Innovations

Empirical Study on the Impact of Artificial Intelligence on the Demand for Skilled Labor —Based on China Macro Perspective

Nannan Shan [1*], Nor' Ain Abdullah[2]

[1&2]Author affiliation: Management and Science University (MSU， Malaysia)

Corresponding author: **Nannan Shan**

Abstract

Purpose: *This study aims to explore the impact of artificial intelligence on the changing demand for skilled labor in China, and to provide empirical evidence for relevant policy formulation and talent training.* ***Methodology:*** *By using the research methods of literature review, data analysis and quantitative model construction, based on the panel data of 30 provinces in China from 2009 to 2019 ,the impact of the popularization and application of artificial intelligence technology on skill demand is empirically analyzed .* ***Conclusion:*** *The research results show that the extensive application of artificial intelligence technology has had a positive impact on the total employment of labor force, but it will reduce the employment opportunities of medium-skilled labor force, and the optimization and adjustment of industrial structure shows a clear growth trend in the demand for advanced skills and professional knowledge. It is also found that AI technologies have differential impacts on labor demand across regions. Relevant developed regions, such as eastern and central China, are more dependent on artificial intelligence technology, and the demand for advanced skills and professional knowledge is more urgent. However, in the western part of China, the development of artificial intelligence technology is relatively slow, and the change in demand for skills is relatively small.*

Keywords*: artificial intelligence technology, labor scale, labor structure, heterogeneity analysis, industrial structure optimization*

1. Introduction

Since the Industrial Revolution, technological change has followed the development track from mechanization to automation, and then to intelligence represented by artificial intelligence. The rapid development of artificial intelligence technology has caused profound changes in the labor market. It not only has a huge impact on the demand for skilled labor, but also has a huge impact on the income level of workers. As artificial intelligence has risen to the level of China's national strategic development, artificial intelligence has ushered in its own best era, and its development has become unstoppable. From sweeping robots, intelligent voice assistants to drones, big data processing, etc. It has gradually penetrated into people's daily lives; various industries have introduced artificial intelligence one after another. The high efficiency and high output it brings has made it the hottest pursuit at present .The artificial intelligence effect has also aroused a research boom in the academic circles.

Regarding the impact of artificial intelligence on labor employment, David (2017) predicts that 55% of jobs in Japan will face the risk of automation in the next three to five years , and the jobs of informal workers will face a higher risk of being replaced; Autor (2015) pointed out that compared with traditional automation technology, artificial intelligence technology is more widely used, leading to more serious job replacement problems; in addition, two studies by Acemoglu and Restrepo (2018) found that automation can create new jobs, The role of technological progress in increasing jobs is greater than the impact, because the creation of new tasks stimulated by technological progress will give labor a comparative advantage, thereby increasing labor demand; Bloom et al. (2018) predict that due to the development of artificial intelligence technology , the global There will be 734 million new jobs created; Yan Xueling et al. (2021) used the data of industrial robots in China's manufacturing industry to study and found that the impact of artificial intelligence technology with a standard deviation of 1 unit will lead to an increase of approximately 0.04-0.045% in labor employment..

The academic circles have produced a lot of researches on the impact of artificial intelligence on employment, but the research on the impact of artificial intelligence on the labor skill structure in China and other developing countries has been slow and insufficient, and relevant research still focuses on developed countries such as the United States and Europe However, the research of Chinese scholars also focuses more on the industrial manufacturing industry where the application of artificial intelligence is relatively mature. From a macro perspective, this study will empirically analyze the impact of artificial intelligence on the demand for skilled labor in China in combination with China's various economic indicators and labor market data, and on this basis put forward countermeasures for the labor force.

2. Literature review and research hypothesis

Applied research on artificial intelligence technology. In the medical industry, explainable artificial intelligence (XAI) is mainly used in medical diagnosis and medical decision-making (Holzinger, Andreas et al. 2019) . In addition, it also includes medical record data analysis, drug development and other aspects (Wang CL, Yu JW, and Chang MW ,2019) . In the software engineering industry, artificial intelligence can complete tasks such as requirement analysis, code generation, and testing (Liu X., Su B., and Wu J. , 2019). The application directions in the manufacturing industry include manufacturing process optimization, product design and manufacturing automation (Li, X., & Xu, X. 2018) . In addition, the application of artificial intelligence in the service industry is becoming more and more extensive. In the catering service industry, the ordering system based on speech recognition and the chef robot based on image recognition are the most direct manifestations of artificial intelligence technology. At the same time, the introduction of artificial intelligence , It has a great positive effect on improving the quality of catering services (Zhang Jianguo, 2021) ; audio guides based on speech recognition and online question-answering systems based on natural language processing are also popular in the tourism service industry (Tian Haiyan, 2021) .

