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Does Industrial Intelligence Promote Sustainable Employment?

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Abstract: One of the key driving factors for achieving the goal of sustainable economic development is to ensure decent employment opportunities. This article explores the relationship between industrial intelligence and sustainable development in China from the perspective of employment. Based on interprovincial panel data from 2006 to 2019, using the fixed-effect regression model and mediating-effect regression model, this study empirically tests the impact of industrial intelligence on sustainable employment in China. The following conclusions are drawn: (1) Industrial intelligence has a significant positive impact on the overall scale of employment. Industrial intelligence has promoted the optimization and upgrading of employment skill structure and industrial structure. Industrial intelligence will reduce the employment proportion of low-skilled labor and increase the employment proportion of medium-skilled labor and high-skilled labor. Industrial intelligence significantly reduces the employment share of the manufacturing sector and increases the employment share of the service sector. (2) Industrial intelligence reduces employment levels through capital deepening effects. Industrial intelligence has significantly improved regional labor productivity and significantly improved employment levels through productivity effects. (3) The results of regional heterogeneity show that industrial intelligence has promoted the improvement of employment level and the upgrading of employment structure in the eastern region but has not had a significant positive impact on other regions.

Keywords: industrial intelligence; sustainable employment; regional differences

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1. Introduction

The United Nations Sustainable Development Goals (SGDs) aim to thoroughly address development issues in the social, economic, and environmental dimensions in a comprehensive manner from 2015 to 2030, shifting towards a path of sustainable development. From the perspective of economic development, sustainable economic development refers to maximizing the net benefits of economic development while ensuring the quality of natural resources and the services they provide [1] and reducing inequality within and between countries and poverty alleviation [2]. One of the key driving factors for achieving sustainable economic development is to ensure decent employment opportunities, and stable employment with equal opportunities is crucial for sustainable economic development [3,4].

Currently, a new round of information technology, represented by the development of digital economy and artificial intelligence, is accelerating its integration with the economy and society, bringing new momentum to economic transformation and upgrading. The China Artificial Intelligence Development Report 2020 shows that the global number of artificial intelligence patent applications in the past decade was 521,264, showing an increasing trend year by year. Artificial intelligence technology is rapidly integrating with industries, helping traditional industries improve quality and efficiency. The development of industrial intelligence provides a new research perspective for economic sustainability [5].

As an extension of the human brain, artificial intelligence has great potential in improving productivity, freeing humans from tedious programmatic work [6,7]. However, compared to previous technological revolutions, the impact of the "artificial intelligence revolution" on employment will be broader, stronger, and longer-lasting [8]. With the development of industrial intelligence, more and more people are concerned that their future work will be replaced by artificial intelligence. Frey and Osborne analyzed the risk of automation disruption in 702 occupations in the United States, and the results showed that 47% of occupations are at risk of being disrupted by artificial intelligence [9]. Some scholars have concluded that the application of industrial robots will reduce employment opportunities through empirical testing [10–13]. The transformation towards industrial intelligence may lead to the loss of employment opportunities in the manufacturing and even service sectors, thereby affecting the achievement of sustainable employment development goals [14,15].

However, some scholars believe that the development of industrial intelligence can promote employment by improving labor productivity [16] and can create new job opportunities [17]. Overall, industrial intelligence will promote sustainable employment growth [18,19]. Additionally, the development of industrial intelligence can make up for the shortage of labor resources in economically underdeveloped areas, narrow the gap with developed regions, and promote sustainable economic development [20].

The existing research on the impact of industrial intelligence on sustainable employment has not reached a unified conclusion. This article uses principal component analysis to measure the development index of industrial intelligence in each region based on 30 provinces in China from 2003 to 2021 and uses a fixed-effect regression model to examine the impact of industrial intelligence on labor employment and its regional differences. The core question to be answered is whether industrial intelligence will affect sustainable employment. What is the mechanism through which industrial intelligence affects sustainable employment? Is there a regional gap in the impact of industrial intelligence on sustainable employment?

2. Literature Review and Research Hypotheses

2.1. The Impact of Industrial Intelligence on Employment Scale

Industrial intelligence refers to the achievement of intelligence of products, production, and decision-making processes by using intelligent tools based on new-generation information technology and artificial intelligence technology in various aspects of industrial production, combined with the industrial internet to connect equipment in each link of the production chain [21,22]. The impact of industrial intelligence applications on the scale of labor employment includes negative substitution effects and positive scale effects.

On the one hand, the development of industrial intelligence has continuously expanded the scope of work tasks that industrial robots can complete, and the substitution effect of intelligent robots on labor will also continue to increase [23–25]. Acemoglu and Restrepo used US labor market data to study the impact of industrial robot applications on labor employment at both industry and regional levels and concluded that industrial robots have replaced labor employment [26,27]. Aghion et al. used labor force data at the regional level in France to test and found that robots have reduced the overall employment level in the region [12]. At the same time, the increasing input factors of intelligent capital will also increase the demand for traditional capital. Deepening capital will not only increase the output of the department but also cause the reallocation of capital and labor in the department [28]. The integration of intelligent capital and traditional capital will have a greater substitution effect on labor [29].

On the other hand, some scholars believe that industrial intelligence will increase labor demand by improving labor productivity [16,30]. An increase in labor productivity can lead to a decrease in product prices and an improvement in product quality, leading to an expansion of the industry's market and production scale [31]. For positions in the production process that have not yet been replaced by intelligent equipment, the expansion of production scale will promote their labor demand. At this time, the increase in product demand brought by intelligence will promote labor employment; this positive promoting effect can compensate for the substitution effect of intelligence on labor [31,32]. In addition, industrial intelligence will create more complex and labor-intensive new work tasks when replacing conventional operational and cognitive tasks that are performed by labor [17,18]. The integration of artificial intelligence technology and traditional industries will lead to the emergence of a large number of new forms of employment, which will provide more employment options for individual labor and compensate for the substitution of industrial intelligence for labor employment, such as intelligent technology research and development personnel, intelligent equipment operation and maintenance personnel, and new infrastructure construction personnel [33,34].

Based on this, the first hypothesis of this article is proposed:

H1a: *Industrial intelligence may have a positive impact on employment scale if the creation effect is greater.*

H1b: *Industrial intelligence may have a negative impact on employment scale if the substitution effect is greater.*

2.2. The Impact of Industrial Intelligence on Labor Employment Structure

2.2.1. The Impact of Industrial Intelligence on Labor Employment Skill Structure

There is controversy about the impact of industrial intelligence on the scale of labor employment, but the impact of industrial intelligence on the employment structure is inevitable [35].

Autor et al. proposed the task bias theory by constructing an ALM model and found that computer technology will mainly replace conventional operational and cognitive tasks but will increase the demand for unconventional cognitive tasks. Computer applications have led to a polarization phenomenon in the US labor market [36]. Subsequently, scholars used the ALM model and data from various countries such as the United States, the United Kingdom, Japan, and Europe to verify the polarized impact of information and communication technology on employment [37,38].

