector. Focusing on the employment data of the secondary industry can more accurately capture the direct impact of industrial intelligence on the employment structure, avoiding the noise interference caused by fluctuations in employment in other industries, thereby enhancing the specificity of the estimation results. The total employment number, as a macro indicator covering all industries, may dilute the specific effect of industrial intelligence on the employment of the secondary industry due to changes in employment in other industries such as the service sector and agriculture. Using the total number of employment in the secondary industry as an proxy variable can amplify the marginal impact of industrial intelligence on the employment of the target industry and improve the model's ability to capture the sensitivity to technological change.

The results of the empirical test are shown in Table 4. The results indicate that after the variable replacement, the model exhibits robust characteristics: the regression coefficient direction of the core explanatory variable, namely the industrial intelligence index, is exactly the same as that of the base model, and the absolute value of the coefficient of the base model has increased, which means that the technological substitution effect after industry focus is more obvious. Through the Hausman test, it can be found that there is no systematic difference in coefficient estimation between the industry focus model and the base model. However, the goodness of fit of the second industry model is slightly improved compared to the base model, and the explanatory power of the model has been enhanced. The variable replacement effectively reduces the model setting error.

Through in-depth analysis of the statistical data, this study finds that the employment number of the secondary industry SIE is significantly correlated with variables such as low-skilled labor, medium-skilled labor, high-skilled labor, and the unemployment rate, indicating that the impact of industrial intelligence on the employment number of the secondary industry is multi-faceted. It may promote the employment of certain skill-level labor, or have a substitution effect on other skill-level labor. These statistical quantities further support the rationality of SIE as the dependent variable and enhance the robustness of the research conclusion.

Table 4. Change of the explained variable

	LSL	MSL	HSL	EMPL	UNEMP
URB	-0.982***	0.508***	0.477***	13.704***	-0.035***
	(-18.047)	(-8.714)	(-14.111)	(-4.536)	(-3.832)
TO	0.123***	0.055***	-0.180***	3.124***	0.004
	(-6.248)	(-2.620)	(-14.652)	(-2.849)	(-1.221)
ISU	0.176***	-0.493***	0.316***	10.672***	-0.007
	(-3.249)	(-8.495)	(-9.385)	(-3.553)	(-0.769)
CL	-0.088	0.276***	-0.182***	-15.767***	-0.055***
	(-1.465)	(-4.273)	(-4.859)	(-4.708)	(-5.494)
SIE	0.004***	-0.003***	0.001*	2.527***	0.001***
	(-5.242)	(-3.543)	(-2.479)	(-53.208)	(-5.493)
_cons	72.975***	32.504***	-6.009	34.889	9.287***
	(-12.298)	(-5.108)	(-1.628)	(-0.106)	(-9.446)
N	540	540	540	540	540
R^2	0.601	0.269	0.846	0.934	0.121
F	151.974	37.176	554.056	1440.43	13.918

Note: The values in parentheses are t-values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(2) Change the explanatory variables. To verify the robustness of the industrial intelligentization indicators, this paper follows the approach of Hu Shengming (2021) and uses the optical cable line density to re-construct the core explanatory variable [26]. The optical cable line density is represented by FOD. This choice was made after comprehensive consideration of multiple requirements. From the perspective of the breadth of indicator coverage, the industrial robot density mainly focuses on the technical equipment level of the manufacturing production end, while the optical cable density, as a key manifestation of digital infrastructure, reflects the intelligent transformation needs in the industrial field and can comprehensively present the underlying supporting capabilities required for the digital transformation of various industries in the digital economy era. This dimensional expansion from a single production equipment to the entire digital infrastructure can capture the combined effect of the dual driving of technology penetration and infrastructure upgrading in the industrial intelligentization process, providing a more systematic explanatory framework for the changes in the employment structure. This standardized treatment enhances the comparability of the

indicators and lays a methodological foundation for analyzing the balance of industrial intelligentization development in different regions.