Empirical research on the impact of artificial intelligence on the skilled workforce .Frey and Osborne, (2013) used machine learning algorithms and expert judgment to assess the extent to which jobs in the United States can be automated. The study found that high-skill and low-skill jobs are relatively immune to automation, while middle-skill jobs are more likely to be automated. Autor and Handel, (2013), McKinsey Global Institute (2017), find that the impact of automation and artificial intelligence on the skilled workforce is complex. AI may create new jobs and increase the demand for high-skilled jobs, but it may also reduce the number of low-skilled jobs. Muro, et al. (2017) examine the impact of automation and artificial intelligence on the job market in the United States. The study found that artificial intelligence is likely to have a greater impact on low-skilled and middle-skilled jobs, but that high-skilled jobs are relatively less affected. Nesta (2017) explores the need for a skilled workforce in the future and considers the impact of automation and artificial intelligence. The study found that a skilled workforce requires greater creativity, leadership, social skills and data science knowledge. Dauth(2018) conducted an empirical test using German employment data and found that the application of industrial robots in Germany significantly reduced the employment demand of the manufacturing industry, mainly including machine operators, processing personnel, and maintenance personnel; at the same time, it increased the employment demand of the service industry. For example, managers, legal experts, and scientific researchers are in greater demand. Han Minchun and Qiao Gang (2020) analyzed the impact of the application of industrial robots on the manufacturing employment market from the perspective of total manufacturing employment and labor skill structure based on panel data from 18 provincial regions in China. The main performance is that it has a significant inhibitory effect on the total employment of the manufacturing industry. In terms of labor force structure, artificial intelligence has no significant impact on the employment of high-skilled labor, but has a significant inhibitory effect on the employment of low-skilled labor. Wang Liyuan's (2021) empirical research found that, overall, the development of China's intelligence has increased the skill premium, and improving the skill structure of labor supply will help reduce the extent of the increase in the skill premium caused by intelligence.

The impact of the rapid development of artificial intelligence on the structure of China's skilled labor force ,the traditional industrial model and skill structure will face changes, and the skill structure will pay more attention to the cultivation and development of high-level skills. The emergence of artificial intelligence in the form of materialized technology enables the improvement of machine equipment productivity and the reduction of equipment capital prices , which leads to the loss of labor force in production, which leads to the extensive use of artificial intelligence and automation technology by enterprises, and accelerates the transformation of industries from labor-intensive to labor-intensive. The transformation to capital-intensive forms the substitution of capital for labor , and also changes the demand for labor force skill structure (Li Xin'e, Yu Xiaoxiu, Xia Jing , et al. 2021). Endogenous economic growth theory refers to an economic theory that focuses on the impact of technological progress and human capital on economic growth. This theory reveals the important role of technological progress and human capital in economic growth, and provides a new framework for explaining economic growth. Combining the actual situation of China's economic growth and Acemoglu's biased technological progress theory, the potential for relying on traditional production factors to drive China's economic growth is getting smaller and smaller. With the application and popularization of artificial intelligence, China needs more high-quality, high-quality Skilled labor to support the development of this emerging industry.

H1: The impact of the application of artificial intelligence on the structure of China's skilled labor force is characterized by the unipolarity of highly educated skills.

Industrial restructuring brought about by technological progress can have an important impact on labor employment. Technological progress and industrial restructuring lead to the transfer of labor demand from traditional industries to technology-intensive industries, which may reduce employment opportunities in some industries, but at the same time increase employment opportunities in emerging industries and technology-intensive industries. Bergeaud, A., Cette, G., &Lecat, R. (2016) found that industrial restructuring and technological diffusion play an important role in labor demand and job creation. Through the diffusion of technology and the improvement of the quality of production factors, the production efficiency of certain industries increases, thereby creating more employment opportunities. As a general-purpose technology, the application of artificial intelligence has its characteristics and advantages such as wide penetration, data-driven, and system intelligence, which have triggered profound changes in traditional production methods and industrial development models, thereby promoting industrial transformation and upgrading (Hu Jun and Du Chuanzhong, 2020).

H2: The adjustment of economic and industrial structure has a significant role in promoting the impact of artificial intelligence on the scale and structure of demand for skilled labor in China.

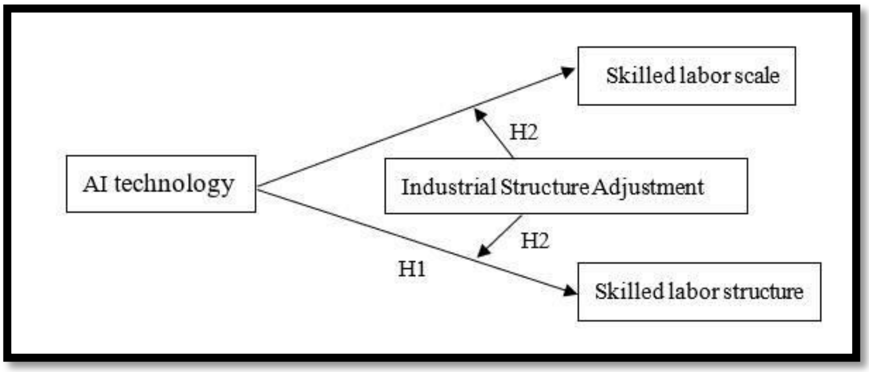

Figure 1Research Framework

3. Research Design

(1)Model setting

The focus of this study is to explore the impact of the application of artificial intelligence technology on skilled labor and the transmission path at the macro level. Based on this research purpose, the following econometric model is set:

$$labor^n_{it}=\alpha^n_0+\alpha^n_1\ ln\ robot\_dens_{it}+\sum_K^n\beta_k Control_{it}+\mu^n_i+v^n_t+\varepsilon^n_{it}(1)$$