Compared with traditional information technology, artificial intelligence can complete more complex work tasks and can lead to an advanced trend in the structure of employment skills [39,40]. Balsmeier and Woerter found that intelligent technology mainly replaces low-skilled and medium-skilled labor, and the new tasks generated are mainly high-skilled labor [41]. Ming Juan and Hu Jiaqi used the education level of labor to measure employment skills, defining primary school and below as low-skilled labor force, middle and high school as medium-skilled labor force, and college and above as high-skilled labor force. They found that the application of industrial robots mainly squeezes out the medium-skilled labor force, promoting the employment level of the high-skilled labor force [42]. Sun Zao and Hou Yulin found that industrial intelligence has led to a "polarization" trend about the employment skill structure, but the employment skill structure in the eastern and southern coastal areas has already shown an advanced trend [43].

2.2.2. The Impact of Industrial Intelligence on Labor Employment Industry Structure

In addition to the employment skill structure, the industrial intelligence will mainly reshape the employment industrial structure because industrial intelligence mainly damages manufacturing employment, and these losses will be offset by the increase in service industry employment [44,45]. On the one hand, the replaced manufacturing labor force will transfer to the service industry, leading to cross-departmental redistribution of labor. Consumer service industries will provide employment opportunities for the replaced workers [46,47]. On the other hand, industrial intelligence will promote the transformation from production-oriented manufacturing to service-oriented manufacturing, creating a large number of productive service positions, such as warehousing and transportation, equipment maintenance and after-sales service, productive cleaning services, etc. Industrial intelligence will significantly increase the employment share of knowledge-intensive modern service industries [48,49].

Based on this, the second hypothesis (H2) of this article is proposed: Industrial intelligence will promote the optimization and upgrading of employment structure.

H2: *Industrial intelligence may promote the optimization and upgrading of employment structure.*

3. Study Design

3.1. Baseline Model Setting

In this section, we adopt the fixed-effect regression model and the mediation effect model to examine the effect of industrial intelligence on employment, based on panel data for 30 provinces in China from 2006 to 2019. The basic econometric model is set as follows:

$$EMP_{pt} = \alpha_0 + \alpha_1 INT_{pt} + \theta X_{pt} + \mu_p + \delta_t + \varepsilon_{pt} \tag{1}$$

where p and t represent the province and year, respectively; EMP_{pt} represents employment scale and employment structure; INT_{pt} is the level of industrial intelligence in each region; and X_{pt} is a set of control variables that may affect employment. At the same time, we also control the province fixed effect μ_p and the time fixed effect δ_t, while ε_{pt} represents the random disturbance term.

Then, we adopt the mediation effect model to examine the impact mechanism by which industrial intelligence affects employment. Referring to Baron and Kenny's (1986) mediation effect test method, the mediation effect model is set as follows:

$$M_{pt} = \beta_0 + \beta_1 INT_{pt} + \beta_2 X_{pt} + \mu_p + \delta_t + \varepsilon_{pt} \tag{2}$$

$$EMP_{pt} = \gamma_0 + \gamma_1 INT_{pt} + \gamma_2 M_{pt} + \gamma_3 X_{pt} + \mu_p + \delta_t + \varepsilon_{pt} \tag{3}$$

where M_{pt} represents the mediating variable. The process of mediating-effect testing is divided into three steps: The first step is to test Equation (1). If the coefficient is significant, the next step is to test. If it is not significant, it indicates that the conditions for mediating effect are not met, and the test is stopped. The second step is to test Equations (2) and (3). If the coefficients are significant, it can be determined that the mediating effect exists; conversely, if one of the coefficients is not significant, proceed directly to the next step. The third step is to perform the Sobel test on the results that are not significant in step 2. If the test statistic is significant, it indicates the existence of mediation effects, while if it is not, it indicates the absence of mediation effects.

Based on the research content of this article, Equation (1) shows the impact of industrial intelligence on employment without considering the mediating effect. Equation (2) represents the impact of industrial intelligence on mediating variables. Equation (3) shows the impact of industrial intelligence on employment after adding intermediary variables to the model, that is, the direct impact of industrial intelligence development on employment after adding intermediary variables.

3.2. Data and Variable Selection

3.2.1. Data Sources

The data related to employment mainly comes from the number of employed individuals in each province in the "China Labor Statistics Yearbook". The data used for calculating the control variables mainly come from the "China Statistical Yearbook", "China Labor Statistics Yearbook", and the statistical yearbooks of each province over the years. The information infrastructure is sourced from the "China Information Industry Statistical Yearbook" over the years. Due to the lack of data for Tibet, Hong Kong, Macau, and Taiwan, and because since 2006, robot scales in China have experienced approximately exponential growth, we have collected data for 30 provinces in China from 2006 to 2019. And the other missing data are supplemented by the average growth rate.

The measurement of intelligent devices is based on the CCD (China Customs Data). Customs Data Network is the world's largest provider of Chinese import and export data and research reports, providing Chinese import and export data about thousands of customers in over 60 countries worldwide. CCD provide two types of Chinese customs data based on the customs code of the product or the code of the enterprise. The main fields in the database include import and export code, import and export quantity, amount, unit price, customs code, commodity name, month, export destination country (import source country), customs port, province and city (receiving and shipping place), trade method, enterprise nature, enterprise location, enterprise, and its contact information. We can filter out import data of intelligent equipment in China over the years based on customs codes and product names. Firstly, the product codes corresponding to various intelligent devices are determined and filtered based on the product codes. Secondly, as the customs database provides monthly data, it needs to be aggregated by year to obtain the import quantity and amount of intelligent equipment in various cities from 2006 to 2019.

3.2.2. Variable Definition

Dependent variable. Sustainable employment refers to creating more employment opportunities and conditions within the carrying range of the sustainable development system, where every worker has fair employment opportunities, a good employment environment, and the ability to develop employment, thereby obtaining great labor benefits. Regarding the measurement of sustainable employment, previous studies have constructed indicators from aspects such as employment opportunities, employment structure, employment quality, and employment environment [50,51]. Based on the availability of data, this article analyzes the sustainable employment level based on the scale and structure of employment in various regions.

The dependent variable is the employment scale and the employment structure in each region. The employment scale is denoted by EMP and is measured by the logarithm of the number of employed urban units in each region. The employment skill structure is measured by the proportion of employment with different levels of education to the total employed population. The education level of employed individuals includes six levels: primary school and below, junior high school, high school, college diploma, undergraduate degree, and graduate degree. We divided the labor force into low-skilled labor force, medium-skilled labor force, and high-skilled labor force based on education level. Among them, low-skilled labor includes primary school and below and junior high school, which is denoted by EMPL; middle-skilled labor includes high school, which is denoted by EMPM; high-skilled labor includes college diploma, undergraduate degree, and graduate degree, which is denoted by EMPH [39–41]. The employment industry structure is measured by the proportion of employment of the industry sector and service sector to the total population in each region. We define the proportion of the industrial sector employed population to the total employed population as EMPI. And we define the proportion of the service sector employed population to the total employed population as EMPS [46,49].

