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Effect of industrial robot use on China's labor market: Evidence from manufacturing industry segmentation

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Abstract: This paper empirically investigates the impact of industrial robot use on China's labor market using data from 13 segments of manufacturing industry between 2006 and 2016. According to the findings, the use of industrial robots has a displacement effect on labor demand in manufacturing industry. The specific performance is that for every 1% increase in industrial robot stock, labor demand falls by 1.8%. After endogenous processing and a robustness test, this conclusion remains valid. This paper also discusses the effects of industrial robots across industries and genders. According to the results, industrial robot applications have a more pronounced displacement effect in low-skilled manufacturing than in high-skilled manufacturing. In comparison to female workers, industrial robot applications are more likely to decrease the demand for male workers. Moreover, this paper indicates that the displacement effect is significantly influenced by labor costs. Finally, we make appropriate policy recommendations for the labor market's employment stability based on the findings.

Key words: industrial robot; labor demand; displacement effect; manufacturing

1 Introduction

The globe is dealing with a fresh wave of technological transformation in the 21st century. The core of information technology, artificial intelligence (AI), has changed the way people live and work. The complete intelligence of production and life systems has led to significant alterations in the process of economic and social development[1, 2]. Internet of things (IoT) technologies have penetrated every corner of our modern society, especially for industrial automation[3, 4]. While all elements jointly drive the development of the intelligent supply chain to become an important engine, which supports enterprises to establish core competitiveness[5].

Technical progress results in higher productivity and cheaper labor costs, but structural unemployment brought on by technology shocks is also widespread. A growing number of professions have been displaced by robotics and AI, and "machine replacement" is now becoming a major worry for workers. As early as the 19th century, Marx expressed concern that "machines are not only the powerful competitors of workers, but also always put workers on the verge of unemployment". In 1930, Keynes predicted that while new technology would gradually increase the average income per person, it would also result in a large-scale increase in technical unemployment as robots would eventually replace workers. According to the *World Development Report 2019*, it is obvious that automation has led to a decline in manufacturing jobs in several industrialized economies and middle-income nations[6]. Those who do repetitive, code-able tasks are the simplest to replace. But technological advancement also presents opportunities to boost productivity, generates new jobs, and provides effective public services. It is impossible to predict how many occupations will robots eventually take over. Is the rapid development of AI technology an opportunity or a challenge? This issue has always attracted social notice.

Industrial robots used in manufacturing are an

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increasingly widespread application of AI technology. The State Council of China places a high value on the development of the robot industry, and robots have been identified as key areas of national scientific and technological innovation. The State Council has issued *Made in China 2025*, the *14th Five-Year Plan*, and other policies to improve China's manufacturing industry's competitiveness. According to statistics from the International Federation of Robots (IFR), the use of industrial robots in China has increased rapidly. In 2000, China has a little bit more than 900 industrial robots in stock. By the end of 2017, it had climbed to 470 000, accounting for about 22% of all industrial robots globally.

In this context, how will the widespread use of industrial robots affect the Chinese labor market? What effect will it have on labor demand? Based on data from China's manufacturing industry segments, this paper will investigate the impact of industrial robot applications on the Chinese labor market. The main structure is as follows. Section 2 presents a review of the literature. Section 3 is model and data, which includes model description, data sources, and descriptive statistics. Section 4 is empirical results and analysis. Section 5 continues with the industrial heterogeneity of the displacement effect, the impact of gender differences in the labor force, and the impact of labor cost. Section 6 presents the conclusions and suggestions.

2 Literature review

2.1 Impact of industrial robot application on labor demand

The effect of industrial robots on labor demand has been the topic of numerous researches. The majority of existing literature discusses this from two perspectives: the displacement effect and the creative effect.

