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Full Length Article

Impact of industrial robot on labour productivity: Empirical study based on industry panel data

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ABSTRACT

This empirical analysis explores the impact of industrial robots on labour productivity using panel data of 17 Chinese industries from 2006 to 2021. The results reveal that the development of industrial robots significantly improves labour productivity; a series of robustness tests validate this outcome. However, the impact of industrial robots on labour productivity varies across industry types. The influence coefficient of the low-density robotics industry is larger than that of the high-density robotics industry. Furthermore, although the scale of industrial robot usage before 2012 was smaller than that after 2012, its effect on labour productivity was more significant. Our findings indicate the possibility of diminishing marginal effect of industrial robots in promoting labour productivity. The mechanism analysis demonstrates that human capital level has a complete intermediating effect between industrial robots and labour productivity. Thus, industrial robot applications can contribute to labour productivity by optimising human capital structure. These findings provide crucial insights for governments and policy makers to improve labour productivity and economic growth.

1. Introduction

The rapid scientific and technological innovation over the past few decades has effectuated profound changes in the current world economy. Such changes affect labour productivity (LP) and supply from multiple technological perspectives (Dahlman et al., 2016; Labaye & Remes, 2015; Nurmilaakso, 2009). Industrial robots are one of the most prominent innovations with great potential for improving LP. Graetz and Michaels (2018) find that more intensive use of industrial robots has a significant positive impact on LP by analysing manufacturing industries in different countries. However, Acemoglu and Restrepo (2020) assert that robots greatly improve overall firm productivity when used to perform simple, low-level, and repetitive tasks but at the cost of increased unskilled unemployment.

Fig. 1 illustrates the relationship between robot density and LP in the Chinese economy during 2006–2020. Robot density is reflected by the number of industrial robots per 10,000 workers in the Chinese labour force. LP is calculated as gross domestic product divided by the number of workers in the labour force. The density of robots in China increased from 0.23 in 2006 to 12.57 in 2020, with an average growth rate of 33%. LP increased from 28,313 yuan/person in 2006 to 135,349 yuan/person in 2020, with an average annual growth rate of 12 % without correction for inflation. Although the increase in robot density and LP in China during this period is relatively high, the productivity level still lags far behind that of developed countries. Owing to an ageing population, China's working-age population continues to decline. Given that growth in LP is an essential component affecting economic growth (Korkmaz & Korkmaz, 2017), a country's continued economic growth becomes increasingly dependent on rising LP to supplant a shrinking labour force (Cai & Lu, 2013).

Previous studies on the effects of robots on LP have primarily been conducted in developed economies (Acemoglu & Restrepo, 2018; Coccia, 2018; Creemers et al., 2022; Datta et al., 2005; Dauth et al., 2017; Graetz & Michaels, 2018). There is insufficient evidence to establish whether research conclusions related to other economies can explain the development of the Chinese robotics industry. Compared with developed nations such as the US and Germany, robot application in China is still at a nascent stage. Furthermore, although a few studies have focused on the development of robotics and artificial intelligence (AI) and their economic impact on the Chinese economy and productivity, most studies concentrated on theoretical dimensions at the country, province, and firm levels (Du and Lin, 2022; Duan et al., 2023; Fan et al., 2021; Fu et al.,

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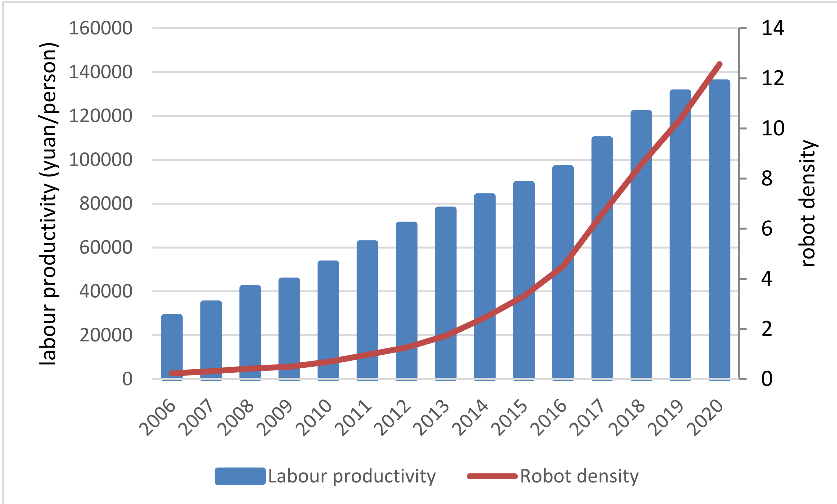

Fig. 1. Robot density and labour productivity from 2006 to 2020.

2021). Therefore, uncertainty still exists regarding the relationship between industry robots and LP at the industry level in China. This study explores the relationship between the use of industrial robots and LP across Chinese industries. It uses the International Federation of Robotics (IFR)'s industrial robot data, China Industry Statistical Yearbook data, and labour market data from the China Statistical Yearbook to construct the penetration index of industrial robots in China. Accordingly, it empirically examines the influence of robot adoption mechanisms on productivity and macroeconomic growth in China. Furthermore, investigating the effect of robots on economic outcomes may provide guidelines for developing optimal public policies that address future LP and economic growth.

The remainder of the study is structured as follows: Section 2 reviews the existing theoretical and empirical literature on the impact of industrial robots on productivity. Section 3 describes the research methods, focusing on the theoretical framework, data description, and empirical model. Section 4 discusses the results, and Section 5 summarises this study and its potential applications.