Explanatory variables. The core explanatory variable is the level of industrial intelligence in each region, which is denoted by INT. The comprehensive index of industrial intelligence at the regional level is calculated using the entropy method. Regarding research on industrial intelligence, scholars initially mainly used investment in communication equipment, computers, and electronic devices as proxy indicators [52,53]. With the continuous increase in the installation of industrial robots, relevant research is mainly based on the application volume of industrial robots [54,55]. Further, scholars attempt to use indicators such as artificial intelligence investment amount and artificial intelligence patent application volume to refer to the level of artificial intelligence [56,57]. Considering that the above analysis can only measure a single indicator of industrial intelligence, Sun Zao and Hou Yulin first constructed a comprehensive measurement indicator of industrial intelligence, and later scholars have mostly improved on this basis [43]. We also construct the comprehensive indicator system for industrial intelligence development from three dimensions: intelligent technology, intelligent equipment, and information infrastructure, based on the indicator construction ideas of Sun Zao and Hou Yulin.

(1) Intelligent technology. Compared to industrial automation, industrial digitization, and industrial informatization, which rely on information and communication technology, industrial intelligence cannot do without the development of artificial intelligence technology. Artificial intelligence technology is a further development of information and communication technology, with a certain degree of autonomy. Referring to the research by Wang Linhui et al., it is measured by the number of artificial intelligence invention patents authorized and the number of artificial intelligence enterprises in different regions [58].

(2) Intelligent devices. With the development of artificial intelligence technology, intelligent devices used in the production process have begun to exhibit intelligent characteristics. We use the logarithmic import quantity of intelligent robots, intelligent control systems (PLCs), precision instruments and meters, and 3D printing equipment to measure the intelligent devices [59].

(3) Information infrastructure. The measurement indicators of information infrastructure mainly include software popularization and application, data processing and storage services, platform operation and maintenance services, and information resource collection capabilities. Specifically, we adopt the proportion of revenue from products such as support software and embedded application software to the main business revenue of industrial enterprises to measure the software popularization and application. Data processing and storage services are characterized by the proportion of revenue from data processing and operation services to the main business revenue of industrial enterprises. Platform operation and maintenance services are measured by the proportion of revenue from platform operation and maintenance services to the main business revenue of industrial enterprises. The ability to collect information resources is measured by the level of internet development in each province.

Control variables. Referring to the research by Jiang Yonghong et al. and Hao Nan et al., the selected control variables include the level of economic development, population aging, urbanization development, human capital level, degree of openness to the outside world, industrial structure, and labor costs in each region [60,61]. The specific measurement method for controlling variables is as follows: (1) Labor cost denoted by LABORC. We adopt the logarithm of the average salary of urban unit employees in each province. (2) The level of regional economic development denoted by GDP. The per capita GDP of each province is used to represent the economic development level of the region. Generally speaking, the higher the level of economic development, the stronger the ability to absorb employment. (3) The degree of population aging denoted by AGE. We use the proportion of elderly people aged 65 and above in the total population in each region to measure the degree of population. The degree of population aging will affect the labor supply structure, and the higher the degree of population aging in a region, the lower the labor participation. (4) The level of urbanization development denoted by UR. We use the proportion of urban population in each province as a measure to control the impact of regional urbanization on employment. (5) Human capital investment denoted by HR. The proportion of national financial education funds in each province to the general budget expenditure of local finance is used to measure the human capital investment, and the proportion of college, undergraduate, and graduate students in the province's employment is used as a replacement variable for robustness testing. (6) Extent of openness to the outside world denoted by OPEN. We use the proportion of total import and export trade in each region to GDP to measure the extent of openness. The employment of a region will continue to increase with the increase in regional trade openness [62]. (7) Upgrading of industrial structure denoted by SR. The proportion of the added value of the tertiary industry to GDP in each province is used to measure the industrial structure. (8) Marketization index denoted by MAR. We use the market-oriented comprehensive index constructed by Fan Gang for measurement [63]. Generally speaking, the institutional environment restricts the development space of technological innovation and human capital. Generally, regions with higher levels of marketization have more complete labor markets and higher levels of employment [64]. (9) Regional R&D investment intensity denoted by RD. We use the proportion of internal R&D expenditure in each province to measure the R&D investment intensity. (10) Cost of living denoted by LIFEC. The high cost of living in the region will squeeze out some labor [65]. The proportion of per capita consumption expenditure (including residential expenditure) of urban households in each province as a percentage of disposable income is used to measure the cost of living.

Mechanism Variables. (1) Capital deepening denoted by KL. We adopt the ratio of capital investment to labor investment in production factors to reflect the degree of capital deepening. Among them, capital investment is measured by the fixed capital stock in the manufacturing industry, and labor investment is measured by the number of employees in the manufacturing industry. (2) Productivity denoted by YL. We refer to the research of Tu Zhengge and Xiao Geng, using per capita industrial added value to measure labor productivity in the industrial sector [66]. The labor productivity of each province is measured by the ratio of industrial added value to the average number of workers in industrial enterprises. The specific data are sourced from the "China Industrial Economic Statistical Yearbook" over the years. Since 2008, the National Bureau of Statistics no longer publishes the added value of industrial enterprises, using industrial sales output value as a substitute, where industrial sales output value is deflated using the corresponding price index.

The specific descriptive statistics of the variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable	Variable Name	Sample Size	Mean	Standard Error	Minimum	Maximum
Explained Variables	EMP	420	7.617	0.797	5.715	8.875
	EMPL	420	84.582	9.983	37.815	96.994
	EMPM	420	14.629	8.717	2.989	52.556
	EMPH	420	0.696	1.248	0.005	9.629
	EMPI	420	41.905	10.874	15.574	68.173
	EMPS	420	54.892	9.453	31.434	84.381
Explanatory Variables	INT	420	0.062	0.101	0.002	0.605
	INT1	420	0.032	0.081	0.0001	1
	INT2	420	0.055	0.114	0.0005	0.819
	INT3	420	0.111	0.136	0.007	0.933
Control Variables	LABORC	420	10.288	0.399	9.455	11.475
	GDP	420	10.235	0.563	8.577	11.647
	AGE	420	9.874	2.107	5.473	16.265
	UR	420	54.631	13.583	27.460	89.607
	HR	420	18.369	2.704	11.959	34.287
	OPEN	420	29.013	32.751	1.137	171.137
	SR	420	43.983	9.629	28.615	83.521
	MAR	420	6.584	1.950	2.330	11.710
	RD	420	1.581	1.135	0.197	8.383
	LIFEC	420	0.703	0.478	0.598	0.815
Mechanism Variables	KL	420	3.616	0.544	1.825	5.0444
	YL	420	13.618	6.521	3.244	38.277

3.3. Typical Scenario

3.3.1. Correlation between Industrial Intelligence and Employment Scale

Before examining the impact of Industrial Intelligence and Sustainable Employment, we can initially verity our hypothesis by observing the correlation between industrial intelligence and sustainable employment. Based on variable settings, this section draws the scatter plot between industrial intelligence and employment scale, employment skill structure, and employment industry structure.