According to several research, industrial robots have a certain displacement effect on labor demand. Industrial robots have taken the place of manufacturing labor, which has resulted in the loss of jobs in the workforce's initial positions. Acemoglu and Restrepo[7] examined the impact of industrial robots on industrial development in the United States from 1993 to 2007. According to the findings, the introduction of industrial robots during this period would reduce the number of labor positions by 670 000, with the manufacturing industry bearing the brunt of the impact; on average, adding one industrial robot for every 1000 workers would increase the unemployment rate by 0.18%–0.34%. Using panel data from 286 prefecture-level cities in China, Han et al.[8] discovered that the use of industrial robots has a significant negative impact on total employment in China's manufacturing industry. A 1% increase in industrial robot adoption causes a 3.35% drop in manufacturing jobs overall. Yan et al.[9] studied the impact of industrial robots on labor demand using data from the manufacturing industry by sector. The findings indicate that the use of industrial robots has a significant negative impact on the number of jobs in the manufacturing industry. The specific performance is that for every 1% increase in the stock of industrial robots, the number of jobs decreases by about 4.6%.

According to some other studies, the use of industrial robots has a creative impact on labor demand. Long-term, the use of industrial robots will create new jobs and enhance the need for labor. Li et al.[10] evaluated the effect of the usage of robots on the employment of Chinese industrial firms. Contrary to popular opinion, the study found that using robots significantly increased an enterprise's requirement for labor.

Concerning the overall impact of industrial robots on labor demand, some research conclusions indicate that the effect of industrial robots is uncertain, and may have both a displacement effect and a creative effect. On the one hand, industrial robots have taken over repetitive and simple labor that people used to do, and have squeezed out this segment of the labor force in the labor market, resulting in a displacement effect. On the other hand, the development of industrial robots will not only result in the creation of new jobs but will also encourage enterprise expansion and job creation by increasing production efficiency. As a result, the impact of industrial robots on labor demand must be thoroughly examined in conjunction with the displacement and creative effects. It will show the displacement effect if it is greater than the creative effect, and vice versa. Dauth et al.[11] investigated the impact of industrial robot use in the German labor market from 1994 to 2014. The findings revealed that the use of industrial robots had no effect on the total employment rate of the local labor market and that the reduction in manufacturing jobs caused by robots would be offset by an increase in service jobs.

2.2 Impact of industrial robot applications on labor skill structure

There have also been studies on the impact of industrial robots on the structure of employment skills. Some studies have confirmed that the usage of industrial robots will result in employment polarization, but the conclusion that the structure of employment skills is polarized or unipolar is inconsistent. Autor et al.[12] used the task model to investigate the impact of AI on labor demand. The model classified the tasks required to complete production as programmed or non-programmed. The former primarily needs unskilled labor, whereas the latter requires advanced skills. Low-skilled labor is not constrained by technology and is more easily replaced by industrial robots. High-skilled labor is required to complete non-programmed tasks that cannot be easily replaced by industrial robots, and the use of industrial robots will also result in the creation of more highly skilled jobs and occupations[13]. Using data on industry skill shares for the United States, Japan, and nine European Union economies between 1980 and 2004, Michaels et al.[14] found that countries and industries (within countries) that differentially increased investment in information and communication technology raised their relative demand for high-skill workers and reduced their relative demand for middle-skill workers. The abilities required for employment are changing as a result of technology, according to the *Global Development Report 2019*[6]. The market's demand for lower-skilled labor that technology can perform instead is declining. In addition, the market is seeing an increase in demand for skill sets linked to increased adaptability, such as superior cognitive abilities, social behavior skills, and skill combinations. Han and Qiao[15] discovered that the use of industrial robots has a significant negative impact on the employment of low-skilled workers and a significant positive impact on high-skilled workers. Industrial robots have a "unipolar" effect on the skill structure of the labor market. Wang and Dong[16] used data from manufacturing enterprises and discovered that the impact of robot application on the demand for labor with different skills was significantly different, promoting the employment of high-skilled and low-skilled labor while squeezing the employment of medium-skilled labor.