In the above model, $labor_{it}$ is the explained variable which indicates the demand for n types of labor force in region i in year t , and n represents the labor force with three different skills: low , medium, and high ; , $robot\_dens_{it}$ is the core explanatory variable of this study. The robot uses density measurement ,*Control* is a set of control variables, μ and v represent fixed effects of region and year respectively, and ε^n is a random disturbance item .

(2)Variable setting

1) Explained variable: labor skill structure

The skill structure of the workforce is usually defined as the distribution of the workforce across skill levels or occupational fields. In the empirical research, there are two main types of standards for the division of workers' skill structure : one is the use of job nature standards. Yao Xianguo et al. (2005), Yu Meici and Xiong Qiquan(2012) defined non-productive workers or white-collar workers who are not on the production line as high-skilled labor, including managers and technicians, and defined productive workers on the production line as low-skilled workers. skilled workforce . The other category is based on education level . Yu Donghua and Sun Ting (2017) divided the labor force into high-skilled labor force, medium-skilled labor force and low-skilled labor force; similarly, Zhang Meisha, Zeng Yutong, Feng Tao (2021) regarded the labor force with higher education (college and above) as For high-skilled laborers, those with junior high school, high school and technical secondary education are classified as medium-skilled laborers, and those with primary school education or below are classified as low-skilled laborers. Sun Zao et al. (2019)explored whether industrial intelligence will lead to corresponding changes in the employment structure of China's labor force at the empirical level, and used the proportion of employed persons with different levels of education to measure the employment of labor with different skills. This article draws lessons from Sun Zao and Hou Yulin(2019) to select the ratio of employed persons with different levels of education to the total employment based on the standard of education level for the division of skilled labor force and the measurement of labor force skill structure.

2) Explanatory variable: artificial intelligence technology

Looking back at previous literature research, there is no unified standard in China for the measurement of the level of artificial intelligence technology in the entire macro economy .Some scholars have drawn on the practice of Jeff & Mi-chael, using "information transmission, computer services, and software industry-wide fixed asset investment" to measure the development level of artificial intelligence. These investments can reflect the role and impact of artificial intelligence in the economy. Of course, this indicator does not fully reflect the development level of artificial intelligence technology, because investment does not necessarily equal the level of technology. Some scholars use the density or penetration of industrial robots as proxy variables for artificial intelligence. For example, Lv Jie et al. (2017)

used the density of industrial robots to measure the degree of automation of industrial manufacturing in a country or region. Han Minchun et al. (2020) used the robot penetration index to measure the distribution density and use degree of industrial robots in a certain area. The penetration of industrial robots reflects the distribution density and use degree of industrial robots, and can more directly reflect the current level of artificial intelligence development in my country. Therefore, this paper uses the installation density of industrial robots to measure the development level of artificial intelligence. Referring to the methods of Kangxi et al. (2021) and Lu Tingting et al. (2021), firstly, based on the installation volume of industrial robots in various industries in China announced by the IRF Alliance, and then collect the number of employed people in each province of the subdivided industries from the "China Labor Statistical Yearbook " As a percentage of total employment in the country, multiply this percentage by the number of robot installations in each industry in the country.

3) Control variables

In order to identify the effect of artificial intelligence technology as much as possible, this paper introduces a series of control variables based on cutting-edge research. Specifically include: socio-economic growth rate (*GDP(%)), represented by the growth rate of the annual regional GDP, R&D* investment level (R&D), represented by the ratio of regional R&D expenditure to GDP, social welfare level (*sec)* , land use The proportion of social security and employment expenditure in the fiscal expenditure of the district government indicates that the social urbanization level (*urb*),Expressed by the proportion of the urban population in the total population at the end of the year in the region, the education input level (*edu*) is expressed by the ratio of the regional financial education expenditure to the total fiscal expenditure, and the consumption level of residents (*cons*) is expressed by the per capita consumption of the regional resident households as a percentage of the disposable income The proportion of the foreign investment level (*fdi*), expressed by the ratio of the region's foreign direct investment to GDP.

(3) Data source and description

The research sample data selected in this paper is the data of 30 provinces (autonomous regions and municipalities) in China from 2009 to 2019. Among them, the data needed to measure the skill structure of the labor force and the control variables come from the "China Statistical Yearbook" and "China Population and Employment Statistical Yearbook ". At present, industrial robots are the key areas for the application of artificial intelligence technology, so the industrial robot data required to measure the level of artificial intelligence technology comes from the International Federation of Robotics (IFR) . Table 1 reports the descriptive statistics of various indicators . It can be seen from the table that the level of artificial intelligence technology has a minimum value of 3.874 and a maximum value of 11.87, implying that there are obvious differences in the level of artificial intelligence in various regions .