Figure 1 shows the scatter plot between the various indicators of industrial intelligence and employment scale. Among them, INT, INT1, INT2, and INT3 refer to industrial intelligence, intelligent technology, intelligent equipment, and information infrastructure, respectively. The horizontal axis represents the indicators related to industrial intelligence.

The vertical axis represents the employment scale of each region. As can be seen in Figure 1, industrial intelligence and employment scale shows a significant positive correlation in our sample.

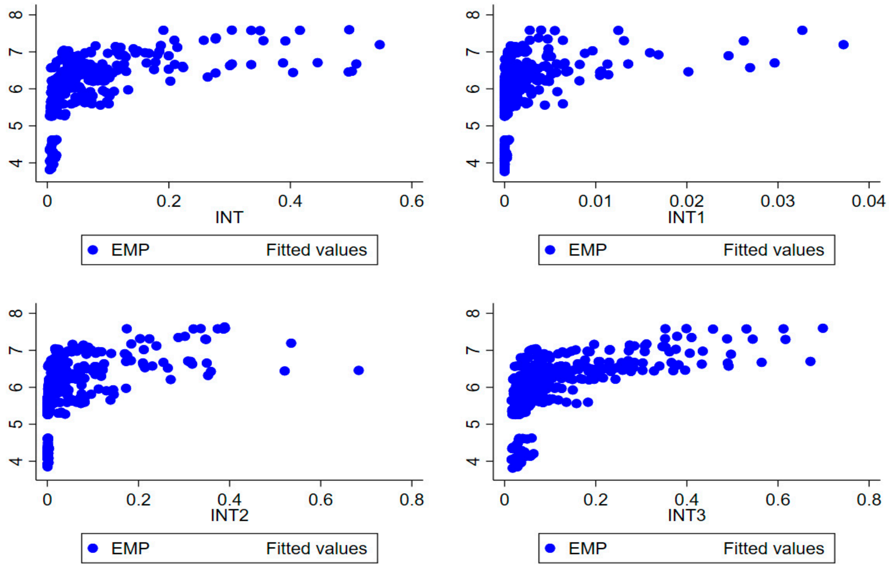

Figure 1. This is a figure of the scatter plot between industrial and employment scale.

3.3.2. Correlation between Industrial Intelligence and Employment Skill Structure

Further combining the development level of industrial intelligence to analyze the trend of changes in labor skill structure, Figure 2 shows the scatter plot of the development level of industrial intelligence in each province and the proportion of skilled labor. The horizontal axis shows the development level of industrial intelligence in each province, and the vertical axis from left to right shows the proportion of low-skilled labor, medium-skilled labor, and high-skilled labor in the employed population. Industrial intelligence leads to a downward trend in the proportion of low-skilled labor in various regions, while the proportion of medium-skilled labor and high-skilled labor shows an upward trend. Industrial intelligence promotes the optimization and upgrading of labor skill structure.

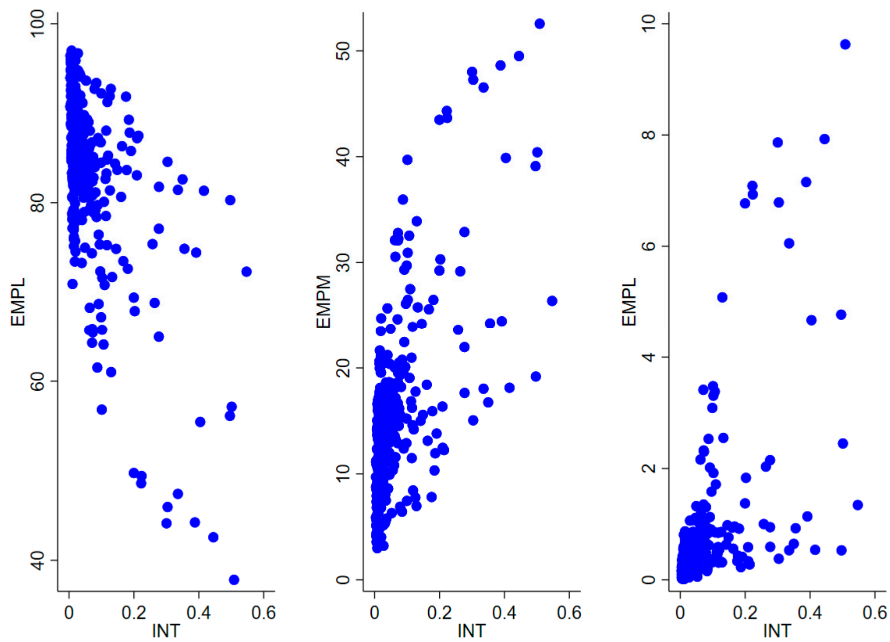

Figure 2. This is a figure of the scatter plot between industrial and employment skill structure.

3.3.3. Correlation between Industrial Intelligence and Employment Industrial Structure

Figure 3 shows the correlation between industrial intelligence and the industrial structure of employment. The horizontal axis represents the level of industrial intelligence development, the vertical axis in the left image represents the proportion of labor in the manufacturing sector, and the vertical axis in the right image represents the proportion of labor in the service sector. The results show that there is a significant positive correlation between industrial intelligence and employment in the service sector, but the correlation with employment in the manufacturing sector is not clear. Only when the level of industrial intelligence development is low is there a positive relationship between industrial intelligence and employment in the manufacturing sector. When industrial intelligence development reaches a certain level, there is no significant correlation in the manufacturing sector. Overall, there is a positive correlation between industrial intelligence and the upgrading of labor employment industry structure.