2. Literature review

The analysis of the impact of robot technology on productivity can be divided into two categories. First, the impact of technological progress in robots on the productivity of different industries within a country can be discussed at the macroeconomic level (Acemoglu & Restrepo, 2018; Aghion et al., 2018; Brynjolfsson et al., 2019; Dauth et al., 2017; Gordon, 2018; Graetz & Michaels, 2018; Kromann et al., 2011, 2020; Remes et al., 2018). Second, the impact of technological progress on specific enterprises or industries can be discussed at the micro level (Acemoglu et al., 2020; Damioli et al., 2021; Koch et al., 2021).

Several studies have indicated that AI applications can boost productivity at the national economic level. For example, Kromann et al. (2020) and Graetz and Michaels (2018) examine the impact of robotic technologies on productivity across multiple countries. Dauth et al. (2017) explore the German labour market and observe that the application of robots increases LP but decreases the labour share of total income. Similarly, Acemoglu and Restrepo (2018) argue that AI technology not only replaces existing jobs but also creates new ones. In addition, they argue that LP increases as these new jobs tend to be highly productive, increasing the proportion of high-productivity industries and reducing the amount of low-skilled, routine labour. Kromann et al. (2020) use the operational number of industrial robots as an indicator to measure the degree of automation. Using multi-national and cross-industry sample data, they show that automation has a significant positive effect on productivity in both the long and short terms. Assuming that the automation level of the sample country increases to the corresponding level of the country with the highest automation level, the total production efficiency of the manufacturing industry in the sample country can increase from 8 to 22%. Graetz and Michaels (2018) use data from 17 countries from 1993 to 2007 to investigate the economic impact of the application of industrial robots and show that every one-unit increase in the use of robots improves LP by 0.36%. Using industry-level panel data from 10 manufacturing industries in 9 countries, Kromann et al. (2020) find that the intensive use of industrial robots has a significant positive impact on total factor productivity (TFP).

At the micro level, several studies have discussed the impact of AI technologies, such as robotics, on firm productivity. Acemoglu et al. (2020), using a sample of 55,390 French manufacturing enterprises during 2010–2015, find that enterprises that use robots in production increase their TFP by 2.4% compared with those that do not. Damioli et al. (2021) examine 5257 global enterprises with AI patents from 2000 to 2016 and observe that the number of AI patent applications held by each enterprise has a significant positive impact on LP. Furthermore, they assert that the effect is more significant in small- and medium-sized enterprises (SMEs) and service enterprises.

The robotics adoption rate is a key indicator of how a nation's technological capabilities change over time. The link between robot adoption and LP has been greatly emphasised in scholarly work. Acemoglu et al. (2020) suggest that robot adoption has a positive effect on productivity (conducted in France at the company level). In addition, Cette et al. (2021) indicate that robots improve productivity by capital deepening and TFP. Among the 30 OECD countries, Japan, Germany, and some European countries exhibit the most significant effects. Moreover, Ballestar et al. (2020) apply data from SMEs in manufacturing sector in Spain and find that robots enhance productivity levels by 5% in 2015. Nevertheless, the extent of robot adoption in determining LP at the industry level remains ambiguous as indicated by widespread disparity over the years. In addition, most studies have focused on developed countries, with few providing theoretical explanations or empirical evidence from the perspective of developing countries. They have not focused on China, which has the largest number of industrial robot installations. This study employs a two-sector model to theoretically investigate the mechanism of robot application on LP. Based on the aforementioned analysis, this study proposes the following hypothesis:

H1.: The development of industrial robots is conducive to improving LP.

Human capital theory advocates that the growth of LP is not simply determined by capital stock but is largely determined by the skills and knowledge level of workers. Specifically, human capital serves as a vital aspect of LP (Pedrini & Cappiello, 2022; Van Lottum and Van Zanden, 2014). The application of AI technology in different industries replaces certain jobs with low skill levels owing to the special characteristics of its technology, thereby eliminating low-skilled workers and encouraging workers to improve their skills to adapt to the application of AI technology at work (Zhu et al., 2024). However, with the increase in labour costs and price advantage of industrial robots, companies use industrial robots to replace traditional labour that performs procedural and repetitive production tasks, thereby replacing low-skilled labour (Cheng et al., 2019; Graetz & Michaels, 2018). This process enables corporations to improve production automation and intelligence, reduce labour costs, optimise human capital structures (Agolla, 2018), and improve productivity. Additionally, using industrial robots realises more complex tasks, creates employment opportunities related to emerging technologies, and supplements the highly skilled workforce (Acemoglu & Restrepo, 2018). Enterprises recruit highly skilled labour to supplement industrial robots and high-quality human capital to absorb novel technologies, equipment, and management experience and drive productivity by improving innovation efficiency (Griffith et al., 2004; Miller & Upadhyay, 2000). Simultaneously, enterprises can enrich the skill levels and quality of their existing workforce through training and other methods. This process assists corporations in optimising their human capital structures. Industrial robots can affect LP with human capital as the mediator. Overall, the application of robot technology improves the level of human capital in the industry, thus improving LP according to the human capital theory. Based on the above analysis, the following hypothesis is proposed:

H2.: Industrial robots have a positive impact on LP through human capital upgrades.

Fig. 2 shows the theoretical analysis framework.

The following analysis empirically examines the impact of industrial robot application on LP using IFR's industrial robot data, combined with data from the National Bureau of Statistics of China, China Population and Employment Statistical Yearbook, and China Labour Statistical Yearbook. This study explores the role of two-way matching between industrial robots and labour capabilities, examines the types of abilities that industrial robots prefer for workers, and compares the differences in labour capabilities across different industries.

3. Research methods

3.1. Theoretical framework

We use a two-sector model to analyse the impact of robot application on LP (Graetz & Michaels, 2018). The first sector uses robots and labour as the productive factors within a constant elasticity of substitution (CES) production function to produce output Y_R. The second sector uses only labour to produce output Y_N.

Assume that the number of robots used is R and rental price is ρ. The labour inputs of the two sectors are L_R and L_N, respectively.

