

Original Paper

Artificial Intelligence, Technological Innovation and the Upgrading of China's Equipment Manufacturing Industry

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Abstract

This article identifies and screens out companies applying Artificial Intelligence (AI) through Enterprise Search, and measures the level of AI empowerment in the industry in terms of the number of companies applying AI as a proportion of the number of companies in the industry as a whole, and based on the panel data of China's equipment manufacturing industry from 2001-2017, we empirically test the impact effect and mechanism of action of AI empowerment on the upgrading of the equipment manufacturing industry. The research results show that: AI empowerment has a significant positive impact on the upgrading of the equipment manufacturing industry, but there is industry heterogeneity, and AI empowerment has a greater positive impact effect on the upgrading of the high-end equipment manufacturing industry. Technological innovation plays a mediating role in the process of AI empowerment for the upgrading of equipment manufacturing.

Keyword

Artificial Intelligence, The Upgrading of Equipment Manufacturing Industry, Intermediary Effect

1. Introduction

With the flourishing of the new round of technological revolution and industrial transformation, the deep integration of artificial intelligence with manufacturing industry in the form of technology empowerment has accelerated the development of manufacturing industry in the direction of intelligence, which has become the main direction of development of manufacturing industry in the new round of industrial revolution. The equipment manufacturing industry is the “backbone” of a

country's manufacturing industry, has long been in the low end of value creation, key core technologies are "stuck" problem, therefore, how to promote artificial intelligence and equipment manufacturing industry under the background of a new round of scientific and technological revolution, deep integration, improve artificial intelligence on the degree of empowerment of the equipment manufacturing industry, become an important means to promote the current equipment manufacturing industry to accelerate the upgrading. Basing on the above content, this article takes the equipment manufacturing industry as the research object, on the basis of exploring the mechanism of upgrading of the equipment manufacturing industry empowered by artificial intelligence technology, and using panel data of seven sub-industries of China's equipment manufacturing industry from 2001-2017 to carry out empirical tests, the relevant research findings obtained, with a view to providing theoretical support and guidance for the practice of China's equipment manufacturing industry empowered by artificial intelligence technology.

2. Literature Review

2.1 Research on the Upgrading of the Equipment Manufacturing Industry

In 1998, "equipment manufacturing industry" was first proposed in the Central Economic Conference, by 2008 the international financial crisis, scholars mainly from the equipment manufacturing industry research significance and value perspective analysis, that this stage of China's equipment manufacturing industry backwardness is mainly due to production capacity and product demand mismatch, low-end product overcapacity, high-end product supply is insufficient, the overall industrial structure is not concentrated (Zhang & Liu, 2001, pp. 121-122). In the process of development of the equipment manufacturing industry there is a lack of motivation for research and development, technological innovation backward and other outstanding issues (Jiang, 2004, pp. 47-51), Shen (2006), for the first time based on the industrial perspective, believes that the equipment manufacturing industry should be transformed as soon as possible from manufacturing to manufacturing-service-oriented industry, thus accelerating the international competitiveness of the equipment manufacturing industry (Shen, 2006, pp. 111-116). From 2009-2014, scholars mainly studied from the level of the driving force of the upgrading of equipment manufacturing industry, and considered financial support (Duan, Li, D. & Li, L. S., 2009, pp. 388-392; Wang, Liu & Zhang, 2013, pp. 72-79), international trade (Chen & Zhong, 2014, pp. 43-53) and technological innovation (Qi, Wang & Cai, 2014, pp. 111-118; Niu & Zhang, 2012, pp. 51-67) as important influencing factors affecting the upgrading of the equipment manufacturing industry. In recent years, mainly based on the value chain perspective, the current situation of the upgrading of equipment manufacturing industry has been analyzed in terms of international competitiveness (Wang & Sheng, 2020, pp. 8-18) and industrial integration (Jiang, Ma & Tang, 2019, pp. 77-86).