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
lnlabor	330	6.945	0.833	4.679	8.872
Low-skill	330	21.74	10.17	2.081	55.77
Medi-skill	330	60.52	8.298	35.73	76.43
lnrob_dens	330	7.885	1.561	3.874	11.87
GDP	330	0.106	0.0731	-0.250	0.299
RD	330	0.0159	0.0110	0.00340	0.0631
sec	330	0.129	0.0322	0.0577	0.275
urb	330	0.564	0.128	0.299	0.896
edu	330	0.164	0.0253	0.0989	0.222
cons	330	0.715	0.0528	0.562	0.894
fdi	330	0.0157	0.0230	0.000328	0.146

4. Empirical analysis

(1) Correlation analysis and multicollinearity analysis

Correlation analysis was carried out on the main variables in the study, and the correlation coefficients among the variables are shown in Table 2. Among them, the correlation coefficients between the level of artificial intelligence and the total number of skilled labor force and different types of skilled labor force are 0.845 ,-0.473 , 0.105 , and 0.389 respectively , which can preliminarily show that the application of artificial intelligence is related to the demand change of skilled labor force . Except for the main explanatory variable artificial intelligence In addition to the level of globalization, the relevant control variables have a high correlation with the employment environment, such as R&D investment, urbanization and foreign investment. According to Table 3, the average VIF value of the explanatory variables is 2.31<5, and the 1/VIF of each variable is less than 1, indicating that there is no multicollinearity problem in the strict sense between the explanatory variables and the control variables. The contributions of the variables to the explained variables are independent and significant, and the prediction effect of the model will be more reliable and accurate.

Table 2: Correlation analysis of main variables

	lnlabor	Lows-kill	Medi-skll	High-skill	lnrob_dens	GDP	RD
lnlabor	1						
Low-skill	-0.325***	1					
Medi -skill	0.205***	-0.411***	1				
high-skill	0.158***	-0.666***	-0.406***	1			
Lnrob_dens	0.845***	-0.473 ***	0.105 *	0.389 ***	1		
GDP	-0.115**	0.270***	-0.0240	-0.251***	-0.294***	1	
RD	0.442***	-0.562***	-0.293***	0.803***	0.478***	-0.0680	1
sec	-0.151***	0.0300	0.0440	-0.0660	-0.0390	-0.284***	-0.157***
urb	0.295***	-0.738***	-0.118**	0.836***	0.475***	-0.232***	0.786***
edu	0.437***	0	0.329***	-0.269***	0.259***	0.129**	-0.0160
cons	-0.386***	0.158***	-0.235***	0.0340	-0.184***	-0.129**	-0.194***
fdi	0.584***	-0.395***	0.0350	0.368***	0.525***	-0.0400	0.538***
	sec	urb	edu	cons	fdi		
sec	1						
urb	-0.104*	1					
edu	-0.495***	-0.242***	1				
cons	0.118**	-0.0700	-0.351***	1			
fdi	-0.334***	0.580***	0.103*	-0.219***	1		

Note: *, ** and *** are at the significance level of 10%, 5% and 1% respectively. The following tables are the same.

Table 3: Multicollinearity analysis

Variable	Low-skill		Medi-skill		High-skill	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
urb	4.190	0.239	4.190	0.239	4.190	0.239
RD	3.050	0.328	3.050	0.328	3.050	0.328
edu	2.460	0.407	2.460	0.407	2.460	0.407
lnrob dens	2.150	0.464	2.150	0.464	2.150	0.464
fdi	2.060	0.486	2.060	0.486	2.060	0.486
sec	1.970	0.508	1.970	0.508	1.970	0.508
GDP	1.340	0.747	1.340	0.747	1.340	0.747
cons	1.270	0.786	1.270	0.786	1.270	0.786
Mean VIF	2.310		2.310		2.310	

(2)Benchmark regression results

In the choice of measurement method, after the Hausman test, it is obtained that prob>chi2=0.0000 <0.1 of all regression models, that is, at the 10% significance level, the null hypothesis that the coefficients of the random effect model and the fixed effect model are similar is rejected, that is, the fixed effect model is adopted model . Moreover, the use density of industrial robots is the main explanatory variable, which is significant at the 1% level in the Ols model, fixed effect model and random effect model . Therefore, the model can be considered robust to the main explanatory variables.