From the perspective of analyzing the reliability of the verification mechanism, the optical cable density exhibits unique dual verification advantages. On the one hand, the fiber optic coverage can directly map the development level of digital infrastructure; on the other hand, the bandwidth supply can indirectly reflect the flow ability of data elements, forming a dual verification chain of "infrastructure - application". This multi-dimensional verification mechanism builds up dual guarantees in the robustness test process. It maintains consistency with the benchmark model in the technical and economic logic and also improves the universality of the conclusion by capturing information from different dimensions.

Using it to measure the development level of industrial intelligentization at the provincial level, and then conducting a regression analysis again, the results of the regression analysis are shown in Table 5. The results indicate that the model after the indicator replacement presents the characteristics of robustness: the core explanatory variable, which is also the optical cable density, has the same direction of the regression coefficient as the benchmark model, meaning that digital infrastructure has a strong explanatory power for the structural impact on employment. After verification, it can be found that the new indicator model and the benchmark model do not have systematic differences in coefficient estimation. The R^2 value indicates that the model has a good fit to the data and can explain most of the variation. The F value also indicates that the model has significant explanatory power overall. These statistical quantities support the rationality of using FOD, the optical cable line density, as the core explanatory variable and enhance the robustness of the research conclusion. Compared with the original model (using RID as the explanatory variable), although the core explanatory variable has changed, the model's fit to the data and overall significance remain stable, indicating that the research conclusion has high robustness.

Table 5. Explanation of variable replacement

	LSL	MSL	HSL	EMPL	UNEMP
URB	-0.897***	0.403***	0.497***	61.676***	-0.015*
	(-16.469)	(-7.178)	(-15.906)	(-8.228)	(-1.709)
TO	0.112***	0.003	-0.116***	-2.735	0.008**
	(-4.790)	(-0.138)	(-8.656)	(-0.849)	(-2.176)
ISU	0.190***	-0.396***	0.205***	17.645**	-0.016
	(-3.193)	(-6.486)	(-6.028)	(-2.161)	(-1.603)
CL	-0.114*	0.226***	-0.105***	-29.964***	-0.052***
	(-1.814)	(-3.480)	(-2.909)	(-3.452)	(-5.054)
FOD	0.024***	-0.177***	0.152**	15.029***	0.021***
	(-0.749)	(-5.249)	(-8.117)	(-3.344)	(-3.898)
_cons	70.857***	39.522***	-10.881***	-1201.954	8.346***
	(-11.450)	(-6.200)	(-3.066)	(-1.412)	(-8.237)
N	540	540	540	540	540
R^2	0.579	0.29	0.862	0.577	0.096
F	139.186	41.182	630.613	137.499	10.701

Note: The values in parentheses are t-values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(3) Adjust the sample period. To verify the stability of the model, this paper follows the approach of Duan Chengyun (2023) and employs a sample period optimization strategy, using a time window sensitivity analysis to conduct a robustness test. By selecting a shorter window period as the robustness test method [27], this is because a shorter window period allows for a more focused

analysis on recent data, reducing the noise and interference factors that may be introduced due to a large time span, and more effectively capturing the current impact of industrial intelligence on the employment structure, thereby enhancing the model's explanatory power and predictive ability. Shortening the window period and facilitating the verification of the model's stability by changing the length of the time window, observing whether the model's estimated results remain consistent, allows for determining whether the model is sensitive to the choice of the time window and ensures the reliability and rigor of the research conclusion.

This paper sets the 2009-2019 period as the core research interval. Analyzing from the data quality perspective, it can be seen that before 2006, the core explanatory variable, namely the industrial intelligence index, had missing provincial data, and the missing values were mainly concentrated in the central and western provinces. After processing the missing values using the multiple interpolation method, the regression results indicate that the standard deviation of the coefficient of the core variable has increased significantly compared to the complete sample, suggesting that data missing may introduce estimation bias. Excluding the samples before 2006 ensures the integrity of the data structure. From the perspective of the technological development cycle, in 2006, the number of industrial robots in China was only 18,000, less than 43% of the 42,000 in 2009. At the same time, considering that after the 2008 US subprime mortgage crisis, a series of loose monetary policies were implemented in China, these policies had many negative impacts. And 2009 was exactly the first year when the "Four Tens Million" stimulus plan of the country was implemented. By constructing the technology penetration rate indicator, it was found that the average annual compound growth rate of the intelligent level after 2009 was 17.3%, which was 2.1 times that of the previous three years. The technology shock then had sufficient intensity to affect the employment structure, conforming to the critical point characteristics of the S-shaped curve of technology diffusion. The exogenous shock filtering mechanism shows that in 2020 during the pandemic, the manufacturing PMI index decreased by 13.5 percentage points year-on-year, and the employment data showed a very prominent outlier. After controlling for the pandemic using dummy variables, although the coefficient of the core explanatory variable remained in the same direction, the significance level was significantly lower compared to the benchmark model. The pandemic interference may distort the estimated results. Stopping the sample at 2019 can effectively isolate the impact of extreme events.

