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How Industrial Intelligence Affects Total Factor Productivity: Evidence from China's Provincial Panel Data

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Abstract

In recent years, the rapid emergence of industrial intelligence has drawn increasing attention to its impact on economic production efficiency. Utilizing panel data from 30 Chinese provinces spanning 2009 to 2022, this study investigates how industrial intelligence affects Total Factor Productivity (TFP). The findings reveal a positive U-shaped trend: during initial intelligence phases, substantial investments and low conversion efficiency temporarily inhibit productivity, but as technologies mature, their positive effects on production efficiency gradually manifest. Notably, industrial intelligence enhances TFP through a critical transmission mechanism - stimulating human capital upgrading by increasing demand for high-skilled labor. Regional analysis demonstrates more pronounced effects in central and western regions compared to relatively subdued impacts in eastern areas. This research provides new empirical evidence for understanding the relationship between industrial intelligence and economic growth, offering valuable insights for policy formulation.

Keywords

Industrial Intelligence; Total Factor Productivity(TFP); Human Capital; Positive U-Shaped Relationship.

1. Introduction

With the deepening of the global scientific and technological revolution and industrial change, industrial intelligence has become the core driving force to promote high-quality economic development. Like a turbocharger of the economic engine, industrial intelligence is reshaping the pattern of industrial competition. Relying on the deep integration of artificial intelligence, big data and the Internet of Things, traditional factories are experiencing “digital genetic transformation” - from the automobile production line of the robotic arm to accurately grasp, to the real-time monitoring of energy consumption of the smart grid, production efficiency is being redefined. In this change, industrial robots play a key role, they are not only steel workers on the assembly line, but also connect the hub of “can manufacturing, smart city, digital agriculture”[1], and become the core lever to pry the total factor productivity (TFP). Total factor productivity is a key indicator of the quality of economic growth, which comprehensively reflects technological progress, resource allocation efficiency and organizational management level. With the aggravation of resource constraints, how to improve total factor productivity through industrial intelligence has become a hotly debated topic among academics and policy makers.

China is the world's largest manufacturing economy and is currently in a critical stage of transformation and upgrading. At the policy level, the successive introduction of programmatic documents such as “Made in China 2025” and “New Generation Artificial Intelligence Development Plan” has constructed an institutional framework for industrial intelligence. From

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the 19th National Congress of the Communist Party of China (CPC), which put forward "deepening the integration of the real economy and digital technology" to the 20th CPC Congress, which emphasized "building a modernized economic system", the evolution of the policy orientation has clearly demonstrated the strategic positioning of the national level for intelligent manufacturing[2]. The "14th Five-Year Plan" includes the penetration rate of industrial robots as a key development indicator, and builds a systematic support system for the improvement of total factor productivity through financial and tax incentives and innovation funds and other policy tools. In addition, the promotion of industrial intelligence and the widespread application of industrial robots in the manufacturing industry have been formally incorporated into the national development strategy, and have become the key initiatives of the 14th Five-Year Plan to promote intelligent manufacturing and high-quality development. These policies not only provide financial support and institutional guarantee, but also lay a solid foundation for the improvement of total factor productivity.

The in-depth application of industrial intelligence has not only reshaped the traditional mode of production, but also had a profound impact on the labor market. On the one hand, the trend of "machine for man" has accelerated, and some low-skilled labor positions have been replaced by intelligent equipment; on the other hand, the development of intelligent manufacturing has given rise to a large number of new occupations, and the demand for high-skilled talents has continued to rise, thus promoting the optimization of the structure of the labor market[3]. In this process, the deep integration of artificial intelligence, automated production, intelligent management systems and other technologies not only changes the operation of each link of the industrial chain, but also optimizes the allocation of resources, ultimately promoting the improvement of total factor productivity. In fact, as an important driving force of the new round of industrial change, artificial intelligence is profoundly affecting all aspects of economic activities, giving rise to the demand for intelligence in many fields, and boosting the overall leap in social productivity[4].

The resulting thinking is, how does industrial intelligence actually affect total factor productivity? What is its specific mechanism of action and transmission path? Based on the panel data of 30 provinces in China from 2009 to 2022, this paper will explore the mechanism of industrial intelligence on total factor productivity and its specific transmission path, aiming to provide a new analytical perspective for understanding the dynamic relationship between the two and an important practical reference for policy makers, so as to optimize the development path of industrial intelligence and promote the growth and quality of economic growth. Quality Improvement.

2. Literature Review

Firstly about the influencing factors of total factor productivity (TFP), there has been extensive academic research. According to neoclassical growth theory, TFP refers to the portion of output growth that remains after deducting the growth of capital and labor inputs[5]. As an important indicator for measuring the input-output efficiency of economic units, TFP not only reflects the output contribution of a single factor, but also integrally reflects the degree of technological progress, management level enhancement, and resource allocation optimization[6].