Table 4: Hausman test and robustness test

	(1)	(2)	(3)
	Ols	F e	Re
lnrob_dens	0.385***	0.144***	0.197***
	(0.017)	(0.015)	(0.014)
GDP	0.293	-0.127	-0.101
	(0.288)	(0.095)	(0.107)
RD	14.395***	12.744***	8.638**
	(2.875)	(3.828)	(3.583)
sec	1.104	-1.412***	-1.517***
	(0.792)	(0.392)	(0.433)
urb	-2.074***	1.645***	0.582*
	(0.292)	(0.338)	(0.310)
edu	3.882***	-0.169	0.859
	(1.125)	(0.519)	(0.569)
cons	-2.230***	0.214	0.053
	(0.388)	(0.208)	(0.228)
fdi	9.393***	2.761***	2.965***
	(1.135)	(0.875)	(0.938)
_cons	5.488***	4.706***	4.904***
	(0.479)	(0.186)	(0.216)
N	330.000	330.000	330.000
r2	0.847	0.862	
r2_a	0.844	0.844	
		prob>chi2=0.0000	

Based on the setting of model (1), this paper conducts an empirical test on the basis of the panel data of each province in China. Table 4 reports the results of the fixed-effect benchmark regression. Column 1 reports that the main explanatory variable, artificial intelligence technology level , and the control variable have an impact coefficient of 0.242 on the total employment of the labor force , which is significantly positive in the 1 % confidence interval, indicating that the level of artificial intelligence and the total employment of China's labor force do show There is an obvious positive correlation, and a 1 percentage point increase in the level of artificial intelligence technology will increase the total employment of laborers by 0.0242%. Column (3) shows that the coefficient of the core explanatory variable artificial intelligence is significantly negative, which indicates that the development of artificial intelligence has a significant negative impact on the employment of middle-skilled labor in China, while the significant coefficients of columns (2) and (4) are positive and have a significant impact on Higher-skilled labor has a larger impact coefficient. This shows that from the perspective of China as a whole, the development of artificial intelligence will lead to the development trend of "polarization" in China's employment structure, and the effect on the "advanced" employment structure will be more obvious , that is, the verification hypothesis 1 is not established. This is because with the development of artificial intelligence technology and the application of intelligent equipment and technology, the labor force with high-skilled endowment has more employment advantages.

Table 5: Fixed effects benchmark regression

Variable _	lnlabor	Low - skill	Medi-skill	High-skill
	(1)	(2)	(3)	(4)
lnrob_dens	0.242***	0.182**	-0.826**	0.646***
	(0.6.68)	(0.20)	(-2.24)	(1.66)
GDP	-0.169	-6.836**	3.1 _	3.645*
	(-1.19)	(-2.49)	(1.23)	(1.77)
RD	4.075***	149.131	-394.362***	245.259*
	(7.30)	(1.03)	(-3.09)	(1.99)
sec	0.242	47.318***	-42.832***	-4.443
	(1.33)	(3.43)	(-2.98)	(-0.71)
urb	0.693***	-14.531	73.788***	-59.252***
	(11.65)	(-1.05)	(4.53)	(-4.32)
edu	1.554***	-59.039***	61.113***	-2.073
	(8.01)	(-3.40)	(4.08)	(-0.23)
cons	-0.191	-17.966***	9.556	8.409
	(-1.61)	(-2.95)	(1.46)	(1.54)
fdi	2.579***	29.203	16.660	-45.826***
	(6.93)	(1.24)	(1.00)	(-2.88)
Constant	-0.342**	2,348.177***	716.322	-2,962.435***
	(-2.45)	(3.89)	(1.24)	(-5.46)
N	3 30	330	330	330
R-squared	0.784	0.680	0.520	0.868
Province FE	yes	YES	YES	YES
Year FE	yes	YES	YES	YES

(3)Hysteresis effect analysis

By analyzing the effects of the main explanatory variables with a lag of the first period and a lag of the second period, it can be seen from the table that the main explanatory variables are still significantly positive at the 5% level after the first and second lags, which means that artificial intelligence Technology has an obvious lag in labor employment.

Table 6: Hysteresis Effect Analysis

	(1)	(2)	(3)
	Lag one period	Lag two	lnlabor
L. lnrob_dens	0.051**		
	(0.049)		
L2.lnrob_dens		0.084**	
		(0.032)	
lnrob_dens	0.125**	0.142***	0.144***
	(0.057)	(0.043)	(0.015)
GDP	0.021	-0.046	-0.127
	(0.108)	(0.107)	(0.095)
RD	9.460**	3.198	12.744***
	(4.328)	(4.694)	(3.828)
sec	-1.420***	-2.500***	-1.412***
	(0.429)	(0.522)	(0.392)
urb	1.210***	0.599	1.645***
	(0.408)	(0.479)	(0.338)
edu	0.139	1.095*	-0.169
	(0.555)	(0.601)	(0.519)
cons	0.558**	0.502*	0.214
	(0.273)	(0.283)	(0.208)
fdi	2.153**	1.639*	2.761***
	(0.904)	(0.888)	(0.875)
_cons	4.455***	4.581***	4.706***
	(0.240)	(0.270)	(0.186)
N	300.000	270.000	330.000
r2	0.841	0.823	0.862
r2_a	0.818	0.794	0.844

(4) Mediating effect test

In the benchmark regression, it can be seen that the development of artificial intelligence level has made the labor market gradually become polarized, especially for the employment promotion effect of high-skilled labor groups. On the basis of this conclusion and previous theoretical analysis, in order to further study the transmission mechanism and effect of artificial intelligence on labor employment, it is to verify whether hypothesis H2 can be supported by empirical evidence. The interaction item between industrial organization optimization and artificial intelligence level is constructed by using the method of interaction item, which is coded as DR . According to Table 7-10 , it can be seen that the main explanatory variables are significant at the 1 % level for the total labor force and labor forces with different structures, and the interactive variable DR is also significant at the 1 % level for the total labor force and labor forces with different structures . It shows that the mediating variable has a mediating effect in the model.