This paper conducts a regression analysis again within the 2009 - 2019 interval, and the empirical test results are shown in Table 6. The results exhibit robust characteristics: the regression coefficient direction of the core explanatory variable, the industrial intelligence index, is exactly the same as that of the benchmark model, and the absolute value of the coefficient has increased. After focusing on the window period, the technological substitution effect becomes more prominent. The shortening window model and the benchmark model do not have systematic differences in coefficient estimation. The adjusted model has improved fit goodness compared to the benchmark. This time window sensitivity analysis verifies the model's independence from the sample period and also points out the stable mechanism of the relationship between technology and employment at different development stages. The R^2 value indicates that the model has a good fit to the data, can explain most of the variation, and shows strong explanatory power. The F value indicates that the model has significant explanatory power overall, further supporting the stability of the model.

Table 6. Adjust the sample period

	LSL	MSL	HSL	EMPL	UNEMP
URB	-0.933***	0.373***	0.561***	26.732***	-0.048***
	(-10.566)	(-4.497)	(-10.728)	(-8.199)	(-8.681)
TO	0.059	0.180***	-0.238***	-7.026***	-0.002
	(-1.375)	(-4.463)	(-9.332)	(-4.423)	(-0.648)
ISU	0.197***	-0.432***	0.236***	-3.483	0.005
	(-2.606)	(-6.079)	(-5.273)	(-1.247)	(-1.009)
CL	0.112	-0.056	-0.054	-5.170	0.009*
	(-1.268)	(-0.679)	(-1.028)	(-1.586)	(-1.699)
RID	0.008***	0.012***	0.006	0.023***	0.018***
	(-0.753)	(-0.322)	(-0.710)	(-22.504)	(-0.394)
_cons	56.676***	57.953***	-14.917***	-132.822	5.238***
	(-6.901)	(-7.520)	(-3.069)	(-0.438)	(-10.184)
N	330	330	330	330	330
R^2	0.456	0.253	0.778	0.862	0.415
F	49.383	20	206.784	369.935	41.858

Note: The values in parentheses are t-values. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

After the above multi-dimensional systematic tests, the core conclusion of this paper shows a high degree of consistency under different model settings, time windows, and indicator selections. The key conclusions have all passed the significance test, and the stability of the model has been fully verified. Such testing methods have enhanced the credibility of the research conclusions and also provided a replicable analytical framework for subsequent studies.

4.3.4. Heterogeneity analysis

There are differences in the economic and social development among regions in our country, which may lead to variations in the impact of industrial intelligence development on the employment of different skilled workers. To analyze the regional differences in the impact of industrial intelligence development on employment in China, this paper will conduct a heterogeneity analysis. Following the approach of Sun Zao and Han Ying (2019), it will use a regional regression model to analyze the differentiated employment effects of industrial intelligence levels in the eastern, central, and western economic regions of China. It will systematically present the reshaping mechanism of the labor market in different development stages in these regions [28]. The three regions exhibit a gradient development pattern, with the eastern region being the area for technological-intensive industrial upgrading, the central region being the main battlefield for the transformation of traditional manufacturing, and the western region being the area for the integration of characteristic industries and emerging fields. There are differences in the stage of regional industrial structure transformation, with the eastern region entering the post-industrialization stage, the central region being in a transitional critical period, and the western region facing the challenges of the early stage of industrialization. Policy responses and factor endowments have regional characteristics. The eastern region has a significant technology spillover effect, the central region has a prominent policy guidance role, and the western region relies on resource transformation and policy support. Through the regional regression model, the differentiated employment effects of industrial intelligence in different economic regions can be systematically revealed, providing empirical support for the formulation of regional differentiated employment policies.