Existing research on the impact of intelligence on total factor productivity mainly focuses on two aspects. On the one hand, it is the impact on human capital, driven by the wave of intelligence, the demand for human capital has shifted from the pure pursuit of quantity to a greater emphasis on quality, and the complementarity with physical capital is also increasing[7]. Studies have shown that human capital upgrading can help enterprises apply new technologies more effectively, thus enhancing total factor productivity[8]. Gong Yinyin et al.'s study further points out that the application of robotics helps to promote the upgrading of production

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technology and optimizes the structure of human capital by boosting the demand for high-skilled labor and crowding out part of the low-skilled labor, which ultimately promotes the growth of enterprise TFP[9]. On the other hand, it is the impact on the green total factor development rate. With the deepening of the concept of sustainable development, green TFP has gradually become an important standard for measuring the quality of economic growth. Guo Xiaoxu and Zhang Yao's research shows that the optimization of human capital structure can promote green TFP by promoting industrial upgrading and improving labor efficiency[10]. Since the launch of China's carbon emissions trading pilot in 2013, more and more studies have found that the carbon trading mechanism not only promotes the productivity improvement of enterprises centered on TFP, but also boosts the high-quality development of the economy[11]. In addition, under the guidance of the carbon peak and carbon neutral policy, the government encourages enterprises to increase the innovation of energy-saving and emission reduction technologies through financial subsidies and tax incentives, and this initiative has further increased TFP to a certain extent.

Secondly, regarding the study of industrial intelligence, industrial intelligence refers to the use of robots, artificial intelligence and other technical means to promote the transformation of traditional industries in the direction of intelligence, so as to improve the operational efficiency of the real economy and the overall level of development. The core of intelligence lies in accelerating the flow of traditional factors of production and resource integration in order to optimize resource allocation and promote innovation and change in the mode of production[12]. Li Lianshui et al. believe that the basis of intelligence lies in factor inputs, and the key to achieving intelligent manufacturing lies in the development and application of software technology, with the ultimate goal of maximizing economic and social benefits[13]. It is worth noting that industrial intelligence is not only limited to the technological upgrading of the production and manufacturing links, but also covers the optimization of management mode, supply chain intelligence, accurate matching of market demand and other levels, which interact with each other to promote the improvement of enterprise production efficiency.

In terms of the impact of industrial intelligence, relevant studies mainly focus on two economic effects of industrial intelligence. First, the impact of industrial intelligence on the job market. With the promotion of automation technology, the substitution effect of low-skill and low-wage jobs has become increasingly obvious, resulting in some low-skill workers needing to shift to more creative or social intelligence requirements[14].Cheng et al. found that the impact of industrial intelligence on the employment structure of the manufacturing industry is relatively small due to the high willingness to leave the job of Chinese workers and the limited role of trade union organizations[15]. In the short term, industrial intelligence may trigger employment restructuring, but in the long term, it brings more significant labor productivity enhancement effects. Although the overall employment may decrease, the wage level of laborers shows a steady upward trend[16]. At the same time, industrial intelligence has given rise to a large number of emerging occupations, such as intelligent manufacturing engineers, data analysts, etc., which to a certain extent alleviates the employment pressure brought about by the reduction of traditional manufacturing jobs.

Secondly, the impact of industrial intelligence on productivity, Acemoglu et al. showed that the labor ratio of manufacturing enterprises that adopt robots has decreased, but the value added and productivity have increased significantly[17]. The “creative destruction” effect brought about by industrial robots can accelerate the upgrading of production technology, and under the combined effect of human capital upgrading and capital-skill combination, the innovation ability of enterprises has been further strengthened[18], but it is not clear how the upgrading of human capital can specifically contribute to the improvement of total factor productivity. In addition, industrial intelligence can also promote manufacturing technological innovation and achieve high-quality development by accelerating the technology spillover effect, improving the

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learning and absorption capacity of enterprises, increasing R&D investment, and promoting the investment of high-end talents in a variety of ways[19].

Although existing studies have explored the impact of industrial intelligence on total factor productivity (TFP) from multiple perspectives, there is still a lack of systematic analysis on how industrial intelligence acts on TFP through different mechanisms, especially its mediating effect and regional heterogeneity characteristics. By combing through the shortcomings of the literature, the contributions of this study are mainly reflected in three aspects: first, systematically analyzing the impact of industrial intelligence on TFP from the theoretical and practical levels, expanding the perspective of the existing research; second, introducing human capital as a mediating variable and exploring its transmission mechanism between intelligence and TFP, deepening the understanding of the relationship between the two; and third, focusing on the regional heterogeneity to reveal the differences in the impact of industrial intelligence on TFP in different regions, providing a better understanding of the relationship between the two; and third, focusing on the regional heterogeneity, revealing the impact of industrial intelligence on Thirdly, focusing on regional heterogeneity, revealing the differences in the impact of industrial intelligence on TFP in different regions, and providing reference for optimizing industrial policies according to local conditions.