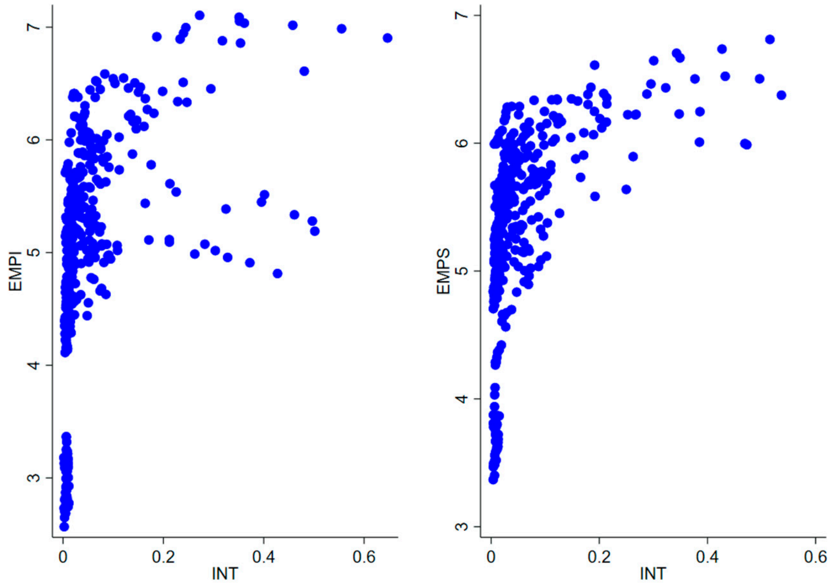

Figure 3. This is a figure of the scatter plot between industrial and employment industrial structure.

4. Empirical Results and Analysis

4.1. The Impact of Industrial Intelligence on Employment Scale

This section uses data from 30 provinces in China from 2006 to 2019 to construct inter provincial panel data and empirically tests the impact of industrial intelligence level on labor employment scale in each region.

Table 2 shows the benchmark regression results of the impact of industrial intelligence on the scale of labor employment in China. The core explanatory variables of models (1)–(4) are the comprehensive indicators of industrial intelligence, intelligent technology, intelligent equipment, and information infrastructure, respectively. The Hausman test was used to select a fixed-effect model for analysis, and the results showed that the coefficient of influence of industrial intelligence on the scale of labor employment was significantly positive. Industrial intelligence will significantly promote the increase in labor employment level. Overall, the development of industrial intelligence has a significant positive net effect on the scale of employment.

Table 2. The impact of industrial intelligence on labor employment.

	(1) Employment	(2) Employment	(3) Employment	(4) Employment
INT	0.808 *** (0.119)			
INT1		−0.008 (0.111)		
INT2			0.711 *** (0.095)	
INT3				0.414 *** (0.085)
LABORC	0.012 (0.056)	0.090 (0.058)	0.021 (0.058)	0.026 (0.059)
GDP	0.194 *** (0.057)	0.203 *** (0.060)	0.176 *** (0.056)	0.222 *** (0.059)
AGE	−0.030 *** (0.005)	−0.025 *** (0.005)	−0.027 *** (0.009)	−0.029 *** (0.005)
UR	0.015 *** (0.003)	0.006 *** (0.003)	0.017 *** (0.003)	0.011 *** (0.003)
HR	0.005 ** (0.003)	0.006 ** (0.003)	0.003 (0.003)	0.006 ** (0.003)
OPEN	−0.003 *** (0.001)	−0.005 ** (0.001)	−0.003 *** (0.001)	−0.003 ** (0.001)
SR	−0.004 *** (0.002)	−0.005 *** (0.002)	−0.006 *** (0.002)	−0.004 *** (0.002)
MAR	0.011 ** (0.007)	0.021 ** (0.007)	0.014 ** (0.006)	0.014 ** (0.007)
RD	0.020 *** (0.014)	−0.031 ** (0.015)	0.019 (0.014)	0.028 * (0.014)
LIFEC	0.035 (0.191)	−0.187 ** (0.130)	−0.082 (0.186)	−0.025 (0.196)
PROVINCE	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
R2	0.778	0.752	0.784	0.766

Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The regression results of various dimensions of industrial intelligence indicators show that intelligent technology has not had a significant impact on labor employment, while intelligent equipment and information infrastructure have a significant positive impact on labor employment. Based on the current development status of various dimensions of industrial intelligence, the current level of intelligent technology development in China is relatively low, concentrated in some industries or regions, and the impact on labor employment has not been shown.

The control variable results show that the level of regional economic development, urbanization, human capital investment, marketization index, and R&D investment intensity will significantly improve the level of labor employment, while the degree of population aging, openness to the outside world, and industrial structure upgrading will significantly reduce the level of employment. The degree of population aging will lead to insufficient labor supply, leading to an increase in labor costs and subsequently reducing labor demand. The negative effects of population aging may encourage economies to apply more intelligent production, further amplifying its promoting effect on employment. The significant reduction in employment levels due to the degree of openness to the outside world may be due to the significant increase in labor productivity, which in turn leads to a decrease in demand for labor [67]. The impact of industrial structure upgrading on labor employment is significantly negative, indicating that compared to employment structure, the development speed of industrial structure is too fast, and there is structural unemployment phenomenon in the process of industrial structure upgrading.

4.2. The Impact of Industrial Intelligence on Employment Skill Structure

This section mainly examines the impact of industrial intelligence on the skill structure of labor employment, as shown in Table 3. The dependent variables in columns (1), (2), and (3) represent the proportion of various types of labor out of total employment. The empirical results show that industrial intelligence has significantly reduced the proportion of low-skilled labor in employment and significantly increased the proportion of medium-skilled labor and high-skilled labor in employment. The development and application of industrial intelligence have led to a unidirectional polarization phenomenon in the labor market, presenting a trend of sophistication. Industrial intelligence, as an advanced manufacturing technology, deeply integrates software and hardware technologies such as computer technology, information technology, and manufacturing technology, putting forward new requirements for the skills of the labor force. The requirements for the physical strength of the labor force are becoming lower and lower, and the requirements for knowledge and skills are becoming higher and higher.

Table 3. The impact of industrial intelligence on the skill structure of labor employment.

	(1) Proportion of Low Skill	**(2) Proportion of Middle Skill**	**(3) Proportion of Middle Skill**
INT	−1.318 ***	1.107 ***	0.341 ***
	(0.276)	(0.299)	(0.048)
INT1	−0.732	0.134	0.683 ***
	(1.967)	(0.189)	(0.355)
INT2	−1.135 ***	0.878 ***	0.248 ***
	(0.222)	(0.216)	(0.039)
INT3	−0.638 ***	0.691 ***	0.208 ***
	(0.195)	(0.187)	(0.034)

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

The impact of intelligent devices and information infrastructure on the employment of heterogeneous skilled labor is basically the same as that of industrial intelligence. Intelligent technology has no significant impact on the structure of employment of low-skilled labor and middle-skilled labor, but significantly increases the proportion of high-skilled labor. According to theoretical analysis, intelligent technology will increase the demand for labor in unconventional cognitive positions through the creation of new tasks, and such positions require high skill improvement for workers, usually requiring them to have a certain level of R&D and innovation ability. Although intelligent technology has not had a significant impact on the overall employment level of the labor market, the creative effect of intelligent technology on labor employment has initially emerged.