2.2 Research on the Upgrading of Equipment Manufacturing Industry Empowered by AI

The development of artificial intelligence first began in 1942 with the 'Three Laws of Robotics' proposed by the American science fiction giant Asimov. Then, in 1950, the Turing Test focused scientists on the connection between machines and intelligence, and robots became the official expression of artificial intelligence. At the Dartmouth Conference in 1956, the term "artificial intelligence" was officially introduced as a technical term by scientists such as John McCarthy, and machines began to simulate human intelligence as a branch of computing that came into the public domain. Since then, scholars have begun to study the proliferation and application of AI across industries at the level of the technological dimension, and AI technology has become a manifestation of innovation activities in high-end manufacturing. Since the turn of the century, scholars at home and abroad have been keen to link AI technology empowerment with industrial integration for research, arguing that the application of AI manifests itself as technological integration between industries and usually occurs in industries such as equipment manufacturing, high-tech industries and pharmaceutical manufacturing. Domestic scholars on artificial intelligence technology to empower the thinking and research began in the 1990s, to the Internet, big data, artificial intelligence and a new generation of information technology as a representative of the continuous development and application of artificial intelligence in the equipment manufacturing industry to give a further breakthrough. "Since the 12th Five-Year Plan, China's economy has paid more attention to the transformation of the development mode, and in the context of scientific development, AI technology empowerment has become an important focus of the new generation of technological revolution and industrial change" (Zhu, Chen, Tian & Wang, 2016, pp. 66-70). Chen (2018) likens AI to the industrial revolution, arguing that the "AI revolution" will have a greater impact than previous technological advances, and that "AI" will enter the mainstream of economics as an important research topic (Chen, 2018, pp. 6-21). The new generation into the deep integration of industrial intelligence and manufacturing industry is mainly reflected in household product intelligence, equipment intelligence, production intelligence, management intelligence, business application intelligence, industrial ecological intelligence and other aspects, and focus on improving the upgrading of equipment manufacturing industry (Gao, 2019, pp. 28-35). Mi etc. (2020) argue that the application of AI technology significantly advances the innovative power of manufacturing firms, optimizes their capital structure, and improves their market valuation (Mi, Jiang & Li, 2020, pp. 46-55).

Throughout the existing research literature, research on AI technology empowerment is mainly focused on the integration of manufacturing with the Internet and productive services, and research topics around AI-enabled equipment manufacturing are still relatively lacking. There are more studies on the upgrading of equipment manufacturing industry, but there are still few studies on the specific mechanism of AI-enabled equipment manufacturing industry upgrading. And these are the focus of this paper's research.

3. Theoretical and Hypothesis

3.1 *The Direct Effect of Artificial Intelligence to Empower the Upgrading of the Equipment Manufacturing Industry*

Firstly, in terms of intelligent organization and management, AI technology empowerment mainly reduces the labor costs of equipment manufacturing from two perspectives (Gao, 2019, pp. 28-35). On the one hand, for production management, intelligent production will directly replace some of the intellectual and physical positions to achieve an unmanned production mode, and the requirements for the workforce will change from simple mechanical operations to more complex technical aspects such as data reading, programming and use of networked machines; On the other hand, in terms of administration, the deep penetration of artificial intelligence will lead to a flatter management model of the enterprise organization, through control, coordination, planning and analysis, artificial intelligence will replace some of the supervisory and decision-making actions of middle-level companies and optimize the structure of the workforce employed at the administrative level (Ren & Song, 2019, pp. 6-13).

Hypothesis 1: AI technology empowerment can promote the rationalization level of China's equipment manufacturing industry.

Secondly, in terms of intelligent equipment production, artificial intelligence technology can significantly improve production efficiency and product quality (Shi, 2020, pp. 30-38). On the production control, artificial intelligence can not only through the perception, maintenance, analysis, and other functions, using adaptive, self-organizing intelligent, network model, thus forming the integration of production line, workshop and plant height with numerical control, but also through the traceability system information, intelligent and thus weaken the barriers to entry, to achieve a high degree of integration with the equipment manufacturing industry. In the production operation mode, intelligent production can meet the individual needs of the product customer as far as possible. Artificial intelligence can enhance the advanced development of the equipment manufacturing industry to a greater extent through industry chain collaboration, big data analysis, dynamic detection of product demand and accurate value setting and subcontracting. Based on the above analysis, this paper puts forward the following research hypothesis.

Hypothesis 2: AI technology empowerment enables to promote the advanced level of China's equipment manufacturing industry.