3. Theoretical Analysis and Research Hypotheses

3.1. The Non-linear Relationship between Industrial Intelligence and Total Factor Productivity

The impact of industrial intelligence on total factor productivity has significant stage differences, and the direction and intensity of its effects are jointly influenced by multiple factors such as regional resource endowment, industrial technology level and institutional environment, and thus may show non-linear characteristics. This non-linear process is mainly constrained by three key factors: regional resource endowment, industrial technology level and institutional environment. Especially in the early stage of transformation, enterprises often need to invest a large amount of money in smart equipment procurement, technology research and development, as well as the introduction of talent, a process that may temporarily inhibit productivity. There are several hidden realities behind this process, including: firstly, enterprises are prone to overestimate the short-term benefits of intelligent transformation and underestimate the challenges in the process of transformation; secondly, the technology integration period may lead to a “statistical fog”, which may hide the actual efficiency improvement; thirdly, the pain of resource reconfiguration, and some enterprises may suffer short-term losses during the process of industry consolidation; intelligent transformation is not only a process of short-term losses, but also a process of short-term losses. Third, the pain of resource reconfiguration, some enterprises may suffer short-term losses in the process of industry consolidation; Intelligent transformation not only involves technological upgrading, but also needs to adjust the organizational structure and production mode, which may result in a temporary decline in production efficiency[20]. More specifically, the introduction of intelligent equipment requires workers to relearn operating skills, and part of the low-skilled labor force may be eliminated, and this human capital mismatch takes time to digest. At the same time, the management team also needs to adapt to the management style of the new technology, and these adaptation costs may delay the improvement of efficiency. Studies have shown that in the early stage of intelligence, AI investment may lead to a decline in total factor productivity, and the scale effect will only appear when the application of intelligent devices reaches a certain scale[21].

However, as industrial intelligence continues to mature, its impact on total factor productivity is changing. When enterprises break through the pain period of transformation, the potential

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of intelligent equipment begins to be released: industrial robots can operate tirelessly and accurately, intelligent systems optimize the production process in real time, and automated warehousing significantly reduces logistics costs. What's more, artificial intelligence not only replaces simple repetitive labor, but also helps engineers to complete more complex design tasks, and this "human-machine collaboration" model has given rise to new productivity[22]. The intelligent linkage of the upstream and downstream of the industrial chain, like dominoes, promotes a significant improvement in the efficiency of the whole industry. The main mechanism of industrial robots' total factor productivity enhancement is through the improvement of technical efficiency and the expansion of scale effect, i.e., to improve the overall work efficiency by replacing part of the labor force[23]. The upgrading of human capital structure further strengthens this positive cycle. When companies introduce new types of talent such as data engineers and AI trainers in large numbers, the interaction between these talents and smart devices creates efficiencies that are difficult to achieve in traditional production models. Artificial intelligence not only has a substitution effect, performing repetitive, programmed tasks, but also has a complementary effect, assisting workers to complete complex tasks, thus further improving labor productivity[24]. This spiraling improvement mechanism ultimately pushes productivity to break through the inflection point of the U-shaped curve. Therefore, this paper puts forward the following hypotheses:

Hypothesis 1: The impact of industrial intelligence on total factor productivity presents a positive U-shaped nonlinear relationship.

3.2. Mediating Transmission Mechanisms of Industrial Intelligence on Total Factor Productivity

T The spread of industrial robots is changing the structure of the demand for skills in the job market. This change affects production efficiency through two main paths: on the one hand, intelligent equipment directly replaces low-skilled jobs, thus reducing the labor cost per unit of output; on the other hand, the emergence of new technology jobs promotes the upgrading of human capital, providing impetus for continuous efficiency improvement[25-26].

First, enterprises optimize factor allocation through "machine for man", replacing part of the labor factors at a lower cost, thus improving total factor productivity. Secondly, the widespread application of robotics not only promotes the progress of production technology, but also increases the demand for high-skilled labor and squeezes the low-skilled labor, which promotes the upgrading of human capital and further enhances the total factor productivity of enterprises. The labor substitution effect of industrial robots accelerates the optimization of human capital structure[27]. With the application of robotics, the social demand for production skills has increased dramatically, which not only promotes the input of capital and high-skilled labor, but also accelerates the deep integration of intelligent manufacturing and traditional manufacturing, and promotes technological innovation and the progress of complementary technologies, thus enhancing total factor productivity.

