Information Systems and Economics (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/infse.2025.060202
ISSN 2523-6407 Vol. 6 Num. 2

Intelligent Manufacturing and Urban-Rural Integration: A Study of the Impact of Industrial Robot Application and Emerging Urban-Rural Relationships in China

Shangru Yang, Yuchen Bai, Zequn Hu*

Jiangxi University of Finance and Economics, Nanchang, Jiangxi, 330013, China
**Corresponding author*

Keywords: Intelligent Manufacturing, Urban-Rural Integration, Industrial Robot Application, Spatio-temporal Heterogeneity, Industrial Coordination

Abstract: Based on the International Federation of Robotics (IFR) data and Chinese prefecture-level city panel data, this paper empirically examines the impact of industrial robot application on urban-rural integration development and its mechanism. It is found that: (1) industrial robot application significantly promotes urban-rural integrated development, and this conclusion still holds after solving the endogeneity problem and passing the robustness test of replacing the measurement method and eliminating special samples; (2) there is spatio-temporal heterogeneity in the promotion of robot application, with the effect in central and western regions being stronger than that in eastern regions, and showing a trend of marginal decreasing over time, with the most significant promotion effect in the policy-guided period (2007); (3) Industrial coordination is an important mechanism for robots to promote urban-rural integration, and robots indirectly enhance the endogenous power of urban-rural integration by optimizing industrial structure upgrading and three-industry synergy. The study suggests that the government should promote the intelligent transformation of agricultural production, strengthen the differentiated policy support in central and western regions, and focus on skills training to alleviate the risk of structural unemployment, so as to unleash the dividends of smart manufacturing on the high-quality development of urban and rural areas.

1. Introduction

Since entering the 21st century, the high-speed development of digital technology has promoted the application and innovation in the field of intelligent manufacturing, in which the high-speed development of intelligent manufacturing represented by artificial intelligence and the planning of "artificial intelligence + manufacturing" has triggered global attention. According to the data released by the International Federation of Robotics (IFR), the total number of robots in China has continued to grow at a high speed. Since 2007, China's industrial robot ownership has continued to increase, and China's intelligent manufacturing industry has entered a period of rapid development. During this period, the urban-rural integration measurement index of China's regions has also increased year by year. It can be seen that while the rapid development of artificial intelligence applications, the labor force and urban-rural integration development level is also increasing. Accordingly, we have questions: is the common growth of the two a coincidence or is there an inevitable correlation, and will the development of intelligent manufacturing affect the development of urban-rural integration?

The rapid development of the smart manufacturing industry has brought unprecedented challenges and opportunities for urban-rural integration. How to grasp this historic opportunity and how to explore new paths to help urban-rural integration and development is the proposition of the times to cope with the new urban-rural relationship in China. On the one hand, the rapid development and application of the intelligent manufacturing field represented by industrial robots can greatly improve the production efficiency[11](Lei and Dace, 2020), and to a large extent, the labor force will be liberated to engage in other fields; on the other hand, there is a relatively large controversy about how the application of artificial intelligence affects the demand for labor and the degree of urban-rural integration, and some studies have shown that, with the continuous innovation and application of intelligent equipment, the capital has a greater effect on the labor market. Some studies show that with the continuous innovation and application of smart devices, capital has produced a large substitution effect on the labor market[5,16](Acemoglu and Restrepo, 2020 , Yanbin et al., 2019). However, the continuous innovation of technology has also led to a certain extent to the problem of job and skill mismatch, which increases the risk of structural unemployment, and then exacerbates the income disparity in the labor market, and lays a certain causative factor for the integration of urban and rural areas; however, there are also some studies pointing out that the artificial substitution effect produced by the application of intelligent manufacturing and the employment creation effect cancel each other out and lead to the demand for labor without significant changes. no significant change in the demand for labor, while having a positive impact on other fields outside the substitution field, improving production efficiency and driving more labor demand. In the context of the rapid development of intelligent manufacturing, will the substitution of the technological dividend for the demographic dividend have a significant impact on urban-rural integration and development, and will the application of intelligent manufacturing become an emerging booster for urban-rural integration and development? In this regard, it is of great practical significance to analyze the relationship between the application of industrial robots and urban-rural integrated development, and the conclusions obtained may provide theoretical evidence for the significance of the development of robots as well as policy insights for realizing high-quality development out of the urban-rural development dilemma.