The production function of the two sectors is

$$Y_R = \left[R^{\frac{\sigma-1}{\sigma}} + L_R^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ and } Y_N = L_N. \tag{1}$$

Normalize the price of Y_R to 1, and the price of Y_N related to Y_R is p.

The profit of the robot-using sector is represented by

$$\pi = Y_R \cdot 1 - R \cdot \rho - L_R \cdot W, \tag{2}$$

where W is the wage.

According to the profit maximization condition,

$$\frac{\partial \pi}{\partial R} = 0 \text{ and } \frac{\partial \pi}{\partial L_R} = 0, \tag{3}$$

$$\Rightarrow Y_R^{\frac{1}{\sigma}} \cdot R^{-\frac{1}{\sigma}} = \rho \Rightarrow \left(\frac{Y_R}{R}\right)^{\frac{1}{\sigma}} = \rho, \text{ and} \tag{4}$$

$$\Rightarrow Y_R^{\frac{1}{\sigma}} \cdot L_R^{-\frac{1}{\sigma}} = W \Rightarrow \left(\frac{Y_R}{L_R}\right)^{\frac{1}{\sigma}} = W. \tag{5}$$

Combining Equations (4) and (5), we get

$$\left(\frac{R}{L_R}\right)^{-\frac{1}{\sigma}} = \frac{\rho}{W}. \tag{6}$$

$\frac{R}{L_R}$ is the robot density, and $\frac{Y_R}{L_R}$ is the LP.

The profit of the non-robot-using sector is

$$\pi = Y_N \cdot p - L_N \cdot W = L_N \cdot p - L_N \cdot W. \tag{7}$$

According to the profit maximization condition,

$$\frac{d\pi}{dL_N} = p - W = 0 \Rightarrow p = W. \tag{8}$$

For consumers, suppose that all outputs from the two sectors are consumed and that consumer have CES utility $U = \left[Y_R^{\frac{\varepsilon-1}{\varepsilon}} + Y_N^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$. The elasticity of substitution is represented by ε. The budget constraint is represented by $Y_R + p \cdot Y_N = I$, where I is the total income.

According to the utility maximization condition, $\frac{\partial U}{\partial Y_N} = 0$.

$$\text{Max } U = \left[Y_R^{\frac{\varepsilon-1}{\varepsilon}} + Y_N^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$$

$$\text{s.t. } Y_R + p \cdot Y_N = I. \tag{9}$$

We get $Y_R = I - p \cdot Y_N$.

$$\frac{\partial U}{\partial Y_N} = \frac{\partial\left[(I - p \cdot Y_N)^{\frac{\varepsilon-1}{\varepsilon}} + Y_N^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}}{\partial Y_N} = 0$$

$$\Rightarrow \left(\frac{Y_R}{Y_N}\right)^{-\frac{1}{\varepsilon}} = \frac{1}{p}. \tag{10}$$

$\frac{Y_R}{Y_N}$ is the value added by the robot-using sector relative to the non-robot-using sector.

Combining Equations (5) and (6), we obtain $\left(\frac{R}{L_R}\right)^{-\frac{1}{\sigma}} = \frac{\rho}{W} = \rho \cdot \left(\frac{Y_R}{L_R}\right)^{-\frac{1}{\sigma}}$. Using production function

$$Y_R = \left[R^{\frac{\sigma-1}{\sigma}} + L_R^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{11}$$

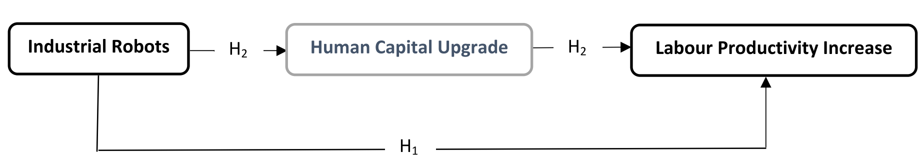

Fig. 2. Theoretical framework of the study.

we get

$$\left(\frac{R}{L_R}\right)^{-\frac{1}{\sigma}} = \rho\left(\frac{Y_R}{L_R}\right)^{-\frac{1}{\sigma}} = \rho\cdot\left[\left(\frac{R}{L_R}\right)^{\frac{\sigma-1}{\sigma}}+1\right]^{-\frac{1}{\sigma-1}}. \tag{12}$$

$$\therefore \frac{R}{L_R} = \rho^{-\sigma}\cdot\left[\left(\frac{R}{L_R}\right)^{\frac{\sigma-1}{\sigma}}+1\right]^{\frac{\sigma}{\sigma-1}} \text{ and} \tag{13}$$

$$\frac{d\left(\frac{R}{L_R}\right)}{d\rho} = -\frac{\sigma}{\rho^{(\sigma+1)}}\left[\left(\frac{R}{L_R}\right)^{\frac{\sigma-1}{\sigma}}+1\right]\cdot\left(\frac{R}{L_R}\right)^{\frac{1}{\sigma}}<0. \tag{14}$$

Thus,

$$\rho\downarrow, \frac{R}{L_R}\uparrow. \tag{15}$$

When ρ increases, $\frac{R}{L_R}$ decreases, implying an inverse relationship between the price of robots and density of the use of robot.

Combining Equations (5) and (6), we obtain

$$\left(\frac{R}{L_R}\right)^{-\frac{1}{\sigma}} = \frac{\rho}{W} = p\cdot\left(\frac{Y_R}{L_R}\right)^{-\frac{1}{\sigma}}. \tag{16}$$

That is, when $\frac{R}{L_R}$ increases, $\frac{Y_R}{L_R}$ increases. Thus, an increase in robot density increases LP in the robot-using sector.