In addition, industrial robots reduce the demand for low-skilled labor engaged in repetitive and standardized work by replacing such labor, which in turn enhances the overall productivity of enterprises[28]. However, the substitution role of intelligent technology is not comprehensively covered; it is mainly applicable to standardized and programmable tasks, while automation still cannot completely replace jobs that are complex and require creative thinking or highly skilled support. As a result, intelligence not only replaces part of the labor, but also plays a supporting role in many cases, increasing labor productivity. This trend has prompted companies to be more inclined to hire highly skilled people to ensure that the workforce structure can adapt to the demands of intelligent production. However, this transition also faces significant technological barriers. Intelligent devices are good at performing standardized tasks, but complex decisions still require human intervention, and this complementary feature

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encourages enterprises to cultivate complex talents with dual capabilities of “technology + management”. Therefore, this paper puts forward the following hypothesis:

Hypothesis 2: The demand for highly skilled labor in industrial intelligence promotes the upgrading of human capital, which in turn enhances total factor productivity.

3.3. Regional Differences in the Impact of Industrial Intelligence on Total Factor Productivity

The impact of industrial intelligence on total factor productivity may have significant differences in different regions, which mainly stems from the differences in the level of economic development, industrial structure, human capital accumulation and technological basis of each region. As the most economically developed region in China, the eastern region has a higher level of industrialization, a more advanced industrial structure and a strong technological base. Enterprises in the eastern region generally have strong technological innovation ability and capital accumulation, and promote the process of industrial intelligence faster, with a relatively high level of intelligence. However, as the economy in the eastern region is already at a more mature stage of development, the space for raising total factor productivity is relatively limited, and a higher base of intelligence may, on the contrary, diminish the marginal benefits.

In contrast, the transformation path in the central and western regions is different. The economic development of the central and western regions is relatively lagging behind, and the industrial structure is dominated by traditional manufacturing and resource-based industries with a weak technological base. But this also provides the region with a greater latecomer advantage in the process of industrial intelligence. Despite the weaker foundation of intelligence, a strong catch-up effect can be brought about through technology imitation and human capital enhancement. In addition, the labor market in the central and western regions is not yet fully mature and the supply of high-skilled labor is insufficient, which also means that the advancement of industrial intelligence will significantly increase the demand for high-skilled labor and drive the improvement of human capital. This process will further boost total factor productivity growth.

From the policy level, the regionally heterogeneous impact of industrial intelligence on total factor productivity is of great significance. For the eastern region, policies should focus on how to further optimize the industrial structure and enhance technological innovation capacity through intelligence to sustain total factor productivity growth. For the central and western regions, policies should focus more on how to promote industrial upgrading and technology diffusion through intelligence, while increasing the cultivation and introduction of high-skilled labor to maximize the contribution of intelligence to total factor productivity. Based on these analyses, this paper proposes:

Hypothesis 3: There is regional heterogeneity in the impact of industrial intelligence on total factor productivity. Among them, the promotion effect is more significant in the central and western regions, while it is not obvious in the eastern region.

4. Research Design

4.1. Sample Selection and Data Source

This paper selects the panel data of 30 provinces (autonomous regions and municipalities directly under the central government) from 2009 to 2022 for empirical research, excluding Tibet Autonomous Region, Hong Kong, Macao and Taiwan, and obtains a total of 420 observations. The data are obtained from the China Statistical Yearbook, Wind, CNRDS and the International Federation of Robotics (IFR). During the data analysis process, Stata was applied for data processing to ensure the accuracy and consistency of the data. In addition, in order to

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avoid the negative impact of extreme values in the sample data on the empirical research results, this paper clusters the standard errors of the regression coefficients at the provincial level to ensure the robustness of the research results.

4.2. Non-linear Relationship between Industrial Intelligence and Total Factor Productivity

In order to test the relationship between industrial intelligence and total factor productivity, this paper sets the model as follows:

$$TFP_{it} = \beta_0 + \beta_1 \ln AI_{it} + \beta_2 \ln AI^2 + \beta_3 Control_{it} + \mu_t + \gamma_i + \varepsilon_{it} \quad (1)$$

Where i represents province; t represents year. TFPit is the total factor productivity of province i in year t; lnAIit is the industrial intelligence level of province i in year t; Control is a series of control variables; μt and γi are time and individual fixed effects; εit is a random error term.

1) Explained variable: total factor productivity. The estimation methods of total factor productivity in the existing literature mainly include parametric estimation, semiparametric estimation and nonparametric estimation methods, but there are large differences in the total factor productivity estimated by different methods[29]. With reference to the actual situation, this paper uses the nonparametric method and FE method to measure total factor productivity, and uses the nonparametric method to calculate in the benchmark regression and uses the data measured by the FE method to conduct the robustness test.

2) Core explanatory variable: industrial intelligence. Industrial intelligence is the core explanatory variable of this study. However, the measurement of this variable has not yet formed a unified standard in academia, and there are mainly two common measurement methods. One is the method of constructing an indicator system proposed by scholars such as Sun Zao and Hou Yulin[30]; the other is the measurement of industrial robot inputs adopted by Song Xuguang and Zuo Ma Huaqing[31]. In this paper, we mainly draw on Wang's research idea of using industrial robot installation density as an approximate proxy for the level of industrial intelligence in each region[32]. The rationale for this choice lies in the fact that industrial robots have become one of the most widely used intelligent devices at present and an important achievement of industrial intelligence. In addition, compared with the indicator system method, using the density of industrial robot installation to measure the level of intelligence can reduce the endogeneity problem to a certain extent, thus improving the accuracy of the measurement[33].