Compared with the existing studies, the marginal contributions of this study are (1) to expand the experience of cross-study between robotics and urban-rural integration, and to explore the intrinsic mechanism between the two. (2) provide policy insights for the development of new urban-rural relationship in China in the context of robot application from industrial, factor perspectives.

2. Theoretical foundations and research hypotheses

2.1 The impact of industrial robots on labor employment and Dual Effects

The existing theoretical research on robot application and labor employment shows that the impact of industrial robot put into use on labor employment is affected by both negative substitution effect and positive creation effect in two directions, resulting in the impact on the total labor employment has not yet formed a clear conclusion[2](Acemoglu and Restrepo, 2018a) . On the one hand, the application of industrial robots will cut jobs in traditional labor-oriented industries. For any economy, the increase in labor productivity will inevitably reduce the demand for labor when the total number of jobs is set constan[14](Schumpeter, 2016) . Accompanied by rising labor costs, gradually squeezing the profit margins of labor-intensive industries, higher labor costs will motivate enterprises to adopt the means of technological progress[9](Habakkuk, 1962) , and the labor force is constantly replaced by automated production technology, thus the extensive use of industrial robots will bring about the absence of most traditional jobs, forming technological unemployment[6] (Arntz et al., 2016). On the other hand, the application of industrial robots can bring new employment opportunities and job demand. The wide application of industrial robots to more efficient and low-cost high-volume automated production mode to replace the labor force to engage in simple and repetitive work tasks, but also create new work tasks with comparative advantages to offset the substitution effect brought about by the development of industrial intelligence, the emergence of high-quality labor force employment of new forms of new models(Acemoglu and Restrepo, 2018b , Acemoglu and Restrepo, 2019)[3,4] . From the perspective of long-term development of AI technology, the employment "creation effect" of industrial robots is often larger than the "substitution effect", which will ultimately have a positive impact on the labor market and labor employment[2](Acemoglu and Restrepo, 2018a) .

2.2 The impact of industrial robots on Industry integration

Industrial robots, as an automated and intelligent production mode, play an important role in promoting the transformation and upgrading of traditional industries and accelerating the construction of a modernized industrial system. The application of industrial robots can reduce the labor cost of labor to a greater extent, and significantly improve the technical level and production efficiency of industries(Menz et al., 2021)[13]. The application of industrial robots can promote the synergistic development of industry and improve the degree of industrial agglomeration, thus promoting the upgrading of industrial structure. Industrial intelligence has a selection bias on the regional distribution of industries, which can promote the technological exchange and knowledge sharing among industries in the region, enhance the synergy of industrial development among industries, accelerate the relocation and agglomeration of industries in medium and high labor cost areas to areas with low labor cost[8](Bao et al., 2013) , so as to drive the transformation of traditional industries to industries with high value-addedness, high technological content, and high innovativeness, and to realize the transformation of traditional The transformation and upgrading of manufacturing industry to high-tech industry and service industry[7](Azadegan and Wagner, 2011) . In addition, the application of industrial robots has a certain industrial spillover effect, and plays a radiation-driven role in other industry fields such as the service industry. In the same industrial chain upstream and downstream, the manufacturing industry's intermediate product inputs are provided by the service industry, and the efficiency enhancement effect of industrial robots on the manufacturing industry promotes the transformation and upgrading of the whole industry through promoting the scale production, specialized operation and technological innovation of the service industry(Acemoglu and Restrepo, 2017)[1] .