Table 7: Test of the mediating effect of artificial intelligence on labor force size

	(1)	(2)	(3)
	lnlabor	DR	lnlabor
lnrob_dens	0.226***	-42.772***	0.232***
	(0.006)	(6.245)	(0.006)
DR			0.000***
			(0.000)
_cons	5.166***	1152.517***	4.993***
	(0.046)	(49.652)	(0.077)
N	330.000	330.000	330.000
r2	0.833	0.136	0.838
r2_a	0.816	0.049	0.821

Table 8: Test of the mediating effect of artificial intelligence on low-skilled labor

	(1)	(2)	(3)
	low-skill	DR	low-skill
lnrob_dens	-3.139***	-42.772***	-3.578***
	(0.168)	(6.245)	(0.167)
DR			-0.010***
			(0.001)
_cons	46.495***	1152.517***	58.321***
	(1.335)	(49.652)	(2.068)
N	330.000	330.000	330.000
r2	0.539	0.136	0.606
r2_a	0.493	0.049	0.565

Table 9: Test of the mediating effect of artificial intelligence on medium-skilled labor

	(1)	(2)	(3)
	medi-skill	DR	medi-skill
lnrob_dens	-1.195***	-42.772***	-0.716***
	(0.176)	(6.245)	(0.174)
DR			0.011***
			(0.001)
_cons	69.944***	1152.517***	57.034***
	(1.400)	(49.652)	(2.153)
N	330.000	330.000	330.000
r2	0.134	0.136	0.270
r2_a	0.047	0.049	0.195

Table 10: Test of the mediating effect of artificial intelligence on high-skilled labor

	(1)	(2)	(3)
	high-skill	DR	high-skill
lnrob_dens	4.334***	-42.772***	4.294***
	(0.117)	(6.245)	(0.125)
DR			0.001**
			(0.001)
_cons	-16.435***	1152.517***	-15.346***
	(0.926)	(49.652)	(1.551)
N	330.000	330.000	330.000
r2	0.822	0.136	0.823
r2_a	0.804	0.049	0.804

5. Heterogeneity Analysis

Further, examine the regional heterogeneity of the impact of industrial intelligence on employment structure. According to the division method of China's economic region given by the National Bureau of Statistics, the 30 provinces and regions in the data set are divided into four regions: the eastern region, the central region, the northeastern region and the western region. In table 11, columns (1) - (3), columns (4) - (6), columns (7) - (9), and columns (10) - (12) represent the east, middle, northeast and west regions respectively Four regions, the impact of artificial intelligence development on low-skilled labor, medium-skilled labor and high-skilled labor. Through comparison, it can be seen that the development of artificial intelligence has led to an obvious "polarization" trend in the employment structure of the labor force in the eastern and central regions of my country. Specifically, the development of artificial intelligence has a significant negative impact on the employment of medium-skilled labor in the eastern and central regions of my country, and has a significantly higher positive impact on the employment of

high-skilled labor than low-skilled labor. However, in the Northeast, the development of artificial intelligence has a positive effect on the middle-skilled labor force, but has a negative impact on the employment of high-skilled labor force. Employment structure did not have a significant impact;
In the western region, with the development of artificial intelligence, there is a "unipolar" trend in which employment opportunities are tilted towards highly educated workers .

Table 11: Regional heterogeneity analysis of the impact of artificial intelligence technology on employment structure