4.3. The Impact of Industrial Intelligence on Employment Industrial Structure

In addition to the skill structure of labor employment, industrial intelligence will also change the industrial structure of labor employment. The benchmark regression results of the impact of industrial intelligence on the industrial structure of labor employment are shown in Table 4. The dependent variables in columns (1) and (2) of Table 4 are the proportion of manufacturing and service sector employment to labor market employment.

The regression results showed that industrial intelligence significantly increased the employment proportion of the service sector and decreased the employment proportion of the manufacturing sector. Correspondingly, it has promoted the upgrading of the employment industry structure. For the service industry, on the one hand, the large amount of replaced labor will be transferred to traditional service industries where it is difficult to achieve large-scale intelligence in the short term, and on the other hand, the improvement of industrial intelligence will lead to an increase in labor demand for other related service industry positions.

Table 4. The impact of industrial intelligence on the industry structure of labor employment.

	(1) Proportion of Manufacturing	(2) Proportion of Service
INT	−0.837 *** (0.361)	0.152 *** (0.035)
INT1	−0.243 (0.251)	0.148 *** (0.030)
INT2	−0.493 *** (0.292)	0.109 *** (0.035)
INT3	−0.670 *** (0.250)	0.957 *** (0.234)

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

4.4. Impact Mechanism of Industrial Intelligence on Employment

4.4.1. Capital Deepening Effect

On the one hand, intelligent devices will directly participate in economic production activities as production factors, which will directly squeeze out some of the labor force. On the other hand, intelligent technology will be integrated with traditional capital elements for production, which is reflected in the deepening of capital deepening in the production process. Table 5 shows the mediating-effect test results of capital deepening, where column (1) shows the impact of industrial intelligence on manufacturing capital deepening. The results show that industrial intelligence significantly promotes the deepening of capital deepening. When column (2) does not include the variable of capital deepening degree, the impact of industrial intelligence on labor employment is significant. Industrial intelligence significantly reduces the level of labor employment. Column (3) shows the impact of industrial intelligence on labor employment after adding capital deepening variables to the model. At this time, the degree of capital deepening also has a significant negative impact on labor employment. At the same time, the impact of industrial intelligence on labor employment is still significantly negative, but the regression coefficient decreases compared to column (2), indicating that capital deepening plays a partial mediating role in the process of industrial intelligence affecting employment.

Table 5. Capital deepening effect.

	(1) Employment	(2) KL	(3) Employment
INT	0.563 *** (0.227)	0.147 *** (0.027)	0.592 *** (0.007)
KL			−0.197 *** (0.041)

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

4.4.2. Productivity Effects

Industrial intelligence, while squeezing out labor, will affect the employment level of labor by improving productivity effects. Table 6 shows the mediating-effect test results of labor productivity. Column (1) shows the impact of industrial intelligence level in each province on labor productivity in the manufacturing sector. For each unit of industrial intelligence increase, labor productivity increases by 0.038%, and industrial intelligence significantly improves labor productivity. Column (2) shows the impact of industrial intelligence on labor employment when labor productivity is not included. At this time, industrial intelligence has a significant positive impact on labor employment. Column (3) shows the impact of industrial intelligence on labor employment in the manufacturing sector after adding labor productivity to the model. After adding labor productivity to the model, the impact of industrial intelligence on labor employment remains significantly positive, but the regression coefficient decreases, indicating that labor productivity plays a partial mediating effect in the process of industrial intelligence affecting labor employment. Industrial intelligence has significantly promoted the improvement of labor productivity effect, significantly improving the level of labor employment, and the productivity effect to some extent compensates for the reducing effect of substitution effect on employment.

Table 6. Productivity effects.

	(1) Employment	(2) TFP	(3) Employment
INT	0.563 ***	0.125 *	0.505 ***
	(0.227)	(0.020)	(0.118)
TFP			0.465 ***
			(0.007)

Cluster-robust standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

4.5. Robustness Testing

To further verify the robustness of the measurement results, this section retests the core problem by replacing the core explanatory variables, removing extreme values, and changing the sample interval.

4.5.1. Replacing Explanatory Variables

Firstly, the industrial intelligence index measured by principal component analysis is used as the core explanatory variable. Secondly, the industrial structure is measured by the ratio of the output value of the tertiary industry to the output value of the secondary industry. The average number of students in higher education institutions per 100,000 population is used to measure the level of human capital for testing, and the regression results are basically similar to the basic regression results.

Column (1) in Table 7 shows the test results of the impact of industrial intelligence on labor employment calculated based on principal component analysis. The regression results are basically the same as the benchmark test regression results. The comprehensive indicators of industrial intelligence, intelligent equipment, and information infrastructure have a significant positive impact on labor employment, while intelligent technology has not had a significant impact on labor employment.

Table 7. Robustness testing.

	(1) Replacing Explanatory Variables	(2) Excluding Extreme Values (Truncation)	(3) Excluding Extreme Values (Discontinuity)
INT	0.029 ***	0.855 ***	0.848 ***
	(0.006)	(0.128)	(0.123)
INT1	−0.001	0.168	0.069
	(0.006)	(0.168)	(0.140)
INT2	0.058 ***	0.894 ***	0.796 ***
	(0.008)	(0.119)	(0.102)
INT3	0.053 ***	0.596 ***	0.514 ***
	(0.012)	(0.096)	(0.091)

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

4.5.2. Excluding Extreme Values

In order to eliminate the interference of a small number of extreme values brought by some provinces and years on the econometric model, it is necessary to perform bilateral truncation on the core variables to handle the extreme values. Next, the explanatory variable and the dependent variable are subjected to bilateral truncation at the 1% percentile. The specific estimates are shown in columns (2)–(3) of Table 7. After excluding outlier interference, the impact of industrial intelligence on labor employment remains consistent with the benchmark regression.

4.5.3. Endogenous Treatment

Generally speaking, the presence of reverse causality and missing variables may lead to endogeneity issues in regression. Firstly, while industrial intelligence affects labor employment, the level of employment in the labor market will also have an impact on the level of industrial intelligence. At present, the labor cost of China's manufacturing industry is constantly rising, and the labor market is showing a clear situation of "supply exceeding demand". The manufacturing industry is facing the dilemma of "labor shortage", which to some extent promotes enterprises to further promote the process of industrial intelligence. There is a two-way causal relationship between industrial intelligence and labor employment. Secondly, labor employment is a complex issue that is influenced by multiple factors. In empirical testing, there is inevitably the problem of missing variables, which can also lead to bias in the regression results. In order to make the test results more robust and reduce regression bias, this section uses instrumental variables to address endogeneity issues and retest the model.