2.3 Research hypothesis

Robots have had a significant impact on a number of areas of urban-rural relations, such as urban-rural income, factor distribution, and industrial synergies, which are important drivers of the dynamics of urban-rural integration and the target system of integration. Combined with existing research results, on the one hand, the application of robots may have a differentiated impact on urban and rural labor groups in the short term, as well as an unequal impact on urban and rural incomes, hindering the further development of urban-rural integration, but robots also have a positive effect on the job market from a long-term perspective. On the other hand, robots are expected to contribute to urban-rural integration by promoting the development of the three industries and upgrading the industrial structure and balancing employment. Accordingly, we propose the basic hypothesis of this paper:

H1a: Robotics applications contribute to urban-rural integration

H1b: Robotics applications act as a barrier to urban-rural integration

Industrial robots as the power engine of manufacturing, in significantly improving the production efficiency of the secondary industry at the same time, but also can actively drive the development of the service industry and other tertiary industries, to promote the synergistic development of the industry, while reducing production costs, saving labor costs to boost the optimization and upgrading of industrial structure. However, industrial robots as an important carrier to promote the automated production of manufacturing industry, limited by the special properties of industrial robots, its role in the development of agricultural production is more limited, which may widen the gap between the primary industry and the secondary and tertiary industries. Therefore, on the one hand, the application of robots can effectively promote the upgrading of industrial structure and synergistic development, and promote urban-rural integration; on the other hand, industrial intelligence may further aggravate the imbalance between the development of the primary industry and the secondary and tertiary industries, and hinder urban-rural integration.

H2a: Robotics to promote the optimization and upgrading of industrial structure and urban-rural integration

H2b: Robots exacerbate the development gap between industries and hinder urban-rural integration

3. Description of the model, data and variables

3.1 Econometric modeling

In order to test the impact of robot application on urban-rural integration, this paper designs the following benchmark model:

$$SCORE_{it} = \alpha_0 + \alpha_1 robot_{it} + \alpha_2 M_{it} + u_i + \varepsilon_{it} \tag{1}$$

Where i and t and their city and year. The explanatory variable$SCORE_{i,t}$ indicates the level of urban-rural integration of city$i$ in year$t$.$robot_{it}$Reflects the level of robotics application of city$i$ in year t.∂_1 is the focus coefficient of this paper, which reflects the impact of robotics application on the level of urban-rural integration development,$M_{i,\mathrm{t}}$ denotes the city-level control variable, andu_p andε_{it} are the city fixed effects and random perturbation terms, respectively.

3.2 Description of variables

3.2.1 Explained variables

Level of integrated urban-rural development ($SCORE$). Urban-rural integrated development not only includes benign interaction between the city and the countryside in the development process, but also pursues sharing between the city and the countryside in the development results. This paper draws on the evaluation system of Xiong Ling[12](Ling, 2024) to construct the evaluation index system of urban-rural integration at the prefecture-level city level, considering the scientificity and accessibility of the indicators. In addition, this paper adopts the entropy weight method to calculate the urban-rural integration development index.The details are illustrated in Table 1.

Table 1: Evaluation Indicators for Urban-Rural Integration

systems	dimension	norm
Level of urban-rural integration and development	Factor flows	urbanization of population
		Passenger turnover
		networking level
		Cell phone penetration rate
	industrial collaboration	Level of agricultural mechanization
		Share of non-farm output
		Binary structure factor
		Share of non-farm employment
	Benefit sharing	Percentage of expenditure on agriculture, forestry and water conservancy
		Investment in fixed assets per capita
	economic sharing	Ratio of per capita income of urban and rural residents
		Ratio of per capita expenditure on urban and rural residents
		Regional GDP per capita
	ecological sharing	Domestic sewage treatment rate
		Industrial solid waste utilization rate
		Coverage of green areas in built-up areas
	Social life sharing	Number of teachers assigned to compulsory school pupils
		Beds per 10,000 population

3.2.2 Core explanatory variables

Level of robot application in cities ($robot$). The data about the number of robots comes from IFR, but its raw data belongs to the robotics indicators at the country-industry-year level, which cannot directly reflect the robotics application level of cities in China. Therefore, this paper draws on Wei Xihai(Xiahai et al., 2020) [16]. Using the industrial enterprise module in the second national economic census data, we calculated the number of people employed in different industries in each area (region, autonomous state, and league), and measured the density of robot installation at the city level by combining the IFR data. The specific calculations are as follows.