The division of China's regional sectors is carried out based on the current mainstream economic significance orientation, rather than solely relying on geographical proximity. The eastern region covers Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. These provinces and municipalities are at the forefront of economic openness, industrial modernization levels, and market maturity in the country. The central region includes Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, and Jiangxi. It mainly assumes the functions of key manufacturing bases and major agricultural production areas in the country, and is responsible for the transformation of traditional industries and the cultivation of emerging economic growth points. The western region includes Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Although the geographical scope is vast, its economic characteristics are more focused on resource development, border trade, and ecological barrier functions, while relying on policy support to develop characteristic advantageous industries. This division method fully considers the regional economic development gradient, that is, the regular spatial decline of economic levels and the industrial correlation, that is, the internal connection formed through product supply and demand among industries. At the same time, it also reflects the policy coordination needs, that is, the coordinated cooperation of policies in terms of goals, means, and effects, jointly promoting regional economic coordinated development, and also presents the functional zoning principles from the perspective of economic geography.

Table 7. Eastern Region

	EMPL	UNEMP	LSL	MSL	HSL
URB	66.551***	-0.022	-0.924***	0.722***	0.200***
	(-6.774)	(-1.261)	(-16.540)	(-9.232)	(-2.637)
TO	7.352***	0.011**	0.111***	0.022	-0.133***
	(-2.956)	(-2.406)	(-7.852)	(-1.113)	(-6.944)
ISU	14.498	0.016	0.162***	-0.863***	0.701***
	(-1.531)	(-0.924)	(-3.008)	(-11.435)	(-9.587)
CL	-23.496***	-0.052***	0.087*	0.038	-0.125*
	(-2.655)	(-3.246)	(-1.738)	(-0.538)	(-1.824)
RID	0.022***	0.026***	0.006***	-0.015***	0.008
	(-16.805)	(-3.807)	(-6.470)	(-4.318)	(-0.305)
_cons	-2949.491***	6.830***	57.298***	52.428***	-9.71
	(-3.310)	(-4.263)	(-11.314)	(-7.386)	(-1.411)
N	198	198	198	198	198
R^2	0.861	0.187	0.81	0.636	0.851
F	226.078	8.356	154.735	63.528	207.7

Note: The values in parentheses are t-values. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

Table 8. Central Region

	EMPL	UNEMP	LSL	MSL	HSL
URB	20.398	-0.072***	-1.086***	0.435**	0.675***
	(-1.511)	(-2.822)	(-5.238)	(-1.993)	(-9.772)
TO	50.654***	0.051*	0.268	-0.071	-0.198***
	(-3.528)	(-1.903)	(-1.216)	(-0.305)	(-2.689)
ISU	-11.827	-0.001	0.218	-0.373**	0.148***
	(-1.242)	(-0.046)	(-1.488)	(-2.424)	(-3.025)
CL	-54.580***	-0.066**	-0.165	0.295	-0.079
	(-3.543)	(-2.288)	(-0.698)	(-1.186)	(-1.007)
RID	0.056***	0.018**	0.004***	0.007***	0.003
	(-8.543)	(-2.599)	(-1.592)	(-1.201)	(-1.011)
_cons	3114.329**	11.121***	77.570***	38.014	-20.028**
	(-2.081)	(-3.957)	(-3.374)	(-1.572)	(-2.613)
N	144	144	144	144	144
R^2	0.833	0.134	0.371	0.115	0.886
F	131.012	4.07	15.427	3.418	204.274

Note: The values in parentheses are t-values. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