Compared to existing research, the contributions of this article mainly include as follows: (1) The current literature on the impact of industrial robots mainly begins at the province level or micro level of manufacturing enterprises. This paper can enrich the research on various manufacturing industry segments. (2) The displacement effect of industrial robots across industries and genders is further examined in this paper. So, we can build specialized job aid solutions based on the features of various industries and the gender characteristics of labor.

3 Model and data

3.1 Description of model

Based on the literature review, to analyze the impact of industrial robots on China's labor market, this paper refers to the research of Acemoglu and Restrepo[7], and constructs an empirical model as follows:

$$labor_{i,t} = \beta_0 + \beta_1 robot_{i,t} + \beta_2 control_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where subscript i represents different industries and subscript t represents different years. *labor* is the total labor demand, *robot* is the stock of industrial robots, and *control* is the collection of control variables. The following four variables are chosen as control variables based on the methods used by Yan et al.[9] and Han and Qiao[15]. (1) Industry added value: expressed by the industrial sales value of enterprises; (2) Fixed assets: expressed by the total fixed assets of enterprises; (3) R&D investment: expressed by the internal expenditure of R&D funds of enterprises; (4) Industry scale: expressed by the number of enterprises in the industry.

The heterogeneity of the industry may affect the total labor demand to some extent due to differences in profitability, technology level, industry scale, and other aspects of different industries. Controlling the industry fixed effect (FE) can help to solve the problem of missing variables caused by unmeasurable industry characteristics to some extent. u_i is industry fixed effect. The industrial robot market in China has been expanding consistently over the study period, while the external macroeconomic environment has changed. To some extent, the problems of missing variables that change over time can be solved by controlling the time fixed effect, λ_t is the time fixed effect. $\epsilon_{i,t}$ is the random error term.

3.2 Data sources

This paper conducts empirical research after combining the two sets of data. First, the International Robotics Federation (IFR) provided global industrial robot data, including the annual new installation and year-end inventory of industrial robots in 14 manufacturing industries in major countries and regions worldwide from 1993 to 2019. The second is data from China's official statistics yearbooks, including the China Labor Statistics Yearbook, China Industry Statistics Yearbook, China Statistics Yearbook on Science and Technology, and China Statistical Yearbook. We use data from 31 manufacturing industries in China from 2006 to 2016. Since the industry classification standard of IFR differs from that of China's manufacturing industry, this paper refers to Yan et al.'s [9] practice of matching the two sets of data based on the industry name. Table 1 displays the matching results. It should be noted that in 2012, China revised industry standards, separating the automobile manufacturing industry from the original transport equipment industry, and adding new branches of railway, ship, aerospace, and other transport equipment manufacturing industries. The new branch is not included in the sample to ensure a long and continuous time series.

Given the fact that the majority of industrial robots are used in manufacturing and the accessibility of data, this study uses 143 samples from 13 manufacturing industries in China from 2006 to 2016 for empirical research.

The definitions of variables and data sources in this paper can be found in Table 2.

Table 1 Matching results.

Classification of IFR	Classification in GB/T 4754—2011
Food and beverages	13 Processing of food from agricultural products 14 Manufacture of foods 15 Manufacture of liquor, beverages, and refined tea
Textiles	17 Manufacture of textile 18 Manufacture of textiles, wearing apparel, and accessories 19 Manufacture of leather, fur, feather, and related products and footwear
Wood and furniture	20 Processing of timber, manufacturing of wood, bamboo, rattan, palm, and straw products 21 Manufacture of furniture
Paper	22 Manufacture of paper and paper products 23 Printing and reproduction of recording media
Pharmaceuticals, cosmetics	26 Manufacture of raw chemical materials and chemical products 27 Manufacture of medicines 28 Manufacture of chemical fibres
Rubber and plastic products (non-automotive)	29 Manufacture of rubber and plastics products
Glass, ceramics, stone, mineral products (non-automotive)	30 Manufacture of non-metallic mineral products
Basic metals	31 Smelting and pressing of ferrous metals 32 Smelting and pressing of non-ferrous metals
Metal products (non-automotive)	33 Manufacture of metal products
Industrial machinery	34 Manufacture of general purpose machinery 35 Manufacture of special purpose machinery
Automotive	36 Manufacture of automobiles
Electrical/electronics	38 Manufacture of electrical machinery and apparatus 39 Manufacture of computers, communication and other electronic equipment 40 Manufacture of measuring instruments and machinery
All other manufacturing branches	16 Manufacture of tobacco 24 Manufacture of articles for culture, education, arts, and crafts, sports and entertainment activities 25 Processing of petroleum, coking, and processing of nuclear fuel 41 Other manufacture 42 Utilization of waste resources 43 Repair service of metal products, machinery, and equipment