3.2. Empirical model

To investigate the effects of industrial robots on LP, this study adopts models used in previous studies (Acemoglu & Restrepo, 2018; Coccia, 2018; Creemers et al., 2022; Datta et al., 2005; Graetz & Michaels, 2018). However, we modified these models to fulfil the objectives of this study. The model specification used in this study is as follows:

$$\begin{aligned} \ln LP_{it} =& \beta_0+\beta_1 \ln Robot_{it}+\beta_2 \ln\left(\frac{K}{L}\right)_{it}+\beta_3 \ln\left(\frac{M}{L}\right)_{it} \\ &+\beta_4 \ln Invent_{it}+\beta_5 lnFP_{it}+\delta_t+\mu_i+\varepsilon_{it}, \end{aligned} \tag{17}$$

where LP_{it} is the dependent variable, representing the LP of industry i in the year t. Further, $Robot_{it}$ is the explanatory variable, representing the industrial robot application level of industry i in the year t. δ_t reflects the time-fixed effect. The unobserved random variable u_i is the intercept term representing individual heterogeneity, –that is, individual effects. ε_{it} is the random term, which is expected to be distributed uniformly across both dimensions i and t.

To test the influence mechanism of the application of industrial robots on LP, we construct the following intermediary effect analysis model (Baron & Kenny, 1986; Wang & Wang, 2022; Wen & Ye, 2014):

$$\ln HR_{it} = \alpha_0+\alpha_1 lnRobot_{it}+\sum_j \alpha_j x_{ijt}+\mu_i+\varepsilon_{it}, \tag{18}$$

$$lnLP_{it} = \gamma_0+\gamma_1 lnRobot_{it}+\gamma_2 lnHR_{it}+\sum_j \gamma_j x_{ijt}+\mu_i+\varepsilon_{it}, \tag{19}$$

where HR_{it} represents the intermediary variable, human capital and Equation (18) tests the impact of industrial robots on the intermediary variable. Furthermore, Equation (19) tests the impact of industrial robots and intermediary variables (human capital) on LP. The settings of the other control variables, fixed effects, and variances are similar to those in Equation (17). Among them, β_1 in Equation (17) represents the total effect of industrial robots on LP, γ_1 in Equation (19) illuminates the direct effect of industrial robots' application on LP. Meanwhile, $\alpha_1 * \gamma_2$ represents the indirect effect of the application of industrial robots on LP.

3.3. Data description

The explained variable is LP, collected from the China Industry Statistical Yearbook. This yearbook contains the economic indicators of China's industrial sectors, including industry-level added value, total industrial output value, fixed assets output value, main business income, number of employees, and other data. Based on the practices of Subrahmanya (2006) and Sraer and Thesmar (2007), the ratio of value added for the year divided by the average number of employees is used as a measure of LP:

$$\mathrm{LP} = \mathrm{VA}/\mathrm{EMP} \tag{20}$$

where *EMP* is the average number of employees in a certain industry.

The key explanatory variable is the number of industrial robots used. To measure the impact of industrial robots on LP comprehensively, this analysis uses IFR data on the stock level of industrial robots rather than the number of new installations in the current year. The number of newly installed industrial robots in China in 2021 far exceeds that in other countries; however, the overall industry application density is still less than the world average. Therefore, the density of industrial robots can be interpreted as a comprehensive measure of the degree to which industrial robots are applied in a certain industry within a country. This eliminates the potential influence that may arise from any differences in the number of employees across industries in different countries and makes inter-industry comparisons of the results more trustworthy. Density refers to the number of industrial robots per 10,000 people in the industry.

The control variables comprise the factor inputs of capital, resources, and labour (K, L, and M) to denote the value of tangible assets, number of employees (labour), and value of materials (including raw materials and energy), respectively (Attar et al., 2012; Creemers et al., 2022). Innovation was also selected as a control variable and measured as the number of patents within a certain industry. Patents play an important role in promoting the development of new technologies. New production modes or tools can cause changes in production processes, making production more efficient and promoting output growth (Coccia, 2018). Moreover, foreign participation influences LP (Boghean & State, 2015). Therefore, the level of foreign investment is included as a control variable.

Table 1 presents a summary of the variable descriptions and data sources for the effects of industrial robots on LP, and Table 2 presents the sample sizes across 17 industries.

4. Results

4.1. Empirical results

Table 3 presents the statistical descriptions of the variables, including the variable name, number of variables, mean value, standard deviation, and minimum and maximum values. The severity of multi-collinearity is further tested using a variance inflation factor (VIF). Hair et al. (2009) suggest that the common threshold value for the VIF is 10.

Table 4 shows the baseline regression results for the influence of industrial robot use on Chinese LP. It provides the regression results of the (1) OLS model, (2) least squares dummy variable method, (3)–(4) FE_robust model, and (5) RE_robust model. Columns (4) and (5) control for industry's fixed and time effects. Stata 15 was used to perform the Hausman test, which provided a P value of less than 0.1. This indicates that the original hypothesis of a random-effects model can be rejected,

Table 1
Summary of independent variable descriptions and data sources for the effects of industrial robots on labour productivity.

Symbol	Variables	Proxy	Unit	Data Source
LP	Labour productivity	Ratio of value added per employee	10 thousand yuan/person	China Industry Statistical Yearbook
Robot	Robot density	Number of industrial robots in operation per 10,000 persons employed	Number	The International Federation of Robotics; China Labour Statistical Yearbook
K/L	Capital labour ratio	Value of tangible assets divided by number of employees	10 thousand yuan/person	China Industry Statistical Yearbook
M/L	Material labour ratio	Value of materials (including raw materials, energy) divided by number of employees	Tons of standard coal/person	China Industry Statistical Yearbook; China Statistical Yearbook
Invent	Invention	Number of patents of Industrial enterprises above designated size by industrial sector	Piece	China Statistical Yearbook on Science and Technology
FP	Foreign participation	Foreign investment	100 million yuan	China Industry Statistical Yearbook
Hr	Human capital	Proportion of the urban employed persons with at least college education	%	China Labour Statistical Yearbook

Table 2
Sample sizes industries classification by IFR.