$$\mathrm{robot}_{i,t} = \sum_{j} \frac{\mathrm{Robot}_{j,t}}{\mathrm{emp}_{j,t}} \cdot \frac{\mathrm{emp}_{i,j,t}}{\mathrm{emp}_{i,t}} \tag{2}$$

Where $\frac{\mathrm{Robot}_{j,t}}{\mathrm{emp}_{j,t}}$ is the ratio of the stock of robots in use in industry j per 10,000 employees in year t, and $\frac{\mathrm{emp}_{i,j,t}}{\mathrm{emp}_{i,t}}$ s the share of employees in industry j in city i of all employees in city i in year t. This variable reflects the level of robot adoption in the city.

3.2.3 Control variables

To minimize the estimation error, the following control variables are selected in this paper. Government intervention (gov), measured by the proportion of general budget expenditures to GDP; financial development level (fin), measured by the ratio of the sum of deposit and loan balances of financial institutions to GDP at the end of the year; population density (pop), measured by the population density of the region; openness to the outside world (ope), measured by the ratio of imports and exports to GDP; the level of residents' savings (sav), measured by the proportion of urban and rural residents' savings deposits to GDP; the level of human capital (sav), measured by the proportion of the population with a general college degree or above to the city's resident population; government's emphasis on education (ed). GDP; human capital level (sav), measured by the proportion of the population with a bachelor's degree or above in the city's resident population; the government's emphasis on education (edu), measured by the proportion of education expenditures in the general budget; science and technology investment (sci), measured by the proportion of science expenditures in the general budget.

3.2.4 Mediating variables

Compared with the commonly adopted industrial structure advanced or industrial structure rationalization index to measure the change of industrial structure, this paper draws on(Jun and Huinan, 2019)[10], adopts the Thiel index to measure the industrial structure rationalization (TL), and uses the proportion of tertiary industry in the total output value to measure the industrial structure advanced (TS), and at the same time uses the entropy weight method to carry out an objective assignment in order to calculate the index of the coordinated development of industrial structure (TL). The calculation methods are as follows:

$$TL = \sum_{i=1}^{n} \left(\frac{Y_i}{Y} \right) \ln \left(\frac{Y_i / L_i}{Y / L} \right) \tag{3}$$

$$TS = \frac{Y_3}{Y} \tag{4}$$

$$SL = \omega_1 TL + \omega_2 TS \tag{5}$$

3.3 Data sources

Robotics data is derived from the IFR database of robotics usage data for our sub-sectors. In addition, the data on employment in each city and industry needed to calculate the level of robot use at the city level comes from the database of industrial enterprises of the Second National Economic Census.

The rest of the data required for the control variables and mediating variables come from the China Regional Economic Database, the China City Database, and the statistical yearbooks of each prefecture-level city. In this paper, we use the linear interpolation method and local statistical yearbooks to fill in the missing values and delete some cities with more missing values, and finally retain 261 prefecture-level cities.

4. Empirical analysis

4.1 Baseline regression

Based on the baseline model (1), this paper first tests whether robotics applications have an impact on urban-rural integration, and Table 3 presents the corresponding regression results. Specifically, column (1) shows the regression results of considering only urban robot application on the level of urban-rural integration development. As can be seen, the coefficient of the level of urban robot application is significantly positive at the 1% level, which indicates that the level of robot application increases the level of urban-rural integration development in each region. After sequentially adding control variables and region fixed effects, columns (2) and (3) still show that the coefficient of robot application level is significantly positive. Therefore, robot application has a positive impact on urban-rural integration development and H1a holds. The above contents are shown in Table 2.