Table 2 Meaning of variables and data sources.

Variable	Unit	Meaning	Data source
labor	Thousand people	Number of employees at the end of the year	China Labor Statistics Yearbook
robot	Piece	Inventory of industrial robots	IFR
addvalue	Billion CNY	Industrial sales value	China Industry Statistical Yearbook
fixcp	Billion CNY	Total fixed assets	China Industry Statistical Yearbook
rd	Million CNY	Internal R&D expenditure	China Statistical Yearbook on Science and Technology
size	Piece	Number of enterprises	China Statistical Yearbook

3.3 Descriptive statistics

Table 3 displays the descriptive statistics for each variable. According to Table 3, the industrial robot stock data's standard deviation is comparatively high, indicating that the stock has greatly increased over the course of the sample period. The low standard deviation of the total labor demand shows that the level of employment during the sample period was mostly stable.

4 Empirical result

4.1 Baseline results

This study employes the regression model (Eq. (1)) with a two-way fixed effect as its basis for empirical investigation. Table 4 displays the baseline results. We find that the use of industrial robots has a strong and significant negative impact on the manufacturing industry's overall labor demand. For every 1% increase in industrial robots, the total labor demand of manufacturing will decrease by approximately 1.8%.

In terms of control variables, R&D investment has no discernible influence on the overall demand for industrial workers. Fixed assets and industry size have a considerable positive impact on labor demand, showing that as an industry accumulates more capital, more jobs are created and it becomes simpler to recruit new workers.

Table 3 Descriptive statistics of variables.

Variable	Mean	Standard deviation	Minimum	Maximum
labor	7.849	0.669	6.457	9.415
robot	5.738	3.304	0.000	11.673
addvalue	10.579	0.799	8.341	12.112
fixcp	9.199	0.771	7.009	10.626
rd	14.539	1.321	10.948	17.249
size	10.069	0.494	9.208	11.015

Table 4 Baseline results.

Regression parameter	Value
Unit influence to *labor* by *robot*	−0.018** (−2.43)
Unit influence to *labor* by *addvalue*	−0.355** (−2.60)
Unit influence to *labor* by *fixcp*	0.495*** (4.38)
Unit influence to *labor* by *rd*	0.047 (0.83)
Unit influence to *labor* by *size*	0.267** (2.52)
Industry FE	Yes
Time FE	Yes
N	143
R^2	0.843

Note: The numbers in brackets are t values. *** p<0.01; ** p< 0.05.

4.2 Endogenous treatment

The empirical analysis above may exist endogenous issues brought on by reciprocal causation. The use of industrial robots will affect labor demand, and the labor market's employment situation will also influence the use of industrial robots. Han et al.[8] used the two-stage least squares (2SLS) to re-estimate the stock of industrial robots with a one-phase lag as the instrumental variable. The estimated findings are presented in Table 5.

Instrumental variable must satisfy the exogenous and relevance conditions to be effective. One-period lagged *robot* is unaffected by other variables in the current period and satisfies exogenous conditions, and it is linked to the stock of industrial robots in the current period and meets the relevance conditions. Therefore, the selection of instrumental variable is rational. Cragg–Donald Wald F and Kleibergen–Paap Wald rk F statistics are used for weak instrumental variable tests. In brief, the estimate based on this instrumental variable has high Cragg–Donald Wald F and Kleibergen–Paap Wald rk F statistics, indicating that

Table 5 IV-2SLS regression results.