	Label	Code Description
1	Mining	Mining and quarrying
2	Utilities	Electricity, gas, water supply
	Manufacturing:	Manufacturing
3	Food and Beverage	Food products and beverages; Tobacco products
4	Textiles	Textiles, leather, wearing apparel
5	Wood and furniture	Wood and wood products (incl. furniture)
6	Paper	Paper and paper products, publishing & printing
7	Pharmaceuticals, cosmetics	Manufacture of basic pharmaceutical products and pharmaceutical preparations
8	Chemical products	Transformation of crude petroleum and coal into useable products, transformation of organic and inorganic raw materials by a chemical process and formation of products
9	Rubber and plastic products	Rubber and plastic products without automotive parts
10	Glass and ceramics	Glass, ceramics, stone, mineral products N.E.C.
11	Basic metals	Basic metals (iron, steel, aluminium, copper, chrome)
12	Metal products	Metal products (non-automotive)
13	Industrial machinery	Machinery for food processing and packaging, machine tools, industrial equipment, rubber and plastic machinery, industrial cleaning machines, agricultural and forestry machinery, construction machinery, etc.
14	Electrical machinery	Household/domestic appliances and electrical machinery N.E.C. (non-automotive)
15	Electronics	Electronic components/devices, semiconductors, LCD, LED, computers and peripheral equipment, NFO communication equipment domestic and professional (TV, radio, CD, DVD-Players, pagers, mobile phones, VTR, etc.) without automotive part
16	Instruments	Medical, precision, optical instruments
17	Vehicles	Automotive and other vehicle

Table 3
Descriptive statistics.

Variables	Mean	Std.dev	Min	Max	Observations
LP	44.7	28.11	3.455	210.1	N = 272, n = 17, T = 16
Robot	40.21	103.4	0.003	890.2	N = 272, n = 17, T = 16
K/L	47.65	46.6	5.76	332.5	N = 272, n = 17, T = 16
M/L	54.72	75.27	3.025	449.5	N = 272, n = 17, T = 16
Invent	32,683	62,969	65	496,094	N = 272, n = 17, T = 16
FP	1037	1013	2.71	5009	N = 272, n = 17, T = 16
HR	19.18	8.108	8.8	52.8	N = 272, n = 17, T = 16

allowing a fixed-effects panel model to be used. A clustering-robust standard error was used to eliminate the heteroscedasticity and autocorrelation associated with the model.

The core explanatory variable of industrial robot application density significantly improves LP in the industry. On average, every 1% increase in industrial robot application density increases LP by 0.018%. This finding is similar to the conclusions of Graetz and Michaels (2018), Dauth et al. (2017), and other empirical studies. Industrial robotics is an emerging technology that exhibits general characteristics of technological innovation. According to Schumpeter's theory, technological innovation can transform labour tools and even change production methods to enhance LP and increase labour value added (Englmann, 1994). We assume that robot technology exhibits the same innovation potential. In manufacturing and other industries, industrial robots perform intelligent work according to human instructions. This changes the production method of workers, improves labour efficiency, and raises the overall LP of the industry. For the control variables, prime inputs (capital and materials) and inventions have a positive effect on LP, while the foreign investment coefficient is negative but non-significant.

4.2. Endogeneity test

An endogeneity bias may exist in the regression of industrial robots on LP. On the one hand, a reverse causal relationship may exist between industrial robot applications and LP. On the other hand, some variables may have been omitted. The model may omit control variables that affect LP, causing endogeneity risks.

We use the two-stage least squares method (2SLS) to solve the endogeneity problem. Referring to Duan et al. (2023), Acemoglu and Restrepo (2020), and Wang and Dong (2020), we used a US robot as an instrumental variable. The US leads the world in industrial robots application, and its development trend is relatively close to that of China during the same period. A strong correlation exists between industrial robot application in China and US robot usage, which satisfies the

Table 4
Effects of robots on labour productivity.

	(1) OLS	(2) LSDV	(3) FE	(4) RE	(5) FE
lnRobot	0.065**	0.035**	0.035**	0.040**	0.018**
	(0.027)	(0.019)	(0.019)	(0.022)	(0.08)
lnK/L	0.508**	0.809***	0.809***	0.854***	0.631***
	(0.207)	(0.167)	(0.162)	(0.128)	(0.066)
lnM/L	0.057	0.095	0.095	−0.050	0.088*
	(0.087)	(0.134)	(0.130)	(0.070)	(0.048)
lnInvent	0.110**	0.008	0.008	0.018	−0.067**
	(0.046)	(0.040)	(0.039)	(0.035)	(0.026)
lnFP	−0.078**	0.227***	0.227***	0.144***	0.032**
	(0.044)	(0.045)	(0.044)	(0.032)	(0.030)
_cons	0.464**	−0.586**	−0.500**	−0.173	0.294***
	(0.207)	(2.147)	(0.210)	(0.151)	(0.110)
Observations	272	272	272	272	272
R-squared	0.8246	0.9609	0.9629	0.9509	0.9739
Industry effect	No	Yes	No	Yes	Yes
Time-effect	No	No	No	Yes	Yes

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

correlation assumption. Simultaneously, the robot application level in the US is not related to the residual term of the current period, thus satisfying the exogeneity assumption. The first-stage regression uses the Chinese robot to regress the US robot and obtains the fitting value for industry-level ageing. The second stage uses the fitting value obtained in the first stage for the regression analysis.