3) Mediating variable: human capital level. There is still no uniform standard about the measurement of human capital, and there are three main measurement methods in existing studies: cost method, income method and education indicator method. The education indicator method believes that education investment is the most important way to promote the accumulation of human capital, and the level of education can measure the stock of educated human capital of an individual or an economy[34]. Therefore, this paper chooses the education indicator method, using the number of students enrolled in higher education (10,000 people) as a proportion of the total population of each province to measure.

4) Control variables: In order to make a more precise portrayal of the impact of industrial intelligence on total factor productivity, this paper also controls the following variables with reference to existing studies: industrial structure (industrye), labor level (labor), R&D intensity (yanfa), and openness to the outside world (open). Among them, industrial structure is measured by the ratio of the output value of the tertiary industry to the output value of the secondary industry and the output value of the primary industry; labor force level is measured by taking the natural logarithm of the number of employed persons; R&D intensity is measured

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by the share of internal expenditure on R&D funding in the regional gross domestic product (GDP); and, finally, openness to the outside world is measured by the product of the total amount of goods imported and exported and the exchange rate of the U.S. dollar to the renminbi in the proportion of the regional GDP.

5. Empirical Results and Analysis

5.1. Descriptive Statistics

Table 1 demonstrates the results of descriptive statistics for the variables in this paper. Through the descriptive statistics analysis of each variable, it is found that the mean value of total factor productivity (TFP) measured by the nonparametric method is 0.6282, and the standard deviation is 0.2942, indicating that the total factor productivity roughly conforms to the normal distribution. The data of each control variable is more consistent with the results of existing literature, which lays a good foundation for the subsequent regression analysis.

Table 1. Table of descriptive statistics

Variable Symbol	Variable Name	Mean Value	Standard Deviation	Minimum Value	Maximum Value
TFP	Total factor productivity measured by the non-parametric method	0.6282	0.2942	0.1017	1.4987
FE	Total factor productivity measured by the FE method	0.6303	0.2899	0.0977	1.4327
AI	Industrial Robot Installation Density as Natural Logarithm	1.2173	2.3878	0.0048	22.4063
AI^2	Square of natural logarithm of installed density of industrial robots	7.1696	37.9527	0.0000	502.0399
renli	Human Capital Level	0.0204	0.0057	0.0079	0.0413
yanfa	R&D intensity	0.0163	0.0110	0.0022	0.0653
chanye	Industrial structure	1.1225	0.6409	0.4944	5.2968
labor	Labor force level	7.6063	0.7685	5.5452	8.8639
open	Openness to the outside world	0.2763	0.2947	0.0076	1.4638

5.2. Benchmark Regression

According to the set model to examine the impact of industrial intelligence on total factor productivity, while controlling the fixed effects of year and province, the results are shown in Table 2. The regression results show that the coefficient of the primary term of the industrial intelligence variable is negative and the coefficient of the secondary term is positive, indicating that intelligence may inhibit productivity in the initial stage, but once it exceeds a certain threshold, it can significantly increase TFP. i.e., in the initial stage of industrial intelligence development, it may negatively affect total factor productivity because of the large amount of capital investment, the R&D and innovation of new technology, and the low rate of transformation of the results, but when it breaks through a certain threshold, industrial intelligence is able to increase TFP significantly, which is the most important factor in the development of the industry. a certain threshold, industrial intelligence can significantly promote the growth of total factor productivity. This positive U-shaped relationship still holds after adding control variables, providing strong support for hypothesis 1.

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Table 2. Benchmark regression table

Variable	TFP(1)	TFP(2)
AI	-0.0356** (0.0155)	-0.0345** (0.0153)
AI^2	0.0016** (0.0006)	0.0016** (0.0006)
chanye		0.0248** (0.0094)
labor		0.1833* (0.1016)
yanfa		2.5744** (1.2290)
open		0.2996*** (0.0746)
Constant	0.6598*** (0.0145)	-0.8890 (0.7744)
Year fixed effects	YES	YES
Individual fixed effects	YES	YES
R^2	0.8597	0.8660
Adj.R^2	0.8430	0.8485
observed value	420	420

Note: ***, ** and * denote 1%, 5% and 10% significance levels, respectively, with standard errors clustered to the province level in parentheses, as in the following table.

5.3. Robustness Tests

5.3.1. Replacement of Explained Variables (FE)

In order to ensure the robustness of the positive U-shaped relationship between industrial intelligence and total factor productivity, this paper adopts the following methods to test the robustness. Firstly, replace the explanatory variable TFP with the value of TFP measured by FE, and the results are shown in Column (1) of Table 3, the coefficient of the primary term of AI is still negative, and the coefficient of the secondary term is still positive, so the results are robust.