Stage	Regression parameter	Value
First-stage regression	Unit influence to *labor* by instrumental variable	0.854*** (19.21)
	Cragg−Donald Wald *F*	749.88 [16.38]
	Kleibergen−Paap Wald rk *F*	369.20 [16.38]
Instrumental variables (IV)-2SLS regression	Unit influence to *labor* by *robot*	−0.036*** (−4.98)
	Control variable	Yes
	Industry FE	Yes
	Time FE	Yes
	N	130

Note: In the brackets are the critical values of the Stock−Yogo weak tool at the 10% significant level. *** $p<0.01$.

no weak instrumental variable problem exists. Additionally, the results of the second stage regression demonstrate that the impact of industrial robots on labor demand is still significantly negative even after employing the instrumental variable to account for potential endogenous issues. Every 1% increase in industrial robots reduces total labor demand in manufacturing by 3.6%. The influence of industrial robot application is overestimated when compared to the baseline results. The pertinent effect coefficient increased from 1.8% to 3.6% when endogenous issues were corrected.

4.3 Robustness checks

We further investigate whether the impact of industrial robot application on labor demand is caused by particular industries. Table 6 displays the proportion of industrial robots in each categorized industry to the total number of robots in manufacturing. Apparently, the manufacturing of automobiles, rubber and plastic goods, and electrical equipment are the main application areas for industrial robots. In the years after 2012, the industrial robots used in the automotive industry made up about 40% of the overall robots used in manufacturing.

We thus analyze whether the peculiar characteristics of the automobile industry are the cause of the impact of industrial robot application on labor demand. We use data from other manufacturing industries besides the automobile industry to run the regression into the model (Eq. (1)). The results are presented in Table 7.

The correlation coefficient is still strongly negative after eliminating data from the automobile industry, and the correlation coefficient value is similar to the baseline result. This can prove that the impact of industrial robots on labor demand is not due to the peculiarities of the automobile industry.

Table 6 Proportion of industrial robots by industry.

Industry	Mean proportion	Rank
Food and beverages	0.020	6
Textiles	0	12
Wood and furniture	0	12
Paper	0.001	11
Pharmaceuticals, cosmetics	0.105	4
Rubber and plastic products	0.286	2
Glass, ceramics, stone, mineral products	0.005	10
Basic metals	0.006	9
Metal products	0.059	5
Industrial machinery	0.017	7
Automotive	0.320	1
Electrical/electronics	0.170	3
All other manufacturing branches	0.010	8

Table 7 Regression results after excluding the automobile industry.

Regression parameter	Value
Unit influence to *labor* by *robot*	−0.018** (−2.40)
Unit influence to *labor* by *addvalue*	−0.415*** (−2.73)
Unit influence to *labor* by *fixcp*	0.482*** (4.07)
Unit influence to *labor* by *rd*	0.061 (0.90)
Unit influence to *labor* by *size*	0.252** (2.28)
Industry FE	Yes
Time FE	Yes
N	132
R^2	0.851

Note: The numbers in brackets are *t* values. *** $p<0.01$; ** $p<0.05$.

5 Discussion

The research above has found that the application of industrial robots tends to have a displacement effect on manufacturing labor demand. Based on this, we discuss how the use of industrial robots affects the demand for labor across industries and genders, as well as whether labor costs have a significant impact on the displacement effect.

5.1 Effects by industry

We are now investigating the effects of industrial robot applications on the demand for labor in different skill industries. The manufacturing sector is firstly split into high- and low-skill sectors. The Organization for Economic Co-operation and Development (OECD) divides the manufacturing sector into four segments: high-technology, medium-high technology, medium-low technology, and low technology. Given that the data used in this paper are a match between the IFR classification standard and the Chinese manufacturing industry classification standard, we classify high-tech and medium-high technology industries as high-skill industries, and medium-low technology and low-technology industries as low-skill industries. Table 8 displays the specific classification results.