Firstly, the selection of instrumental variables needs to satisfy the assumptions of correlation and exogeneity, that is, to find an instrumental variable that is highly correlated with the level of industrial intelligence, but not with the random perturbation term in the model, that is, it will not affect the level of labor employment. Referring to Huang Qunhui et al. (2019)'s approach to constructing instrumental variables and considering indicators related to industrial intelligence, according to the concept of industrial intelligence, both intelligent technology and devices cannot do without the operation of massive big data and the support of information infrastructure. The earliest information infrastructure in China was the total number of telephones and postal and telecommunications services. Regions with higher telephone installations and postal and telecommunications services would have more complete information infrastructure and higher levels of industrial intelligence. At the same time, the data from 1984 are relatively old and do not have a significant impact on labor employment during the sample period, which is consistent with the correlation hypothesis and exogenous hypothesis of instrumental variables. Due to the cross-sectional data of 1984 and the panel data as the research sample, and referring to the research method of Huang Qunhui et al., the interaction between the number of telephones, total postal and telecommunications business volume, and time trends in 1984 was used as instrumental variables to handle endogeneity problems [68].

The regression results of instrumental variables are shown in Table 8, where columns (1) and (3) are the first-stage regression results. In the first-stage estimation results, there is a significant positive relationship between instrumental variables and explanatory variables, both of which are significant at the 1% level, meeting the correlation conditions. Secondly, the weak instrumental variable test showed that the F-statistic exceeded the significance level by 10% of the critical value, and the results showed that there were no weak instrumental variables present. Finally, an overidentification test was conducted, and the *p*-value corresponding to the overidentification test statistic was significant. It is believed that the instrumental variable is exogenous and not related to the disturbance term. The above results indicate that the instrumental variable selected in this paper is effective. Columns (2) and (4) represent the second-stage regression. In the second-stage regression, the impact of industrial intelligence on labor employment is consistent with the basic regression results.

Table 8. Instrumental variable estimation.

	Quantity of Telephone Installation		The Total of Posts and Telecommunications Business	
	(1)	(2)	(3)	(4)
IV	1.388 *** (0.031)		1.009 *** (0.011)	
INT		0.823 *** (0.115)		0.323 *** (0.016)
Unidentified LM	2173.21		2173.21	
Overidentified P	0.001		0.001	
Weak IV test F	2878.85		2878.85	
S-Y critical value	16.38		16.38	
PROVINCE	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
R2	0.781	0.752	0.780	0.742

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

5. Regional Heterogeneity Analysis

China has a vast geographical area, with significant regional differences, and there are also significant differences in the development of industrial economy among different regions. As an emerging tool for advanced manufacturing process technology and information society, the promotion and application scope of industrial intelligence transformation is bound to be different among regions. The regional distribution characteristics of the development level of industrial intelligence in the previous text indicate that there are significant differences in the level of industrial intelligence among different regions. Will this difference lead to regional heterogeneity in the employment effect of industrial intelligence? Based on the distribution characteristics of industrial intelligence in different regions, intelligent equipment is mostly concentrated in the eastern region. At one stage, the development of northeast China is higher than that of the central and western regions. Overall, there is a significant gap between northeast China, the central and western regions, and the eastern regions. Studying the impact of industrial intelligence on employment by considering regional heterogeneity can avoid the mutual cancellation of the development level of industrial intelligence between regions in the full sample analysis, thereby weakening the impact of industrial intelligence on employment.

China is divided into the eastern region, northeast region, central region, and western region, and group regression is used to examine the regional heterogeneity of the impact of industrial intelligence development on labor employment. The regression results are shown in Table 9. Column (1) of the table shows the impact of the comprehensive index of industrial intelligence in each region on employment scale, while columns (2)–(4) show the impact of intelligent technology, intelligent equipment, and information infrastructure in each region on employment scale. The regression results show that the impact of intelligent technology on labor employment is not significant in any region, and neither the comprehensive index nor sub indicators of industrial intelligence have a significant impact on the central and western regions. The comprehensive indicators of industrial intelligence have significantly promoted the employment level of labor in the eastern and northeastern regions. From the breakdown of indicators, the positive scale effect in the eastern region mainly comes from intelligent equipment and information infrastructure, while the positive scale effect in the northeastern region mainly comes from intelligent equipment.

Table 9. Regional heterogeneity.

	(1) INT	(2) INT1	(3) INT2	(4) INT3
East	0.630 ***	−0.039	0.501 **	0.354 ***
	(0.169)	(0.111)	(0.125)	(0.131)
Northeast	2.616 **	2.345	1.344	2.095 ***
	(1.076)	(2.961)	(0.796)	(0.685)
Central area	−3.688 ***	−2.197 ***	−1.490	−0.739
	(1.470)	(0.742)	(1.586)	(0.567)
North	−0.138	−1.776	0.081	0.052
	(0.428)	(0.508)	(0.370)	(0.212)

Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Table 10 shows the impact of industrial intelligence on the employment skill structure in different regions. Overall, industrial intelligence in the eastern region has had a significant impact on the employment skill structure of labor. The development of industrial intelligence in the northeastern region has significantly reduced the employment proportion of low-skilled labor and increased the employment proportion of medium- and high-skilled labor. Industrial intelligence has not had a significant impact on the labor skill structure in the northeast and western regions. Mainly reducing the proportion of medium-skilled labor force employment in the central region. The labor productivity in the eastern region is relatively high, and the level of industrial intelligence is much higher than that in other regions. Intelligence has developed to a certain stage, and the employment scale effect is gradually emerging, especially with the increasing demand for highly skilled labor.

Table 10. The regional heterogeneity of the impact of industrial intelligence on different skills of labor employment.

	(1) INT	(2) INT1	(3) INT2	(4) INT3
East	0.630 ***	−0.039	0.501 **	0.354 ***
	(0.169)	(0.111)	(0.125)	(0.131)
Northeast	2.616 **	2.345	1.344	2.095 ***
	(1.076)	(2.961)	(0.796)	(0.685)
Central area	−3.688 ***	−2.197 ***	−1.490	−0.739
	(1.470)	(0.742)	(1.586)	(0.567)
North	−0.138	−1.776	0.081	0.052
	(0.428)	(0.508)	(0.370)	(0.212)

Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

The regional heterogeneity of the impact of industrial intelligence on labor employment industrial structure are shown in Table 11. The results shows that industrial intelligence significantly reduces the proportion of labor employment in the secondary industry in the eastern region, increases the proportion of labor employment in the tertiary industry, and mainly promotes the upgrading of labor employment industrial structure in the eastern region. For the northeast region, industrial intelligence has mainly increased the proportion of labor employment in the secondary industry, but also reduced the proportion of labor employment in the tertiary industry.

The labor productivity in the eastern region is relatively high, but the degree of capital deepening is not high. Currently, the development of industrial economy mainly relies on high-tech industrial industries, and the overall economic level has reached a stage where the tertiary industry dominates. However, the northeast region relies on its unique advantages in equipment manufacturing industry, with intelligent equipment ranking among the top in the country. It has unique advantages in the fields of industry and manufacturing, but the overall level of economic development is relatively low, which has not led to an increase in employment levels in the service industry. The deepening of capital in the central region is relatively deep, but the main focus is on developing traditional industrial industries, which may have undertaken the industrial transfer of some low-tech manufacturing industries in the eastern region, thus increasing the demand for employment in the manufacturing industry.