In addition, different types of industries have different characteristics in terms of production models and other aspects, and their AI transformation requirements differ from their impact on the industrial upgrading process (Shi, Ji & Cheng, 2017, pp. 64-71). Compared to the middle and low-end industries, the special equipment manufacturing industry, computer, communication and electronic equipment manufacturing industry, instrumentation manufacturing industry, as the high-end industry of the equipment manufacturing industry, in the context of the upgrading of China's manufacturing industry

and the development of global economic integration, the demand for technological innovation and industrial change is stronger, in the development of artificial intelligence in the manufacturing industry in the forefront. As high-end industries are more capital-intensive in terms of the type of production and have higher requirements for big data, AI, algorithms, etc., in the process of AI development and application, not only do they belong to the use of AI for production, but the continuous progress of high-end industries themselves also promotes the further development of AI. As a result, the industrial upgrading of high-end industries is progressing more rapidly. For the middle and low-end industries, their production types are more labor-intensive using AI-enabled products, relatively low in terms of technological requirements, with insufficient AI technology-enabled dynamics, and the breadth and depth of industrial upgrading lagging behind that of the high-end industries. Therefore, from the perspective of technology-enabled equipment manufacturing heterogeneity analysis, this paper puts forward the following research hypothesis.

Hypothesis 3: The impact effect of AI technology empowerment on the upgrading of different types of equipment manufacturing industries is heterogeneous, and the promotion effect of technology empowerment on upgrading is stronger in high-end industries.

3.2 The Indirect Effect of AI Technology Empowerment to Promote the Upgrading of the Equipment Manufacturing Industry

Artificial intelligence technology empowerment can not only directly stimulate the process of upgrading of China's equipment manufacturing industry, but also by stimulating the level of technological innovation, which in turn can enhance the level of industrial rationalization and advanced (Zhao & Pei, 2019, pp. 70-76). Artificial intelligence presents significant advantages in terms of cross-border integration, cloud processing, and connectivity of things, and its applications involve a variety of fields such as biology and computer science: on the one hand, AI technology empowerment continues to enhance technological innovation by improving the structure of highly skilled human capital, advanced production processes, and the organizational process of technological research and development (Yang, Gong, Wang & Chao, 2018, pp. 138-148). On the other hand, the development of artificial intelligence, while being applied and popularized to more fields, will further reduce the cost of innovation, stimulate the incentive of technological innovation in enterprises and obtain the incentive effect of innovation; at the same time, the allocation of resources will be continuously optimized in the application of innovation, the organizational model and production efficiency will be improved, and knowledge spillover will play a greater value in the production process (Fu, Li & Zhao, 2020, pp. 187-193). Based on the above analysis, this paper puts forward the following research hypothesis.

Hypothesis 4: AI technology promotes the upgrading of China's equipment manufacturing industry by stimulating technological innovation

4. Research Design

4.1 Empirical Model Setting

To empirically examine AI-enabled equipment manufacturing upgrading, the following econometric model was developed:

$$trup_{it} = \alpha + \beta fu_{it} + \Theta X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

Among them, *trup* indicates upgrading of equipment manufacturing; *fu* representing Level of artificial intelligence technology empowerment in equipment manufacturing industry; *X* are control variables, it includes foreign firm capacity, human capital investment, firm size; μ and v represent the factors that do not change with industry and time respectively, ε is the random disturbance term; *i* and *t* representing industry and time respectively.

4.2 Variable Selection and Measurement

4.2.1 Explanatory Variable

The upgrading of the equipment manufacturing industry is the explanatory variable in this study, the paper measures the upgrading of China's equipment manufacturing industry in two dimensions: the industrial rationalization (*rea*) and the industrial advance (*high*) of China's equipment manufacturing industry, respectively. Combining the structural deviation index with the Hamming closeness method to measure the level of structural rationalization of China's equipment manufacturing industry, the specific measurement formula is as follows:

$$rea = 1 - \frac{1}{7} \sum_{i=1}^7 |S_i^y - S_i^l| \quad (2)$$

In this formula, S_i^y indicates the proportion of output value of the *i* equipment manufacturing industry in the total output value of the whole equipment manufacturing industry. S_i^l indicates the proportion of the number of employees in the *i* equipment manufacturing industry in the total number of employees in the whole equipment manufacturing industry. *rea* the closer to 1, the more reasonable the structure of the equipment manufacturing industry is.