Table 9 displays the regression results of how industrial robots have affected the labor demand for both high- and low-skill industries in manufacturing. The results show that although the main explanatory variable's coefficient is still negative in high-skill industries, it is no longer statistically significant. However, the use of industrial robots has a significant displacement effect on labor demand in low-skill industries, specifically seen as a 2.3% decrease in labor demand for every 1% increase in industrial robots. In comparison to the baseline results, the influence coefficient of the main explanatory variable in low-skill industries increased from 1.8% to 2.3%. It proves that the use of industrial robots is having a more significant displacement effect in low-skill industries than in high-skill industries.

5.2 Effects across genders

We also use regression model (Eq. (1)) to examine how the usage of industrial robots affects the demand for different genders' labor in manufacturing. In this study, the demand for labor of different sexes is calculated using the number of men and women in different industries from China's Labor Statistics Yearbook. Table 10 displays the results of the regression.

The usage of industrial robots has a negative effect on the demand for both male and female labor.

Table 8 High/low skill industries classification.

Category	IFR classification
High-skill industry	Pharmaceuticals, cosmetics
	Industrial machinery
	Automotive
	Electrical/electronics
Low-skill industry	Food and beverages
	Textiles
	Wood and furniture
	Paper
	Rubber and plastic products
	Glass, ceramics, stone, mineral products
	Basic metals
	Metal products
	All other manufacturing branches

Table 9 Regression results of effects of industrial robots across high- and low-skill industries.

Regression parameter	All industries	High-skill industry	Low-skill industry
Unit influence to *labor* by *robot*	−0.018** (−2.43)	−0.029 (−1.66)	−0.023*** (−3.19)
Unit influence to *labor* by *addvalue*	−0.355** (−2.60)	−0.763** (−2.52)	−0.341*** (−2.87)
Unit influence to *labor* by *fixcp*	0.495*** (4.38)	−0.178 (−0.60)	0.439*** (4.60)
Unit influence to *labor* by *rd*	0.047 (0.83)	0.186 (0.81)	0.182*** (3.10)
Unit influence to *labor* by *size*	0.267** (2.52)	1.729*** (6.22)	0.117 (1.27)
Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
N	143	44	99
R^2	0.843	0.926	0.912

Note: The numbers in brackets are *t* values. *** p<0.01; ** p<0.05.

Table 10 Regression results of effects of industrial robots across genders.

Regression parameter	Female	Male
Unit influence to *labor* by *robot*	−0.013* (−1.78)	−0.026*** (−3.03)
Unit influence to *labor* by *addvalue*	−0.145 (−1.07)	−0.534*** (−3.45)
Unit influence to *labor* by *fixcp*	0.438*** (3.92)	0.510*** (3.97)
Unit influence to *labor* by *rd*	0.079 (1.42)	0.066 (1.03)
Unit influence to *labor* by *size*	0.115 (1.09)	0.348*** (2.88)
Industry FE	Yes	Yes
Time FE	Yes	Yes
N	143	143
R^2	0.804	0.834

Note: The numbers in brackets are t values. *** p<0.01; * p<0.1.

However, the correlation coefficient is higher and more statistically significant for male labor. According to this finding, the displacement effect of industrial robot use for male labor is more significant than for female labor. Because of this, men are more likely than women to be replaced by industrial robots.

5.3 Labor cost

We further discuss the influence factor of how industrial robot applications would affect the total demand for labor. According to certain research[17], labor costs are a significant factor in "machine replacement", and by taking this into account, we can examine the displacement effect of robot application in an indirect way. We use the average wage of manufacturing industries to evaluate labor costs. The specific approach is to add an interaction term between the average wage and the stock of industrial robots to the model (Eq. (1)). The regression results are shown in Table 11.