Table 9. Western Region

	EMPL	UNEMP	LSL	MSL	HSL
URB	24.583***	-0.016	-1.079***	0.421***	0.660***
	(-2.700)	(-1.222)	(-11.970)	(-5.081)	(-15.994)
TO	11.708	-0.002	0.029	0.007	-0.028
	(-1.206)	(-0.172)	(-0.297)	(-0.386)	(-0.639)
ISU	8.657	-0.055***	0.151	-0.177*	0.025
	(-0.835)	(-3.640)	(-1.468)	(-1.874)	(-0.536)
CL	-15.316	-0.060***	-0.349***	0.395***	-0.046
	(-1.446)	(-3.883)	(-3.324)	(-4.096)	(-0.956)
RID	0.067***	0.006**	0.005	-0.008*	0.002
	(-5.978)	(-2.533)	(-1.248)	(-1.750)	(-0.757)
_cons	-172.348	10.920***	102.799***	12.964	-15.820***
	(-0.160)	(-6.997)	(-9.649)	(-1.325)	(-3.244)
N	198	198	198	198	198
R^2	0.653	0.18	0.681	0.168	0.893
F	68.632	8.017	77.678	7.342	304.616

Note: The values in parentheses are t-values. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

The results of the research are presented in Tables 7, 8 and 9. The findings indicate that the impact of industrial intelligence on employment exhibits a highly distinctive regional heterogeneity. This heterogeneity is not merely reflected in the total employment volume, but is more deeply manifested in multiple dimensions such as employment structure, skill requirements, and changes in the unemployment rate. Regarding the creation effect on the total employment, the marginal effect of industrial intelligence in the eastern region on the number of employed people is $\beta = 0.022$, $p < 0.01$. Although this effect is significantly lower than that in the central and western regions, the explanatory power of the model ($R^2 = 0.861$) ranks first among all regions. This implies that the eastern region has created a large number of high-quality jobs by developing technology-intensive industries, such as artificial intelligence and high-end equipment manufacturing, as well as emerging employment forms, like platform economy. However, due to the prominent capital deepening feature, the employment elasticity per unit of technological input is relatively low. In contrast, the marginal effect of industrial intelligence in the central region is $\beta = 0.056$, $p < 0.01$, which is higher than that in the eastern region and the model's explanatory power reaches 0.833. This is probably mainly due to the fact that the central region actively absorbed industrial transfer from the eastern region and benefited from the technology spillover effect, forming a "technology upgrading - employment expansion" virtuous cycle, reflecting the catch-up effect in the later stage of industrialization. The marginal effect of industrial intelligence in the western region is $\beta = 0.067$, $p < 0.01$, although this effect is the highest, the model's fit degree is $R^2 = 0.653$, which is relatively low. This reflects that the western region has released a large amount of labor demand through policy support and technology diffusion in infrastructure construction and traditional industry transformation, but the depth and breadth of technology penetration are still limited.

The industrial intelligence has led to an increase in unemployment rates in all three regions - the east, the central region, and the west. The degree of impact shows a gradient difference where the east has a greater impact than the central region, and the central region has a greater impact than the west. The east, as the technological frontier, has seen industrial robots deeply penetrate traditional manufacturing industries to replace low-skilled positions, while the supply of new high-skilled positions lags behind, resulting in a mismatch of skills. Coupled with the economic activity level amplifying the unemployment fluctuations, the impact is the most significant in the east. The central region, as the undertaken area for industrial transfer from the east, has seen traditional manufacturing industries become automated, reducing middle-skilled positions, but the rapid development of the tertiary industry has absorbed some of the replaced labor force. Enterprises tend to address the shock through job rotation rather than layoffs, and the "time gap" between industrial upgrading and employment structure adjustment makes its impact fall between the east and the west. The western region, still in the early stage of industrialization, is dominated by labor-intensive industries and has a high reliance on low-cost labor. The policy focuses more on economic scale expansion, and the application of technology has not become the mainstream for industrial upgrading. Moreover, the digitalization advancement is lagging, which slows down the substitution speed of technology for traditional positions, resulting in the smallest increase in unemployment rate. The polarization and reconfiguration of the skill structure belong to another key aspect of the impact of industrial intelligence on employment. In the eastern region, it presents a dual characteristic of "high-end concentration and low-end emergence". On one hand, industrial intelligence has increased the proportion of high-skilled labor; on the other hand, the upgrade of automation may have given rise to some low-skilled friendly positions, resulting in no decrease but an increase in the proportion of low-skilled labor. The central region presents a situation of "middle collapse and two extremes". Industrial intelligence has compressed middle-skilled positions, which may be due to the close connection between manufacturing intelligence and the substitution of middle-skilled positions such as quality inspection and assembly. Low-skilled positions have experienced counter-trend growth due to the upgrading of labor-intensive industries. The skill structure in the western region faces the risk of "low-end lock-in". The impact of industrial intelligence on the proportion of low-skilled labor is not significant. Technological upgrading has failed to effectively create new positions suitable for low-skilled workers, while middle-skilled positions have been significantly impacted, while the impact on high-skilled positions is relatively weak and has not significantly increased.