Columns (1) and (2) of Table 5 show the regression results using the US robot as an instrumental variable. Column (1) represents the one-stage regression result, where the ratio coefficient of Chinese robots to US robots is significantly positive. This implies that the instrumental variables are significantly and positively correlated with the adoption of Chinese robots. Column (2) shows the two-stage regression result, and the coefficient of robots is significantly positive, indicating that after considering endogeneity issues, the adoption of China's industrial robots still has a promotion effect on LP. Meanwhile, the value of the F-statistic is 236.51, that is, greater than 10, and the P value is less than 0.01; therefore, no weak instrumental variable exists. Column (3) shows the regression result using limited information maximum likelihood (LIML), which is similar to the previous result.

4.3. Robustness check

A robustness test was conducted to verify the reliability of the conclusions and avoid accidental phenomena caused by the selection of specific variables in the empirical results.

4.3.1. Replacement of core explanatory variables: Annual installations of industrial robots

The annual installations of industrial robots (Robot2) reveal the industrial robot development index (Graetz & Michaels, 2018), which is substituted in this specification to replace the explanatory variable of robot density (Robot). Table 6 (1) presents the estimated results. The results indicate that the positive and negative signs between the parameter estimates remain unchanged and are significant at the 5% level despite differences in the parameter estimates between the substitute and explained variables. Furthermore, the goodness of fit of the two models is similar.

Table 5
Estimation results of instrumental variable.

	(1) First Stage Robot	(2) 2SLS LP	(3) LIML LP
US Robot	0.670***		
	(0.054)		
Robot		0.067***	0.067***
		(0.012)	(0.012)
Control variables	Yes	Yes	Yes
P value		0.000	
F statistic		236.51	
N	272	272	272
R-squared	0.7702	0.8246	0.8246

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3.2. Replacement of core explanatory variables: Industrial robots in operation

We replace the core explanatory variable with the operational stock of robots (Robot3) to measure industrial robot development. The operational stock measures the number of robots currently deployed. Accordingly, Table 6 (2) presents the effect of industrial robots on the LP of listed industries. A significant positive correlation exists between the operational stock of robots and LP, which supports the benchmark results of this study.

4.3.3. Replacement of core explanatory variables and dependent variables: The lagged period of independent and dependent variables

The lagged periods of the independent and dependent variables are selected as instrumental variables (L. lnRobot and L. lnLP). In this specification, the disturbance term of the current period cannot affect the result of the lag period of the robot density, thus satisfying the condition of exogenesis. Table 6 (3) presents the estimated results. The results indicate that after using the lag time of robot density as an instrumental variable to control the endogeneity problem, the application of industrial robots is still significantly positive at the 1% level, and the coefficients retain their positive and negative signs and their levels of statistical significance. Therefore, the promotion effect of industrial robot development on LP is still strongly evident, indicating that the empirical results are robust. Finally, column (4) shows the regression result using the lag time of LP, which is similar to the prior result, and the empirical results are robust.

4.3.4. Sub-industry regression

This study employs Ding et al.'s (2016) method to perform regressions by industry. Table 7 shows the coefficients of the regression analysis depicting the influence of industrial robot applications on LP in various industries in terms of the sample. The relevant outcomes

Table 6
Result of robustness check.

	(1) lnLP	(2) lnLP	(3) lnLP	(4) L.lnLP
lnRobot				0.052***
				(0.015)
lnRobot2	0.018**			
	(0.007)			
lnRobot3		0.0369***		
		(0.00963)		
L.lnRobot			0.023***	
			(0.009)	
lnK/L	0.868***	0.810***	0.742***	0.590***
	(0.067)	(0.0685)	(0.062)	(0.098)
lnM/L	0.107	0.124*	0.076	0.138
	(0.075)	(0.0739)	(0.065)	(0.102)
lnInvent	0.021	0.00140	0.060***	0.089***
	(0.018)	(0.0188)	(0.018)	(0.028)
lnFP	0.221***	0.221***	0.081**	0.300***
	(0.035)	(0.0338)	(0.038)	(0.060)
_cons	−0.665***	−0.585***	−0.149	−0.814***
	(0.107)	(0.107)	(0.118)	(0.177)
Industry effect	Yes	Yes	Yes	Yes
Time-effect	Yes	Yes	Yes	Yes
Observations	272	272	255	255
R-squared	0.9516	0.953	0.9462	0.9087

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Regression coefficients of industrial robot applications on labour productivity for sub-industry.

Industry	lnLP	Industry	lnLP
1.Mining	0.022	10.Glass and ceramics	0.056*
2.Utilities	−0.058	11.Basic metals	0.094*
3.Food and beverage	0.088***	12.Metal products	0.083**
4.Textiles	0.089*	13.Industrial machinery	0.032*
5.Wood and furniture	0.070*	14.Electrical machinery	0.019
6.Paper	0.040*	15.Electronics	0.047**
7.Pharmaceuticals, cosmetics	0.019	16.Instruments	0.095*
8.Chemical products	0.001	17.Vehicles	0.027*
9.Rubber and plastic products	0.044		

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

highlight that Industries represented by 3, 4, 5, 6, 10, 11, 12, 13, 15, 16 and 17 show significant positive coefficients. This implies that the application of industrial robots in these industries improves LP. For instance, every 1% increase in industrial robot application density increases LP by 0.094% in the basic metal industry. Only industry 2 exhibits negative coefficients. Overall, the industry regression outcomes moderate support the conclusion that employing industrial robots improves industrial LP.

4.4. Heterogeneity analysis

Based on the development situation in China, this study analyses the heterogeneity of the impact of industrial robots on LP at different robot densities and periods. The results are summarised in Table 8.