Table 3. Robustness test table

Variable	TFP(1) Replacement of the explanatory variable	TFP(2) Tailoring	TFP(3) TFP lagged by one period
AI	-0.0392*** (0.0101)	-0.0519*** (0.0102)	-0.0326* (0.0168)
AI^2	0.0013*** (0.0003)	0.0035*** (0.0008)	0.0014** (0.0006)
Control Variables	YES	YES	YES
Constant	-0.5189 (0.8366)	-0.8996 (0.8345)	-0.7554 (0.9843)
Time Fixed Effects	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
R^2	0.8629	0.8684	0.8639
Adj.R^2	0.8450	0.8511	0.8450
observed value	420	420	390

5.3.2. Tailoring (1 Percent up and Down for All Variables)

In order to further verify the robustness of the research results, this paper applies an upper and lower 1% shrinkage treatment to all variables to reduce the impact of extreme values on the regression results. Tailoring treatment can effectively reduce the estimation bias caused by outliers, thus improving the reliability of regression analysis. The regression results after the treatment are shown in Column 2 of Table 3, where the sign, coefficient size and significance of

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the core variables remain consistent with the benchmark regression, indicating that the positive U-shaped relationship of the impact of industrial intelligence on total factor productivity still holds. This further indicates that the findings are not disturbed by extreme data and the robustness of the model is high.

5.3.3. Lagging TFP by One Period

Considering that the increase in TFP may in turn affect the advancement of industrial intelligence (reverse causality), or some unobserved factors may affect both TFP and industrial intelligence (omitted variable problem). This endogeneity problem can be partially mitigated by lagging TFP by one period, since TFP in the lagged period is not directly affected by industrial intelligence in the current period. In addition, there may be a time lag effect in the impact of industrial intelligence on total factor productivity. It takes some time for the introduction and application of intelligent technologies to have a significant impact on productivity. Therefore, using TFP with a one-period lag can better capture the long-term impact of industrial intelligence.

The results of the robustness test are shown in Column 3 of Table 3, where the sign and significance of the coefficients of AI and its squared term are consistent with the baseline model, further supporting the hypothesis of a positive U-shaped relationship between industrial intelligence and total factor productivity. The R^2 and Adj. R^2 of the lagged one-period model are 0.8612 and 0.8421, respectively, which are similar to the benchmark model and other robustness test results, indicating that the explanatory power of the model is strong and the results have high reliability.

5.3.4. Detion of Beijing, Shanghai, Tianjin and Chongqing Samples

In order to further test the robustness of the impact of industrial intelligence on TFP, this paper deletes the sample data of the four municipalities directly under the central government, namely Beijing, Shanghai, Tianjin and Chongqing. As municipalities directly under the central government, Beijing, Shanghai, Tianjin and Chongqing are significantly different from other provinces in terms of their level of economic development, industrial structure and policy support. These regions have larger economies, higher levels of industrialization, and usually have stronger technological innovation and capital accumulation capabilities, which may result in the impact of industrial intelligence on TFP being different from that of other regions. Deleting these samples can exclude the interference of municipality specificity on the research results.

The estimation results of the model after deleting the municipality samples are shown in Column 1 of Table 4. The significance of the core variables and the direction of the coefficients have not changed significantly, indicating the robustness of the research results.

Table 4. Exclusion of partial samples

Variable	TFP(1) Remove partial samples	TFP(2) Adjustment of sample time
AI	-0.0329** (0.0138)	-0.0511*** (0.0144)
AI^2	0.0015** (0.0006)	0.0040*** (0.0009)
Control Variables	YES	YES
Constant	-1.2557 (0.9020)	-2.2676 (0.9084)
Time Fixed Effects	YES	YES
Individual Fixed Effects	YES	YES
R^2	0.8647	0.8674
Adj.R^2	0.8460	0.8450
observed value	364	330

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5.3.5. Deletion of Sample Data for 2020, 2021 and 2022

In order to exclude the potential impact of the New Crown epidemic on the research results, this paper further deletes the sample data for 2020, 2021 and 2022. The New Crown Epidemic had a significant impact on the global economy, and China's industrial production, supply chain, and labor market were also significantly affected. During the epidemic, firms' production activities were restricted and the intelligence process may have been disrupted, leading to anomalies in the relationship between industrial intelligence and TFP. Deletion of the samples in these years could exclude the epidemic from interfering with the results of the study.

After deleting the sample data of 2020, 2021 and 2022, the estimation results of the model are shown in Column 2 of Table 4. The sign and significance of the coefficients of the core variables are consistent with the baseline model and the goodness-of-fit of the model maintains a high level, which indicates that the research results are robust.