The moderating effect of control variables shows significant regional differences. In terms of urbanization level (URB), the east significantly promotes the growth of total employment and squeezes out low-skilled positions while stimulating high-skilled demand, reflecting the characteristics of post-industrial industrial upgrading; the central region has no significant impact on the increase in total employment, but boosts middle-skilled position demand; the west simultaneously drives total employment and high-skilled demand, presenting a trend of integration of urbanization and characteristic industries and emerging industries. In terms of trade openness (TO), the east has a significant positive impact on total employment, but inhibits high-skilled demand and raises the unemployment rate; the central region has a stronger impact on total employment and more prominent inhibition on high-skilled positions; the west has no significant impact on total employment and fails to effectively transform into job demand.

The degree of industrial structure upgrading (ISU) creates high-skilled job demand in the eastern region, while the industrial upgrading in the central region suppresses middle-skilled position demand. The western region's industrial upgrading may mainly rely on technological transformation of resource-based industries, although it creates a small number of jobs, it mainly reduces the demand for middle-skilled positions. The impact of living cost (CL) on the number of employed people is the weakest in the western region. This may be due to the lower living cost in the western region, attracting labor-intensive industries, which have a large demand for low-skilled labor, thereby offsetting the substitution effect of technological progress on low-skilled positions, and policy support also helps to alleviate the impact of technological progress on employment.

5. MAIN CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1. Research Conclusions

This study is based on the provincial panel data of China from 2006 to 2023. By constructing a comprehensive analytical framework that includes industrial intelligentization level, urbanization, trade openness, industrial structure upgrading and living costs, and using the fixed effect model and instrumental variable method, it deeply analyzed the multi-dimensional impacts of industrial intelligentization on the employment structure of the labor force. The research results show that the impact of industrial intelligentization on the employment structure has significant skill stratification characteristics and regional heterogeneity. The control variables also have a profound impact on the skill demand structure of the labor market.

5.1.1. The effect of skill stratification is significant

The skill stratification effect of industrial intelligence is remarkable, and the differentiated impact on the demand for different skill levels is prominent. The demand for medium-skilled labor has been verified by the fixed effect model and instrumental variable regression, showing a significant reduction due to industrial intelligence. The increase in the density of industrial robots has replaced conventional repetitive positions such as assembly and inspection, which aligns with the theory of technological polarization. The demand for low-skilled labor has shown a significant positive impact, challenging the traditional assumption that they are easily replaced by technology. This group quickly adapts to new directions through career changes and training, obtaining opportunities in informal employment, demonstrating employment resilience. Regarding high-skilled labor, although industrial intelligence has created related positions, the overall demand impact is not significant. This is constrained by multiple factors such as technological barriers, education supply, and enterprise investment intentions.

5.1.2. Regional heterogeneity is prominent

The impact of industrial intelligence on employment shows significant regional heterogeneity, with a notable difference between the eastern region and the central and western regions. The eastern region, leveraging its advantage in technology-intensive industries, has developed emerging industries such as artificial intelligence and platform economy, creating a large number of high-quality jobs and demonstrating a strong employment absorption capacity. The central and western regions, however, face structural unemployment risks due to lagging technology adaptation: the central region has alleviated some pressure by absorbing industries from the east, but the transition from low-skilled to high-skilled positions is significantly hindered; the western region has released labor demand through policy support and technology diffusion, but is limited by technology penetration and has lagged in employment structure adjustment, requiring policy and technology transfer to promote optimization.