Table 11 Regression results of impact of labor cost.

Regression parameter	Value
Unit influence to *labor* by *robot*	−0.248*** (−5.22)
Unit influence to *labor* by *wage*	−0.252*** (−3.50)
Unit influence to *labor* by *robot*×*wage*	0.021*** (4.95)
Unit influence to *labor* by *addvalue*	−0.095 (−0.71)
Unit influence to *labor* by *fixcp*	0.297*** (2.71)
Unit influence to *labor* by *rd*	0.124** (2.30)
Unit influence to *labor* by *size*	0.254** (2.62)
Industry FE	Yes
Time FE	Yes
N	143
R^2	0.873

Note: The numbers in brackets are t values. *** p<0.01; ** p<0.05.

The results demonstrate that even after taking into account labor cost factors, the impact of industrial robot use on labor demand is still strongly negative. The interaction term coefficient is significantly positive, suggesting that labor costs play a substantial role in determining the displacement effect of industrial robots, and this effect is more pronounced with the lower average wage level. A possible explanation is that these low-wage positions only require simple and repetitive tasks, and workers in these positions are more likely to be replaced by industrial robots.

6 Conclusion

This research empirically investigates the effects of industrial robot applications on China's labor market using data from 13 segments of manufacturing industry between 2006 and 2016. We discover that the use of industrial robots generally has a displacement effect on labor demand, as evidenced by the fact that the entire labor demand will decrease by 1.8% for every 1% increase in the number of industrial robots. The stock of industrial robots with a one-phase lag is chosen as instrumental variable to estimate and solve the potential endogenous issues, and the result is still reliable. In addition, considering the impact of the particularity of the automotive industry, after excluding the automotive industry data for regression, the result remains valid.

Also, the industry heterogeneity of the industrial robot displacement effect is further explored. As compared to high-skill industries, the use of industrial robots has a more profoundly negative effect on the labor demand of low-skill industries. Furthermore, the results show that the use of industrial robots has a negative impact on demand for both male and female labor, but has a greater negative impact on demand for male labor. Finally, we find that labor costs play a significant role in determining the displacement effect of industrial robots. The displacement effect is more pronounced the higher the industry's labor cost. We offer the following suggestions based on the research findings presented:

Firstly, according to the research results, the application of industrial robots has a displacement effect on the overall demand for manufacturing labor. Therefore, the government should take action to prevent the widespread use of industrial robots from having a negative influence on the labor market shortly. On the one hand, appropriate job support and social security measures must be implemented to efficiently deal with the unemployment crisis. On the other hand, the government should cultivate the abilities necessary for the intelligent transformation of manufacturing, aggressively support worker job-transfer training and on-the-job training, and promote the development of vocational skills and employment mobility.

Secondly, according to the research results, industrial robot application has different effects on labor demand across industries and genders. Therefore, the government should implement specialized employment policies that take into account the traits of various industries and individuals. On the one hand, it is important to take into account the uneven rate of new technology innovation across industries and apply targeted support measures based on the specific characteristics of each industry. On the other hand, the use of industrial robots has a more significant negative impact on the demand for male workers. Therefore, when creating employment rules, the job conditions of male and female employees can be taken into different consideration.

Thirdly, according to the research results, the displacement effect of industrial robots is the more pronounced, the lower the industry's labor costs are. Therefore, the government should raise employee pay and benefits, enact talent subsidy programs, optimize the labor force's skill distribution, and encourage high-quality employment.

The following problems with this article still exist, and it is advised that more analysis be done to solve them. (1) The data used in this study are incomplete due to difficulties with accessibility. Research can continue to move forward if data on the use of industrial robots over a longer period and in industries other than manufacturing can be obtained in the future. (2) This research investigates whether the displacement effect of industrial robots is significantly affected by labor costs. We can examine the mechanism underlying how the use of industrial robots affects labor demand in the future, include labor costs as an intermediary mechanism in the research model, and seek more intermediary mechanisms.

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