Table 2: Baseline Regression

	(1)	(2)	(3)
VARIABLES	SCORE	SCORE	SCORE
robot	0.0874***	0.0747***	0.0684***
	(0.00243)	(0.00280)	(0.00309)
pop		0.186***	0.231***
		(0.0160)	(0.0524)
gov		0.0189***	0.0362***
		(0.00660)	(0.00794)
fin		0.00366***	0.00365**
		(0.00127)	(0.00144)
sav		-0.00173	-0.000145
		(0.00146)	(0.00156)
hum		1.64e-05***	3.24e-05***
		(3.73e-06)	(6.06e-06)
ope		-2.00e-05	-7.82e-06
		(6.59e-05)	(6.69e-05)
Constant	0.0319***	0.0167***	0.00785**
	(0.00111)	(0.00177)	(0.00305)
Regional Fixed Effects	no	no	yes
Observations	3,393	3,393	3,393
R-squared	0.286	0.305	0.308
Number of id	261	261	261

Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Estimates of endogeneity

Despite the robustness of the previous benchmark estimates, the benchmark model may still suffer from endogeneity problems due to omitted variables and bidirectional causality. Based on this,this paper chooses to adopt the instrumental variable method to alleviate the possible endogeneity problem. Based on the requirements of instrumental variable validity (relevance and exogeneity), this paper chooses to use the U.S. robot penetration rate and the average robot penetration rate of the five countries (the U.S., Japan, Germany, Sweden, and South Korea), respectively, as instrumental variables.

4.2.1 Using the U.S. robot penetration rate as an IV

On the basis of the generalized approach, we used the U.S. robotics data provided by IFR to calculate its penetration rate in China's cities and used it as an instrumental variable. This approach is mainly based on the following considerations: on the one hand, the U.S. robot penetration rate is a good proxy for the trend of intelligence, and the U.S. robot application has a similar trend to China's during the sample period, which satisfies the relevance assumption; on the other hand, the U.S. robot application does not have a direct impact on China's social integration of rural migrant workers, which satisfies the exogeneity assumption.

Columns (1) and (2) of Table 4 show the results of the first and second stage regressions of the instrumental variable method1 respectively. The results of the first stage regression (endogenous variables regressed on instrumental and other control variables) show that the coefficients of the instrumental variables are significantly positive, implying that both instrumental variable correlation and exogeneity requirements are met. And observation of column (2) shows that the regression results of the instrumental variables in the second stage are significantly positive, indicating that robotics applications still have a positive effect on urban-rural integration development after considering possible endogeneity problems.

4.2.2 Average robot penetration in five countries as IV

In addition, this paper also draws on (Xiahai et al., 2020)[15] to use the average robotics penetration rates of the United States, Japan, Germany, Sweden, and South Korea (These five countries are our main sources of robot imports.)robotics in Chinese cities as instrumental variables. Like the robot penetration rate in the United States in the previous study, the average robot penetration rate in the five countries theoretically satisfies the validity condition of the instrumental variable.

The results of the regression using the average robot penetration rate of the five countries as an instrumental variable are shown in columns (3) and (4) of Table 3. The first stage regression results show that the coefficients on the instrumental variables are significantly positive, indicating that the validity requirements of the instrumental variables are met. A further look at the results of the second stage shows that robot application still has a significant positive impact on urban-rural integration development after excluding endogenous disturbances. The above contents are shown in Table 3.

Table 3: Endogeneity Estimation

VARIABLES	(1) robot	(2) SCORE	(3) robot	(4) SCORE
robot		0.129***		0.118***
		(0.0200)		(0.0172)
robot_ivus	1.330***			
	(0.109)			
robot_iv5			9.998***	
			(1.143)	
Control variable	yes	yes	yes	yes
Regional Fixed Effects	yes	yes	yes	yes
Constant	-0.189***	0.0241***	-0.253***	0.0208***
	(0.0250)	(0.00589)	(0.0253)	(0.00510)
Observations	3,393	3,393	3,393	3,393
R-squared		0.644		0.656
Weak identification test		1939.380		1623.828
		[16.38]		[16.38]
Underidentification test		57.544		51.450

Note: *** p<0.01, ** p<0.05, * p<0.1, clustered standard errors are reported in parentheses, control variables are the same as in the baseline estimates of Table 2, and in columns (2) and (4), weak instrumental variable tests are performed using the Cragg-Donald Wald F statistic, with the tolerance provided by Stock & Yogo (2005) corresponding critical values at 10% distortion; identifiable tests for instrumental variables were performed using the Kleibergen-Paap rk LM statistic, with the corresponding p-values reported in pointed brackets.