The following analysis aims to determine the heterogeneous impact of robot adoption using data from mining, utility, and 15 manufacturing sub-industries for 17 separate industries. Using the value of the industrial robot density variable, the samples of 17 industries are divided into high- and low-density industries. Specifically, the classification standard identifies industries with a density of industrial robots greater than 60 units per 10,000 people as high-density samples and industries with a density less than 60 units per 10,000 people as low-density samples (Han & Pang, 2021). This taxonomy has determined that the rubber and plastic products, metal products, electronics, industrial machinery, electrical machinery, and vehicle sectors are high-density industries, while the remaining industries are classified as small-density industries. The regression results for each of these three categories are presented in Table 8 (1) and (2).

A comparative analysis of industries with different robot density levels reveals that industries with high or low levels of industrial robot application produce a positive and significant coefficient estimate for the explanatory variable of industrial robot application density. These results indicate that robot applications play a substantial role in promoting LP in both high- and low-robot-density industries as the density of industrial robots increases.

The influence coefficient of the low-density robot industry is larger than that of the high-density robot industry, reflecting that an increased use of industrial robots does not necessarily imply a greater effect on LP. The overall positive influence is comparatively limited among capital-intensive industries with large-scale industrial robot applications. For example, the automobile industry itself is a heavy industry with a high degree of capital intensity and long history of using industrial robots. In contrast, industries such as electronics, chemistry, and food have a relatively short history of using industrial robots. Although their scale is significantly smaller than that of the automotive industry, their effect on LP is more significant. To a certain extent, it shows a possibility of diminishing marginal effect of industrial robots in promoting LP. This result supports the inference from the empirical analysis of Graetz and Michaels (2018) that the application of robots has diminishing marginal returns. Specifically, the application density of industrial robots in the automotive industry may already be quite large because of their large scale, with newly added industrial robots having a diminishing impact on LP. However, there is rapid application of industrial robots in the instruments, chemicals, wood products, and clothing industries. Robot applications within a smaller production base have a greater effect on LP. In the current situation, where industrial robot installations in China are growing rapidly but the actual use of robots varies considerably across industries, the extent of the positive influence of industrial robots on LP shows signs of industry heterogeneity.

Industrial robots' development has prominent time-period characteristics. Shortly after the beginning of the fourth industrial revolution (Industry 4.0) in Germany, China initiated the rapid development of industrial robots in 2012. Industry 4.0 intends to enhance efficiency, flexibility, and productivity while allowing more intelligent decision-making and customisation in manufacturing and supply chain operations (Kagermann et al., 2013). The 12th Five-Year Plan of the government in 2011 mandated the enhanced application of robots and integrated information technology across China's manufacturing industries. Therefore, this analysis takes 2012 as the time node to analyse the influences of the two periods: 2006–2012 and 2012–2021. The relevant outcomes are presented in columns (3) and (4) in Table 8. Accordingly, the results reveal that the effect of industrial robots on LP is significant in both periods. However, the regression coefficient of industrial robots on LP is most significantly positive from 2006 to 2012. There are possible reasons for this observation. Although the scale of industrial robot usage before 2012 was smaller than that after 2012, its

Table 8
Result of heterogeneity analysis.

Variables	Industries		Time Period	
	(1) High-Density	(2) Low-Density	(3) Year ≤2012	(4) Year > 2012
lnRobot	0.019**	0.083***	0.038***	0.032**
	(0.010)	(0.026)	(0.014)	(0.015)
lnK/L	0.986***	0.594***	1.088***	0.503***
	(0.079)	(0.126)	(0.087)	(0.057)
lnM/L	0.035	0.211	−0.164**	0.085*
	(0.087)	(0.128)	(0.067)	(0.046)
lnInvent	−0.000	−0.050	−0.011	0.077**
	(0.019)	(0.047)	(0.027)	(0.034)
lnFP	0.206***	0.284***	0.174***	−0.083**
	(0.045)	−0.055	(0.044)	(0.041)
_cons	−0.562***	−0.266	−0.318**	0.636***
	(0.138)	(0.258)	(0.124)	(0.131)
Observations	176	96	119	153
R-squared	0.9628	0.9473	0.9615	0.8966
Industry effect	Yes	Yes	Yes	Yes
Time-effect	Yes	Yes	Yes	Yes

Table 9
Result of intermediary mechanism.

Variables	(1) lnLP	(2) lnHR	(3) lnLP	(4) lnLP	(5) lnHR2	(6) lnLP
lnRobot	0.018**	0.011*	0.031	0.018**	0.047**	0.022
	(0.08)	(0.008)	(0.019)	(0.08)	(0.021)	(0.017)
lnHR			0.393***			
			(0.074)			
lnHR2						0.279***
						(0.033)
lnK/L	0.631***	0.327***	0.681***	0.631***	−0.010	0.812***
	(0.066)	(0.057)	(0.178)	(0.066)	(0.148)	(0.084)
lnM/L	0.088*	−0.312***	0.217	0.088*	−0.241	0.162
	(0.048)	(0.060)	(0.128)	(0.048)	(0.156)	(0.100)
lnInvent	−0.067**	0.152***	−0.052	−0.067**	0.379***	−0.098***
	(0.026)	(0.015)	(0.040)	(0.026)	(0.039)	(0.019)
lnFP	0.032**	−0.005	0.229***	0.032**	−0.083	0.250***
	(0.030)	(0.028)	(0.046)	(0.030)	(0.073)	(0.037)
_cons	0.294***	0.595***	−0.734	0.294***	3.937***	−1.599***
	(0.110)	(0.094)	(0.202)	(0.110)	(0.244)	(0.243)
Observations	272	272	272	272	272	272
R-squared	0.9739	0.9061	0.9578	0.9739	0.7903	0.9696
Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Time-effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

impact on LP was more profound. To a certain extent, this implies the possibility of diminishing marginal effects of industrial robots in promoting LP, which also confirms the inference of diminishing marginal returns from robot applications by Graetz and Michaels (2018).