5.1.3. The differential impact of controlling variables

Controlling variables have a profound impact on the structure of skill demands in the labor market, and the effects vary significantly. The improvement of urbanization levels expands high-skilled positions in both directions while reducing traditional low-skilled employment areas; industrial structure upgrading gives rise to both high and low-skilled positions, while compressing medium-skilled positions, presenting a "dual expansion at both ends and contraction in the middle" characteristic. Under the influence of trade openness, the demand for high-skilled positions decreases due to technological substitution and production relocation, low-skilled positions benefit from the advantages of labor-intensive industries, and medium-skilled positions do not show significant fluctuations. The cost of living leads to the expansion of medium-skilled positions due to their cost-effectiveness advantage, high-skilled positions are constrained by the return period of human capital investment and thus suppressed, and low-skilled positions experience a decrease in demand due to low substitution costs, forming a unique skill demand differentiation pattern.

5.1.4. Long-term impact and future trends

In the long term, the employment structure will continue to optimize towards higher skills and higher value-added positions. The demand for high skills will further increase, while the demand for medium skills will decrease. The proportion of low-skilled labor in the service sector is expected to stabilize or increase slightly. Regional development imbalances may intensify. The east will continue to lead in high-quality employment, while the central and western regions need to accelerate the introduction of technologies and the training of talents to address the risks of structural unemployment. The differentiation of skill demands will be more prominent, and the transformation pressure on medium-skilled laborers will be greater.

In the future, the integration of emerging technologies will give rise to more emerging occupations and opportunities as well as challenges. Flexible employment and remote work models are expected to become more regularized. The lifelong vocational skills training system will be continuously improved. The government, enterprises, and educational institutions will work together to alleviate structural unemployment and ensure the sustainable development of the labor market.

5.2. Policy Suggestion

Based on the research conclusions, to address the employment challenges in the era of intelligence, suggestions are proposed from three aspects: skill reshaping, regional collaboration, and institutional innovation. In the skill reshaping aspect, referring to the research of Daron and Pascual Restrepo (2019) [29], a "pyramid-shaped" labor adaptation system is constructed: for low-skilled workers, a skill certification connection system is implemented, a supporting industry fund is set up to support related service industries, and vocational transition training is provided to facilitate the transfer to emerging service industries; for medium-skilled workers, a transformation assistance plan and cross-industry training are implemented, job replacement subsidies are provided to small and medium-sized enterprises, and a re-employment service center is established; for highly skilled workers, universities adjust their enrollment scale dynamically according to industry needs to cultivate scarce talents, and pilot "research and development tax deferral" policies in hub cities, and establish a high-skilled talent pool.

In the regional collaboration aspect, referring to the research of Carl and Michael (2017) [30], a "vulture formation - gradient" intelligent advancement model is created: the eastern region builds an industrial intelligent innovation corridor, strengthens technology transfer and industrial cooperation with the central and western regions; the central region implements intelligent adaptability transformation, creates "skill outposts" and collaborates with the eastern region to jointly establish training bases, and promotes manufacturing transformation; the western region relies on policy support to develop characteristic industries and emerging industries, and introduces advanced technologies and management experiences through cooperation with the eastern and central regions.

In the institutional innovation aspect, referring to the research of David (2015) [31], the "incentive - buffer" policy combination is improved: in the incentive mechanism, the contribution of intelligent employment is included in the assessment of local governments, a special fund is set up to encourage enterprises to hire transition workers, and tax incentives and financial subsidies are given to enterprises adopting intelligent technologies; in the buffer mechanism, a job replacement warning system is established, and enterprises' profits are forcibly extracted as a job replacement fund, and transitional basic income is piloted in old industrial bases; at the same time, a "dual circulation" technology - employment ecosystem is constructed, in the technology autonomy aspect, strengthen core technology support, in the global aspect, establish an intelligent manufacturing technology sharing pool, and implement relevant employment quotas and training standards output.

In the future, in-depth micro-mechanism research will be carried out, international comparison perspectives will be expanded, and long-term impacts will be dynamically evaluated. Through precise identification of the changing patterns of skill structures and the construction of differentiated policy intervention systems, China will be assisted in achieving a leap in employment quality and regional coordinated development.

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