4.3 Robustness check

1) Transformation of the dependent variable measurement method: this paper adopts the entropy weight method to calculate the urban-rural integration development index, as an objective empowerment method, the entropy weight method is widely used in the comprehensive evaluation of multi-indicators, but in the urban-rural integration measurement index system, there may be correlation between multi-indicators, and the direct calculation may produce the problem of multiple covariance of multivariate variables, which will make the calculation results distorted. As a data dimensionality reduction technique, Principal Component Analysis (PCA) is able to linearly transform multiple variables and re-compose them into independent principal component factors, thus eliminating multiple covariance among multiple variables and making the calculation results more realistic, and thus PCA has become a widely recognized comprehensive measurement method. This paper also draws on this method to recalculate the urban-rural integration development index and conduct benchmark regression again.2) Tailoring: to avoid the influence of extreme values, this paper tails off the urban-rural integration development index by 2.5%, and then conducts the benchmark regression.3) Eliminating some special samples: considering that the key cities have significant differences from the ordinary prefecture-level cities in terms of social and cultural aspects, economic conditions, financial levels, educational levels, scientific and technological development, this paper eliminates some special samples, and then conducts benchmark regression.4) Considering the significant difference between key cities and ordinary prefecture-level cities in terms of social culture, economic status, financial level, education level, scientific and technological development, etc., this paper deletes the municipalities directly under the central government, sub-provincial cities and provincial capitals, and then carries out the baseline regression again.4. Adding more control variables: Considering that the level of regional economic development and the inputs of education and science and technology may have a certain impact on the level of urban-rural integration and development, therefore, adding more control variables.

The results of the above tests are shown in the table below. After several robustness tests, the estimated coefficients of the robot application level are always significantly positive, and the results of the benchmark regression are well robust, indicating that the core conclusion of this paper always holds true, and that the increase in the level of robot application has a significant positive impact on urban-rural integration development. The above contents are shown in Table 4.

Table 4: Robustness Checks

	(1)	(2)	(3)	(4)
VARIABLES	SCORE	SCORE	SCORE	SCORE
industry_density	2.1925***	0.0609***	0.0686***	0.0283***
	(0.077)	(0.002)	(0.004)	(0.003)
Control variable	yes	yes	yes	yes
eco				0.0206***
				(0.001)
edu				-0.0173
				(0.014)
sci				0.0499
				(0.034)
Regional Fixed Effects	yes	yes	yes	yes
Constant	1.8701***	0.0223***	-0.0056	-0.3103***
	(0.076)	(0.002)	(0.005)	(0.015)
Observations	3,393	3,393	2,938	3,393
Number of id	261	261	226	261
R-squared	0.515	0.507	0.295	0.404

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

4.4 Heterogeneity analysis

Spatial heterogeneity. There are significant differences in the level of robot application in different regions, according to the law of diminishing marginal effect, when technology development reaches a certain level, the marginal effect on production continues to diminish. The development of robots for regional production and economic development is also diminishing, based on this, by the different levels of regional robot application and the impact of government policies and economic levels, the application of robots in different regions on urban-rural integration there is a significant difference in the impact of the possibility. Based on this, this paper explores the heterogeneity of robot use in different regions from an East-Middle-West perspective using group regression.

Table 5 reports the results of the impact of robotics on the level of urban-rural integration in different regions. The results show that there is a significant positive effect of robot application on the level of urban-rural integration in both the eastern, central and western regions, with a significantly greater effect on the central and western regions, with the western region being the most significantly affected. Possible explanations are: 1. the eastern region is more profoundly affected by government policies and the level of opening up to the outside world; 2. there is a certain threshold effect of the level of robot application on urban-rural integration, and the industrial robot industry is more developed in the eastern region, so by the influence of the diminishing marginal effect, the degree of gain of robots on urban-rural integration is relatively small, but this hypothesis needs to be further tested. The above contents are shown in Table 5.