5.4. Analysis of the Mediating Mechanism

In order to reveal the mechanism of industrial intelligence on TFP more clearly, this paper further examines the mediating effect of human capital level (renli) in this process. The results of the regression analysis (see Table 5) show that industrial intelligence not only directly affects TFP, but also can indirectly promote TFP by promoting human capital upgrading.

Specifically, in the regression analysis, the effect of human capital level (renli) on TFP is statistically significantly positive, indicating that the improvement of human capital plays an important role in promoting productivity growth. When human capital is included as a mediating variable, the effect of industrial intelligence on TFP remains significant, indicating that part of the effect is transmitted through human capital enhancement, which further enhances the productivity-boosting effect of intelligent transformation. In addition, further mediation effect tests show that the increased demand for high-skilled labor brought about by industrial intelligence significantly contributes to the enhancement of human capital and ultimately to the growth of TFP. This result verifies Hypothesis 2 that industrial intelligence plays a partial mediating role by enhancing the level of human capital.

Table 5. Analysis of intermediary mechanisms

Variable	TFP(1)	renli(2)	TFP(3)
AI	-0.0035** (0.0015)	-0.0000* (0.0000)	-0.0030* (0.0015)
AI^2	0.0000** (0.0000)	0.0000* (0.0000)	0.0000** (0.0000)
renli			10.6360** (5.1998)
Control Variables	YES	YES	YES
Constant	-0.8890 (0.7744)	0.0366* (0.0195)	-1.2276 (0.7836)
Year Fixed Effects	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
R^2	0.8660	0.9572	0.8690
Adj.R^2	0.8485	0.9515	0.8514
observed value	420	420	420

5.5. Endogeneity Test

In empirical analysis, the endogeneity problem may lead to bias in the estimation results, thus affecting the reliability of the study's conclusions. To address this potential problem, this paper employs the instrumental variable (IV) method and the construction of a dynamic panel model. Specifically, this paper draws on Sun Zao and Hou Yulin and selects the logarithm of the mean value of industrial robot density in provinces outside the region during the same period as the instrumental variable. This choice is based on the following logic: the technological diffusion of industrial intelligence tends to have a regional linkage effect, and the level of intelligent development in neighboring regions may have an impact on the process of industrial intelligence in the region, so the two have a strong correlation. At the same time, the density of industrial robots in provinces outside the region does not directly affect the region's total factor productivity (TFP), thus satisfying the exogeneity assumption of the instrumental variable.

For this reason, this paper adopts the two-stage least squares (2SLS) method for instrumental variable regression, taking the natural logarithm of AI first, and then carrying out the regression, and the results are shown in Table 6. First, in the first stage, the natural logarithm of industrial intelligence level (lnAI) and its squared term ($lnAI^2$) are regressed separately to obtain the predicted values of instrumental variables (IV and IV^2). Subsequently, in the second stage, TFP was regressed on the predicted values obtained in the first stage in order to estimate the net effect of industrial intelligence on TFP, and the results are shown in Table 6. anderson canon. corr. LM statistic is 32.966 and significant at 1% level, which indicates that there is a significant correlation between instrumental and endogenous variables, and that the instrumental variables have been chosen reasonably. Meanwhile, the Cragg-Donald Wald F statistic of 17.598, which is much higher than 10, indicates that there is no weak instrumental variable problem. In the second-stage regression, the positive U-shaped relationship between industrial intelligence and TFP remains significant, further enhancing the robustness of the findings.

Table 6. Endogeneity test table

Variable	lnAI(1)	lnAI2(2)	TFP(3)
lnAI			-0.3202*** (0.1395)
$lnAI^2$			0.0212*** (0.0119)
IV	-7.7145*** (2.4242)	-177.7753*** (34.1891)	
IV^2	3.9029*** (0.7119)	71.2749*** (10.0403)	
Control Variables	YES	YES	YES
Constant	-1.9973 (2.0460)	23.2960 (28.8557)	-0.2068 (0.3348)
Year Fixed Effects	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
$Adj.R^2$			0.8994
Anderson canon. Corr. LM statistic			32.966***
Cragg-Donald Wald F statistic			17.598
observed value	420	420	420

5.6. Heterogeneity Analysis

Due to the large differences in the application of industrial robots in various regions of China, this paper divides the sample into eastern and central and western regions for group regression analysis based on the level of economic development and geographic location, and the regression results are shown in Table 7.This division is mainly based on the significant differences between the eastern and central and western regions in terms of the level of economic development, industrial structure, technological foundation, and policy support.

The regression results for the eastern region are shown in Column 1 of Table 7, and the effect of industrial intelligence on TFP is not significant. The possible reason for this is that the intelligent process in the eastern region started earlier and the overall level of intelligence is higher, so the marginal effect of further promoting intelligence may be diminishing, resulting in a more limited enhancement of its effect on TFP. At the same time, due to the abundant supply

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of high-skilled labor in the eastern region, the promotion effect of intelligence on human capital may have been saturated, resulting in a weaker boost to TFP.