4.5. Mechanism analysis

Table 9 shows the intermediary effect regression outcomes using the ratio of urban employed individuals with at least a college education (lnHR) to measure human capital. Columns (1), (2), and (3) show the test outcomes of the human capital intermediary mechanism. Column (1) shows the regression estimations based on Equation (17). Column (2) shows the regression estimations based on Equation (18), with a significantly positive coefficient for the robot. This implies that the application of industry robots supplements an increase in human capital structure. The application of robot technology has improved human capital. Column (3) presents the regression estimation based on Equation (19), with industrial robots and human capital indices included simultaneously. The HR coefficient is significantly positive, revealing the existence of an intermediary effect of human capital. Moreover, the coefficient for the robot is statistically non-significant, suggesting that the human capital level exhibits a complete intermediating effect between industrial robots and LP. Furthermore, columns (4), (5), and (6) adopt R&D personnel (lnHR2) to measure human capital; the results also reflect the existence of a complete intermediary effect of human capital.

4.6. Discussion

Extant literature suggests a strong correlation between robot technological progress and productivity (Acemoglu et al., 2020; Damioli et al., 2021; Dauth et al., 2017; Duan et al., 2023; Graetz & Michaels, 2018; Kromann et al., 2011). This study explores the connection between changes in industrial robot applications and LP in China. This is similar to the research implications presented by Acemoglu et al. (2020), Graetz and Michaels (2018), and Dauth et al. (2017) based on data related to the US, France, and Germany, stating that industrial robot application density significantly improves the industry's LP. In this study, as an emerging technology, industrial robotics displays the general characteristics of technological innovation. According to Schumpeter's theory of technological innovation, technological innovation not only transforms labour tools but also changes production methods to ensure that labour can produce greater value, thereby improving LP (Kurt & Kurt, 2015). This feature is also applicable to robotics. Industrial robots can perform intelligent work according to human instructions in the manufacturing and other industries, which changes the production techniques of workers and improves labour efficiency, improving the overall LP of the industry. The influence coefficient of the low-density robot industry is larger than that of the high-density robot industry, reflecting that an increased usage of industrial robots does not necessarily imply a stronger effect on LP. A possibility of diminishing marginal effect of industrial robots exists in augmenting LP. This outcome supports the inferences from the empirical analysis of Graetz and Michaels (2018), who state that the application of robots demonstrates diminishing marginal returns. The effect of new industrial robots on LP tends to decrease in industries with a high density of industrial robot applications. The rapid development of industrial robot applications in textiles, instruments, basic mental, and other industries creates a greater promotional influence of robot applications on LP on a smaller basis. One possible explanation may be the principle of diminishing marginal productivity (Pullen, 2009). It states that as additional input units are added to a production process, each extra unit's marginal (additional) output eventually declines.

5. Conclusions and policy implications

Based on a panel data sample of 17 different Chinese industries from 2006 to 2021, this study explores the impact of China's industrial robots on LP. The results indicate that the development and adoption of industrial robots significantly improve LP across multiple industries. A series of robustness tests validates this conclusion. On average, every 1% increase in industrial robot application density raises LP by 0.018%. However, the impact of industrial robots on LP varies over time and is heterogeneous across industries. The influence coefficient of the low-density robot industry is larger than that of the high-density robot industry, reflecting it is not that the more industrial robots are used, the greater the effect on labour productivity. Although the scale of industrial robot usage before 2012 was smaller than that after 2012, its effect on LP was more significant. The study outcomes highlight the possibility of diminishing marginal effect of industrial robots in promoting LP. Furthermore, the mechanism analysis establishes that human capital level has an intermediating effect between industrial robots and LP. A key limitation of this study is that it analyses data for a relatively short period of 16 years. The robot data are only from 2006, as the use of robots in China started late but has increased rapidly since the 2000s. Future studies may evaluate the long-term influences of the potential impact of industrial robots. Furthermore, this study explores only industrial robots. Future studies should investigate service robots.

Although China is a large manufacturing country and has achieved rapid development since market reforms and opening up to world markets, there remains a gap compared with Western economies such as Germany, France, and other developed countries. According to IFR data, the density of industrial robots in China in 2021 is slightly higher than the world average of 99 units per 10,000 people but lower than that of developed countries such as the United States, Japan, and Germany. Further efforts to increase robot applications to catch up with developed economies can target the most receptive industries that would generate the greatest increase in LP. The application of industrial robots has boosted LP improvements. However, the possible effects on different subsectors vary. This does not imply that the more the industrial robots are used, the stronger the influence on LP. The overall promotion effect is relatively limited for capital-intensive industries where industrial robot applications have reached a considerable scale. Regarding labour-intensive industries that exhibit minor applications of industrial robots, the improvement in LP demonstrates a stronger promotion effect on industrial added value. These implications suggest that improving robot adoption among industries with a high capacity for LP improvement should be prioritised when the goal of government policy is to increase the application of industrial robots across the Chinese economy to promote LP. The results of this empirical analysis can help policymakers identify the most effective industries to promote further increases in industrial robotics adoption, such as basic metals and instruments, to obtain optimal output growth benefits. China's manufacturing industry has huge potential to improve LP through industrial robot application. Such targeting of resources for the effective technological transformation and upgradation of China's manufacturing industry is possible by identifying and subsidising appropriate industry sectors. Therefore, many local governments in China have recently formulated preferential policies to promote the development of the industrial robot industry.

CRediT authorship contribution statement

Yantong Zhao: Conceptualization, Data curation, Methodology, Resources, Software, Writing – original draft. **Rusmawati Said:** Investigation, Supervision, Validation. **Normaz Wana Ismail:** Conceptualization, Supervision, Writing – review & editing. **Hanny Zurina Hamzah:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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