		East area		Central Region		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low-skill	Medi-skill	High-skill	Low-skill	Medi-skill	High-skill
lnrob_dens	0.671*	-0.792***	0.124**	0.067*	-0.043**	0.521**
	(0.997)	(-1.286)	(1.298)	(1.313)	(-1.244)	(1.205)
GDP	-8.262**	5.622	2.643	-4.984	8.994	-4.000
	(3.948)	(5.092)	(5.141)	(5.708)	(5.409)	(5.241)
RD	-99.818	-126.660	226.746	-200.006	551.057***	-350.781**
	(109.080)	(140.697)	(142.035)	(163.924)	(155.311)	(150.498)
sec	-17.258	-32.423	49.754**	54.858	-121.512***	66.727**
	(16.118)	(20.790)	(20.987)	(34.966)	(33.129)	(32.102)
urb	-49.955***	100.810***	-50.848***	-11.474	-9.067	20.535
	(10.144)	(13.085)	(13.209)	(32.718)	(30.999)	(30.038)
edu	28.705	14.831	-43.572	20.212	10.742	-30.977
	(22.157)	(28.579)	(28.851)	(23.105)	(21.891)	(21.213)
cons	1.048	9.287	-10.277	-9.656	-16.041	25.709***
	(7.911)	(10.204)	(10.301)	(10.199)	(9.663)	(9.363)
fdi	-13.260	45.611**	-32.359	-176.218	111.924	64.202
	(15.500)	(19.993)	(20.183)	(106.015)	(100.445)	(97.332)
_cons	42.624***	20.864	36.430***	47.571**	70.122***	-17.673
	(10.144)	(13.084)	(13.209)	(22.981)	(21.773)	(21.099)
N	110	110	110	66	66	66
r2	0.969	0.968	0.986	0.978	0.966	0.970
r2_a	0.959	0.957	0.981	0.966	0.947	0.953

(continued from the above table)

	North-east area			Western Region		
	(7)	(8)	(9)	(10)	(11)	(12)
	Low-skill	Medi-skill	High-skill	Low-skill	Medi-skill	High-skill
lnrob_dens	-0.222	0.295 *	-0.529 **	-0.880	-0.283	0.168*
	(6.619)	(4.762)	(4.265)	(1.359)	(1.277)	(0.816)
GDP	-5.188	2.901	2.281	-10.167	8.928	1.243
	(12.459)	(8.964)	(8.028)	(6.918)	(6.500)	(4.152)
RD	-19.329	-122.559	141.773	-351.231	-21.524	372.381**
	(514.832)	(370.410)	(331.722)	(247.628)	(232.664)	(148.612)
sec	-63.207	-3.354	66.565*	48.400***	-44.441***	-3.938
	(57.079)	(41.067)	(36.778)	(16.485)	(15.489)	(9.893)
urb	-114.343	108.372	5.949	-9.093	55.473	-46.421**
	(110.126)	(79.233)	(70.958)	(37.313)	(35.058)	(22.393)
edu	149.138	-56.053	-93.110	-49.613*	61.908**	-12.218
	(98.905)	(71.160)	(63.728)	(28.258)	(26.551)	(16.959)
cons	30.189	1.542	-31.748	16.783	-8.885	-7.891
	(39.071)	(28.110)	(25.174)	(11.758)	(11.047)	(7.056)
fdi	345.733	181.187	-526.790	297.617	-482.114**	184.409
	(748.208)	(538.318)	(482.093)	(253.387)	(238.075)	(152.068)
_cons	101.536	-1.825	0.304	33.109*	34.062*	32.797***
	(86.707)	(62.384)	(55.868)	(18.845)	(17.706)	(11.309)
N	33	33	33	121	121	121
r2	0.910	0.891	0.974	0.951	0.915	0.947
r2_a	0.761	0.710	0.930	0.936	0.889	0.931

6. Conclusions and Recommendations

This study starts from the perspective of macro research, sets up corresponding econometric models, and uses macro panel data to scientifically evaluate the employment effect of artificial intelligence. The empirical results at the macro level show that the application of artificial intelligence technology in my country can stimulate the demand in the job market and significantly increase the total employment. Using the education level of the labor force as the classification basis for measuring human capital, it is found that under the background of artificial intelligence, the employment of the two labor groups with the education level of "college and above" and "primary school and below" has increased significantly, while the middle, The employment of labor groups with an education level of "above primary school and below college" has declined significantly due to the impact of intelligent development. The labor market is being disrupted by technology. Based on the conclusion that the development of artificial intelligence will lead to the development trend of "polarization" in China's employment structure, the employment structure is more inclined to the development trend of "advanced" . The heterogeneity analysis found that the labor market in the eastern and central regions also showed a trend of "polarization" of skill endowments, while the western region showed a unidirectional polarization trend in which employment opportunities favored highly educated workers . Affected by the adjustment of industrial structure, the integration of industrial structure upgrading and intelligent development has further strengthened the employment-driven effect of artificial intelligence on China's labor force, but it has had a negative and significant impact on the employment of low-skilled labor.

Artificial intelligence has had a profound impact on labor employment, which requires policymakers to take corresponding measures to respond to and adapt to this change, promote the labor force to adapt to the work needs of the artificial intelligence era, and create an inclusive and sustainable job market. First, governments should develop and support broad upskilling and reskilling programs to help the workforce adapt to the demands of work in the AI age. Including supplementary education and training courses to equip people with skills related to artificial intelligence technologies, such as data analysis, machine learning and automation. This helps to improve the competitiveness of the employed and enables them to obtain employment opportunities in the new working environment. Second, the government promotes the application of artificial intelligence technology in different industries by establishing cross-industry and interdisciplinary cooperation mechanisms. This is achieved through the establishment of innovation funds, support for R&D centers and joint projects. Such collaborations help foster new job opportunities, provide employment options across fields, and foster technological innovation and industrial growth. Third, the government can encourage people to actively participate in artificial intelligence innovation and entrepreneurial activities by providing financial support, tax incentives, and entrepreneurial training. This will foster the development of innovation and create new job opportunities , especially in AI start-ups and technological innovation hubs. Finally, governments should develop regulations and policies to ensure that the use of AI systems in the workplace does not result in unfair employment conditions or discrimination. Establish supervision and review mechanisms to ensure fair and reliable decisions made by artificial intelligence systems, and strengthen data privacy and security protection measures to protect personal information from misuse.