Table 5: Regional Disparities

	(1)	(2)	(3)
	East China	Central China	West China
VARIABLES	SCORE	SCORE	SCORE
industry_density	0.0518***	0.0767***	0.0773***
	(0.005)	(0.008)	(0.004)
Control variable	yes	yes	yes
Regional Fixed Effects	yes	yes	yes
Constant	0.0100	0.0128*	0.0190***
	(0.007)	(0.007)	(0.005)
Observations	1,144	1,118	1,131
R-squared	0.348	0.215	0.456
Number of id	88	86	87

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

4.5 Mechanism testing

The above analysis demonstrates that urban robotics applications have a significant positive impact on urban-rural integration. However, it is not yet known through which channels robotics applications promote urban-rural integration. Further, based on the previous theoretical analysis, this paper develops a mechanism test for industrial coordination. The mechanism test model of this paper is designed as follows.

$$Mv_{i,t} = \beta_0 + \beta_1 robot_{i,t} + \beta_2 M_{i,t} + u_i + \varepsilon_{i,t} \tag{6}$$

$$SCORE_{i,t} = \beta_0 + \beta_1 robot_{i,t} + \beta_2 Mv_{i,t} + \beta_3 M_{i,t} + u_i + \varepsilon_{i,t} \tag{7}$$

In the above equation, $Mv_{i,c}$ is the mediating variable, and the other variables are the same as the baseline estimates in the previous section. In this paper, the direction and significance level of the coefficients of β_1 are used to determine whether the impact mechanism is valid.

Tables (1)-(3) report the results of the mechanism test for industrial coordination, which shows that industrial coordination assumes a partially mediating role in the path of robot-urban-rural integration, and the application of industrial robots promotes the development of industrial coordination, which, in turn, positively affects the development of urban-rural integration.The above contents are shown in Table 6.

Table 6: Mediation Effect

	(1)	(2)	(3)
VARIABLES	SCORE	LS3	SCORE
SL (Industry Integration)			0.0753***
			(0.008)
industry_density	0.0684***	0.0581***	0.0640***
	(0.003)	(0.007)	(0.003)
Control variable	yes	yes	yes
Regional Fixed Effects	yes	yes	yes
Constant	0.0078**	0.0977***	0.0005
	(0.003)	(0.007)	(0.003)
Observations	3,393	3,393	3,393
R-squared	0.308	0.183	0.329
Number of id	261	261	261

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions and Implications

The integrated development of urban and rural areas is an important outcome of the exploration of new urban-rural relations, and is of great significance in promoting mutual assistance between urban and rural areas and enhancing people's well-being. However, the huge impact of automation technology represented by robots on various industries and sectors in cities has further exacerbated the incoherence of development between urban and rural areas, as well as between industry and agriculture. In order to analyze the impact of robot application on urban-rural integration, this paper combines existing research results and empirical research based on the construction of an index of robot application at the city level using robot data provided by IFR and urban-rural data. We find:

(1) Robot application has a significant role in promoting urban-rural integration development. The results of both the benchmark regression and the endogeneity test indicate that the increase in the level of industrial robot application can effectively promote the development of urban-rural integration (H1a holds), a conclusion that always holds in robustness tests such as replacing the dependent variable measurement method, eliminating special samples, shrinking the tail treatment, and adding control variables.

(2) There is spatial and temporal heterogeneity in the promotion effect of robot application. From the spatial dimension, the central and western regions are more significantly affected by robot application, and the effect is strongest in the western region; from the time dimension, the promotion effect of robot application on urban-rural integration shows a marginal decreasing trend with the popularization of the technology, and the promotion effect is most significant in the policy-guiding period (2007-2012) and weakens in the technology breakthrough period (2016 -2019) weakened.