Table 11. The regional heterogeneity of the impact of industrial intelligence on different industrial labor employment.

	(1) Proportion of Manufacturing	(2) Proportion of Service
East	−0.838 ***	0.152 ***
	(0.361)	(0.035)
Northeast	−0.243	0.149 ***
	(0.251)	(0.031)
Central area	−0.493 ***	0.109 ***
	(0.292)	(0.035)
North	−0.670 ***	0.957 ***
	(0.250)	(0.234)

Cluster-robust standard errors in parentheses. *** $p < 0.01$.

Overall, industrial intelligence has significantly promoted the optimization and upgrading of labor employment skill structure and industrial structure in the eastern region but has not had a positive impact on other regions, especially causing a low-level trend in the employment skill structure in the central region and a reverse industrialization phenomenon in the employment industry structure in the eastern region. With the continuous improvement of industrial intelligence level, this trend may further deteriorate, and in the long run, it will exacerbate the economic development gap between regions, which is not conducive to balanced economic development between regions.

6. Conclusions, Policy Implications, and Limitations

6.1. Conclusions

In the context of the digital economy, intelligent technology has become an important factor affecting sustainable economic. The article explores the relationship between industrial intelligence and sustainable development in China from the perspective of employment. This article uses the fixed-effect regression model to examine the industrial intelligence on employment based on the provincial panel data in China from 2006 to 2019.

The results show the following: (1) Overall, the industrial intelligence has a significant positive impact on the employment scale; however, from the perspective of employment skill structure, the industrial intelligence can only increase the proportion of middle-skilled labor and high-skilled labor, while reducing the proportion of low-skilled labor. From the perspective of employment industrial structure, the industrial intelligence will have a significant negative impact on the employment proportion of the manufacturing sectors and have a significant positive impact on the employment proportion of the service sectors. (2) The development of industrial intelligence mainly reduces the employment level of labor through capital deepening and increases employment through productivity effects. (3) The development of industrial intelligence in China is mainly concentrated in the eastern region, promoting the optimization and upgrading of employment skills structure and industrial structure in the eastern region.

Overall, the results are consistent with some research findings [16,17,45], and industrial intelligence has promoted sustainable employment development. But there are differences with the research conclusions of some scholars [12,26,27,44]; this may be due to differences caused by factors such as research subjects, data selection, and variable measurement. There is a certain gap between China's industrial intelligence and developed Western countries. The level of intelligent development in China has not reached the level of large-scale substitution of the labor force for employment. Zheng and Liu (2023) found that the employment effect of intelligent devices exhibits a non-linear characteristic, with an inverted U-shaped pattern from a positive effect to a negative effect [69]. Currently, in the context of the rapid development of intelligent technology, we still need to be constantly vigilant about the negative impact of intelligent technology on sustainable employment.

Meanwhile, the results indicate that this positive impact is mainly concentrated in the eastern regions in China. At the arrival of a new round of technological revolution, Guangdong, Jiangsu, Shanghai, and other eastern regions have fully utilized their superior geographical location, strong economic foundation, and sufficient talent reserves to launch a series of industrial intelligence transformation strategies, which have determined the leading development of industrial intelligence level in the eastern region. However, for the northeast region, the lack of economic development momentum, insufficient innovation capabilities, and continuous outflow of talents have all led to serious difficulties in intelligent transformation. For the central and western regions, due to their insufficient level of intelligence and need to undertake some low-skilled industries and labor, the employment structure is showing a low-level trend. From the perspective of regional balanced development, it is not conductive to the sustainable economic development.

6.2. Policy Implications

To summarize the research findings of this study, the following issues need to be addressed: (1) How can the overall level of industrial intelligence in China be improved? (2) How should the upgrading of labor employment skill structure be promoted? (3) How should we narrow the regional gap in the development of intelligence? We propose the following measures to solve the existing issues.

Firstly, the government has further strengthened policy support for "industrial intelligence", incorporating artificial intelligence into key development areas, and creating a favorable policy environment for the development of industrial intelligence. In response to the problem of low innovation ability in key technologies of artificial intelligence, the government needs to further increase financial support for artificial intelligence, attract more highly skilled R&D talents, form a complete talent system, and continuously strengthen cooperation with R&D institutions, universities, and enterprises to enhance the independent innovation ability of intelligent technology and break away from the dependence of core technology and key hardware equipment on developed countries.

Secondly, the government should continuously promote education reform and streng then vocational skills training and promote the employment transfer of workers. In vocational skills education, professional settings should be continuously adjusted and optimized, a professional structure and layout that matches industrial transformation and upgrading should be formed, and the sustainability of technical and skilled talent services required for industrial upgrading should be improved. For example, Beijing is located in the political and cultural center of China, gathering more than 90 universities and over 1000 research institutions. With outstanding scientific research capabilities and strong talent reserves, it has a unique advantage in cutting-edge technology research and development. Through school enterprise cooperation, it aims to create a new system of high-precision and cutting-edge industries for the future.

Thirdly, the government needs to formulate industrial intelligence development strategies tailored to local conditions, such as the level of economic development, population structure, and technological reserves in each region. We need to further leverage the demonstration effect of industrial intelligence development in the eastern region. The central and western regions need to further increase investment in funds and efforts to transform achievements, accelerate the implementation and application of artificial intelligence technology, and expand the scope of artificial intelligence pilot projects. For example, relying on the construction of the Chengdu–Chongqing dual city economic circle, Sichuan Province continuously promotes the digital transformation of the manufacturing industry and creates a demonstration zone for emerging industrial bases; as a traditional manufacturing equipment province, Shaanxi Province has carried out intelligent manufacturing pilot demonstration special actions since 2015.

6.3. Limitations

Firstly, in addition to intelligent development, employment will also be influenced by a comprehensive range of factors such as economic development level, industrial structure, human capital investment, and cost of living. Further consideration can be given to the comprehensive impact of industrial intelligence and these factors on sustainable employment, in order to analyze the reasons behind the regional differences in the employment effects of industrial intelligence.

Secondly, due to limitations in data resources, this article has certain limitations in measuring sustainable employment from the dimensions of employment scale and employment structure. Further, micro-individual-level data can be used to measure the level of sustainable employment from various aspects such as employment stability, employment capacity, and employment benefits, in order to more accurately analyze the impact of industrial intelligence on sustainable employment.

Thirdly, the article has chosen the traditional panel regression model, which has certain limitations in analyzing the problem. Further research methods such as machine learning and numerical simulation can be used to predict the impact of future industrial intelligence on sustainable economies.

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