References

1. *David, B(2017). "Computer Technology and Probable Job Destructions in Japan : An Evaluation", in Journal of the Japanese and international Economies, Vol. 43, p77-87.*
2. *Autor DH (2015), Why are There Still so Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives. 29(3): 3-30.*
3. *Acemoglu D, Restrepo P(2018). The race between man and machine: Implications of technology for growth, factor shares, and employment [J]. American Economic Review, 108(6): 1488-1512.*
4. *BloomD. E (2018), "Demography, Unemployment, Automation, and Digitalization: Implications for*

the Creation of (Decent) Jobs, 2010-2030", in NBER Working Papers, No. 24835 .

5. *Yan Xueling, Li Wenxin, Gao Ran (2021). The impact and impact of artificial intelligence technology on my country's labor market. Industrial Economics Review, (2): 65-77*
6. *Frey and Osborne, (2 013). The Future of Employment: How Susceptible Are Jobs to Computerisation? .The Oxford Martin School at the University of Oxford. 9,01*
7. *Autor &Handel, (2013).Automation, Skills Use and Training. Journal of Labor Economics,7(3) ,469-517*
8. *Mark Muro, Siddharth Suri &Scott Andes, (2 017). The Impact of Artificial Intelligence -Widespread Job Losses.*
9. *D auth W, Findeisen S, Dekum J, et al. (2 017)German Robots: The Impact of Industrial Robots on Workers. N u mberg: Institute for Employment Research*
10. *Wang Liyuan (2021). Intelligent development, labor supply skill structure and skill premium .Journal of Shanxi University of Finance and Economics, 5 (0 5), 4 5-60*
11. *Han Minchun, Qiao Gang (2020) Structural impact and regional differences of industrial robots on labor employment in manufacturing .Sankei Review, 5(3), 49-63*
12. *Li Xin'e, Yu Xiaoxiu, Xia Jing, etc. (2021) . Research on the Employment Effect of Manufacturing Enterprises under the Application of Artificial Intelligence Technology ——Based on the Empirical Test of 101 Listed Companies. China Soft Science, S1*
13. *Bergeaud, A., Cette, G., &Lecat, R. (2016). The role of production factor quality and technology diffusion in 20th century productivity growth. The Economic Journal, 126(595), 1452-1492.*
14. *Hu Jun, Du Chuanzhong (2 020). The mechanism, path and countermeasures of artificial intelligence promoting industrial transformation and upgrading. Economic Aspect ,(03): 94-101*
15. *Yao Xianguo, Zhou Li, Lai Jun (2005). Technological progress, skill demand and employment structure—a test of the skill skewness hypothesis based on manufacturing micro data. Chinese Population Science ,5 , 47-53 , 95-96*
16. *Yu Meici, Xiong Qiquan(2012). Intermediate product imports, technology spillovers and wage inequality in China's manufacturing industry. Economic Dynamics , 3 , 55-62*
17. *Yu Donghua, Sun Ting (2017) . Environmental Regulation, Skill Premium and Manufacturing International Competitiveness. China's Industrial Economy, (5)*
18. *Zhang Meisha, Zeng Yutong, Feng Tao (2 021) The impact of artificial intelligence on employment demand : From the perspective of labor force structure.China Science and Technology Forum, 12(12),125-134*
19. *Sun Zao, Hou Yulin (2019) . How does industrial intelligence reshape the labor employment structure. China Industrial Economy ,(5): 61 - 79*
20. *Lv Jie, Du Chuanwen, Li Yuanxu(2017). Will the application of industrial robots force the transformation of a country's manufacturing labor force structure? ——Based on the empirical analysis of 22 countries from 1990 to 2015 . Technology Management Research, 22 :32-41*

21. *Han Minchun, Han Qingjiang, Xia Lei (2020). The Impact of Industrial Robot Application on Manufacturing Employment——An Empirical Study Based on the Data of Chinese Prefectural-level Cities. Reformation, 3 :22-39*
22. *Kang Xi , Lin Guanghua. Industrial Robots and Employment of Migrant Workers: Substitution or Promotion[J]. Journal of Shanxi University of Finance and Economics, 2021,43(02):43-56.*
23. *Lu Tingting, Zhu Zhiyong.Whether Artificial Intelligence Will Reduce Labor Income Share——A Test Based on Fixed Effect Model and Panel Quantile Model[J].Journal of Shanxi University of Finance and Economics,2021,43(11):29-41*.