(3) Industrial coordination is an important mechanism for robotics to promote urban-rural integration. The mediation effect test shows that robot application indirectly enhances the

endogenous dynamics of urban-rural integration development by promoting the optimization and upgrading of industrial structure (H2a is established), especially by enhancing the level of synergy among the three industries.

The findings of this paper provide empirical evidence with policy implications for understanding the impact of robotics applications on urban-rural integration.

Firstly, we should further adjust the exchange and integration between urban and rural industries and vigorously develop agricultural production towards automation and intelligence. The Government should take into account the level of intelligent production and the level of agricultural and rural development in the region. On the one hand, it should actively encourage exchanges between agricultural production and the manufacturing and service industries, and guide the development of single-phase agricultural production into the agricultural service industry; on the other hand, it should introduce advanced agricultural production equipment and experience in agricultural production, e.g., through the transfer of land and the introduction of advanced facilities, to create a model of high-standard farmland and high-standard agricultural production.

Secondly, strengthen the differentiated support for intelligent manufacturing in the central and western regions. For the application of robots in the central and western regions of the urban and rural integration of the significant role of the Government should increase financial subsidies and tax incentives to guide the extension of industrial robots to the modernization of agriculture, services and other areas of intelligent, narrowing the gap in the application of technology between regions. At the same time, combined with the endowment of labor resources in the central and western regions, to promote "machine for man" and skills training, to alleviate the risk of structural unemployment.

References

[1] Acemoglu D, Restrepo P. 2017. Secular stagnation? The effect of aging on economic growth in the age of automation. American Economic Review, 107: 174-179.

[2] Acemoglu D, Restrepo P. Artificial intelligence, automation, and work[C]//The economics of artificial intelligence: An agenda. Chicago: University of Chicago Press, 2018a: 197-236.

[3] Acemoglu D, Restrepo P. 2018b. The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review, 108: 1488-1542.

[4] Acemoglu D, Restrepo P. 2019. Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33: 3-30.

[5] Acemoglu D, Restrepo P. Unpacking skill bias: Automation and new tasks[C]//AEA Papers and Proceedings. Nashville, TN: American Economic Association, 2020: 356-361.

[6] Arntz M, Gregory T, Zierahn U. 2.16.The risk of automation for jobs in OECD countries: A comparative analysis [R]. OECD Social, Employment and Migration Working Papers, No. 189. OECD Publishing.

[7] Azadegan A, Wagner S M. 2011. Industrial upgrading, exploitative innovations and explorative innovations. International Journal of Production Economics, 130: 54-65.

[8] Bao C, Chen Z, Wu J. 2013. Chinese manufacturing on the move: Factor supply or market access? China Economic Review, 26: 170-181.

[9]Habakkuk H J. 1962.. American and British technology in the nineteenth century: The search for labour - saving inventions [M]. Cambridge: Cambridge University Press.

[10] Jun H, Huinan Z. 2019. Measurement of regional energy consumption under the background of high-quality development of China's economy. The Journal of Quantitative & Technical Economics, 36: 42-61.

[11] Lei L, Dace X. 2020. Can robots improve labor productivity?——Mechanism and facts. Industrial Economics Research: 127-142.

[12] Ling X. 2024. Urban-rural integrated development in the process of Chinese-style modernization: Evaluation system and dynamic measurement. On Economic Problems: 98-105.

[13] Menz M, Kunisch S, Birkinshaw J, et al. 2021. Corporate strategy and the theory of the firm in the digital age. Journal of Management Studies, 58: 1695-1720.

[14] Schumpeter J. Theorie der wirtschaftlichen Entwicklung[C]//United States Association for Small Business and Entrepreneurship. Conference Proceedings. Nashville, TN: United States Association for Small Business and

Entrepreneurship, 2016: FI1.
[15] Xiahai W, Peikang Z, Yuhong D. 2020. How robots reshape the urban labor market: A perspective from migrant workers' job tasks. Economic Perspectives: 92-109.
[16] Yanbin C, Chen L, Xiaoliang C. 2019. Artificial intelligence, aging, and economic growth. Economic Research Journal, 54: 47-63.