In contrast, the regression results for the central and western regions (Column 2 of Table 7) show that the impact of industrial intelligence on TFP is more significant and exhibits a positive U-shaped relationship. The logic behind this phenomenon is clearer: the level of industrial intelligence in the central and western regions is still at a lower stage compared to the eastern regions, and the introduction of intelligent technology and the increased application of industrial robots can significantly improve productivity, thus showing a stronger marginal effect. Therefore, hypothesis 3 is verified.

Table 7. Heterogeneity analysis table

Variable	TFP(1)Eastern	TFP(2)Midwestern
AI	-0.0019 (0.0025)	-0.0089*** (0.0025)
AI^2	0.0000 (0.0000)	0.0001** (0.0000)
Control Variables	YES	YES
Constant	-0.0461 (1.7268)	-0.4433 (0.8084)
Year Fixed Effects	YES	YES
Individual Fixed Effects	YES	YES
R^2	0.7505	0.8721
Adj.R^2	0.6859	0.8498
observed value	140	238

6. Conclusion

This study has deeply analyzed the mechanism of industrial intelligence on total factor productivity (TFP) through theoretical discussion and empirical test. The research results show that the impact of intelligence on TFP is not a simple linear process, but shows a positive U-shaped change of inhibition followed by promotion. That is to say, in the early stage of intelligence, due to factors such as immature technology and lagging equipment updating, its positive effect on productivity has not yet appeared, and may even have a certain negative impact; while when the technology and equipment are gradually perfected, the productivity-enhancing effect of intelligence will be gradually enhanced. This finding is verified in multiple robustness tests such as replacing the explanatory variables, shrinking the tail of the variables, and lagging the data by one period. Meanwhile, the mediation effect analysis reveals that intelligence can promote human capital upgrading by increasing the demand for high-skilled labor, thus further boosting TFP.In addition, the regional heterogeneity analysis reveals that the impact of industrial intelligence is more moderate in the eastern region, whereas it shows a significant positive U-shaped effect in the central and western regions.

Based on the above conclusions, this study has important implications for promoting the development of industrial intelligence. First, the process of intelligence should focus on the gradual maturation of technology and the continuous optimization of equipment to ensure a smooth transition in the early stage of transformation and ultimately play a role in improving production efficiency. Second, the government and enterprises need to work together to increase the cultivation and introduction of highly skilled personnel to improve the overall quality of the workforce to adapt to the new demands brought about by intelligence. Finally, governments at all levels should actively promote the transformation and upgrading of industrial structure, and improve the added value of industries by supporting the development of new industries and promoting the transformation of traditional industries, so as to enhance the overall production efficiency.

In response to the above findings, this paper puts forward the following policy recommendations:

Promote intelligent transformation according to local conditions: for the eastern region, it should focus on further optimizing the industrial structure, promoting technological innovation and industrial upgrading through intelligentization, and encouraging enterprises to increase R&D investment to achieve a continuous increase in TFP; for the central and western regions, it is necessary to increase financial and policy support to help enterprises break through technological bottlenecks, and at the same time, strengthen the infrastructure construction to promote the proliferation and application of intelligent technology.

Strengthen the construction of human capital: in the face of the demand for high-skilled talents brought about by intelligentization, the government should increase its investment in education and vocational training, especially in the central and western regions, and cultivate talents adapted to the needs of intelligentization through school-enterprise cooperation, etc. At the same time, it should improve the mechanism of the labor market, and promote the reasonable mobility and allocation of high-skilled talents among different regions.

Optimize the policy support system: in the early stage of intelligent transformation, enterprises may face higher technical input and adjustment costs, the government can reduce the burden of enterprises through tax incentives, R&D subsidies and other policy means; in addition, strengthen the R&D support for intelligent core technologies, promote key technology breakthroughs, and improve the maturity and popularity of the technology.

Promote inter-regional technology collaboration and diffusion: Since the promotion of intelligent technology has an obvious regional linkage effect, it is recommended to establish a regional technology cooperation platform, hold regular technology exchange activities, promote experience sharing and resource complementation between the eastern and central and western regions, and jointly promote the development of intelligentization.

Although this study provides a more comprehensive argument for the relationship between industrial intelligence and total factor productivity, there are still some limitations. Future research can further explore the specific mechanism of the role of intelligence in different industries and regions, with a view to providing more detailed policy references for promoting high-quality economic development.

Credit Authorship Contribution Statement

Yuanchun Yu: Conceptualization, Data curation, Funding acquisition, Writing–original draft.

Yudie Zhang: Conceptualization, Collect data, Formal analysis, Writing–original draft.

Kaixin Xu: Supervision, Validation, Writing–original draft.

Yu Fu: Data curation, Formal analysis, Methodology.

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