As the equipment manufacturing industry is the pillar industry of China's manufacturing industry, this paper uses the ratio of equipment manufacturing output value to manufacturing output value to measure the advanced level of the structure of the equipment manufacturing industry, the closer the indicator is to 1, the more advanced the structure of the equipment manufacturing industry.

4.2.2 Core Explanatory Variable

AI empowerment is the core explanatory variable in this study, and this paper draws on Zhang, L. P. (Zhang, L. P. & Zhang, S. Z., 2020, pp. 74-88) and others to measure the level of AI empowerment in an industry using the number of companies applying AI as a proportion of the total number of companies in that industry, with the following measurement process. Step 1: A preliminary screening

of the “business name” and “business scope” of the enterprise is carried out by using the Enterprise Search application to capture the raw data using advanced queries. Step 2: The raw data from the initial query is cleaned and then merged and the merged data is aggregated into Dbever, which is integrated into Access for processing through Debever. Step 3: Create a table using the MySQL default program and import the initial processed data into the table. Write query statements in MySQL to get all the basic information of all the enterprises containing at least one of the five keywords “big data”, “intelligent”, “cloud”, “IOT”, “robotics” and at least one of the five keywords. Step 4: A query in the further filtered results, grouped by year and industry type and then sorted by year, to obtain the combined results of all data categories. Step 5: The Count function is used to combine the processes and calculate the percentage of the number of companies applying AI in each industry.

4.2.3 Control Variables

Control variables includes: (1) Capacity of foreign enterprises (fc), expressed by the proportion of industrial output value of Hong Kong, Macao and Taiwan’s investment enterprises in the total industrial output value; (2) Human capital input (hr), expressed by the proportion of the industrial R&D employees in the total employment; (3) The enterprise scale (gm), expressed by the proportion of the number of enterprises with a registered capital more than 10 million in the total number of enterprises.

4.2.4 Intermediate Variable

Technological innovation (ti) is the intermediary variable of the study. Technological innovation includes two levels: technological innovation output and technological innovation transformation. The literatures usually take the number of patents (technological innovation output), new product sales revenue (technological innovation transformation), etc. as the proxy variables of technological innovation. Here, with reference to the research of Zhang et al. (Zhang, L. P. & Zhang, S. Z., 2020, pp. 74-88), the number of invention patent applications is taken as the proxy variable of technological innovation.

4.3 Data Sources and Descriptive Statistics

Considering the availability and the statistical caliber of data, the paper selects panel data of seven sub-industries of China’s equipment manufacturing industry from 2001-2017. The data were obtained from China Statistical Yearbook, China Industrial Statistical Yearbook, China Industrial Economic Statistical Yearbook, China Science and Technology Statistical Yearbook, and the Qichacha application software. As an enterprise information search software, it covers 80 million enterprises’ credit information data, including industrial and commercial information search, credit information search, business scope and other classification indicators, which is the main data source for the search of artificial intelligence enterprises in this paper. The data used in this paper are all based on the year 2001 and are processed by price deflating to remove the confounding price factor. Descriptions of variable measures and descriptive statistics are shown in Table 1 in detail.

Table 1. The Descriptive Statistics of Variables

| Variable | Mean | Std. Dev. | Min | Max |
|-------------|-------|-----------|-------|-------|
| <i>rea</i> | 0.781 | 0.125 | 0.501 | 1.000 |
| <i>high</i> | 0.183 | 0.065 | 0.089 | 0.300 |
| <i>fu</i> | 0.143 | 0.064 | 0.040 | 0.292 |
| <i>ti</i> | 0.703 | 0.182 | 0.355 | 1.000 |
| <i>gm</i> | 0.721 | 0.086 | 0.363 | 0.969 |
| <i>hr</i> | 0.045 | 0.023 | 0.003 | 0.093 |
| <i>fc</i> | 0.082 | 0.010 | 0.062 | 0.104 |

5. Empirical Analysis

5.1 Benchmark Regression Analysis

Table 2 shows the benchmark regression results, where (1)-(4) list the regression results of the impact of artificial intelligence technology empowerment on the rationalization of restructuring of equipment manufacturing industry. Column (1) shows the degree of impact of AI empowerment on the rationalization of China's equipment manufacturing industry without the inclusion of control variables. The results show that the coefficient of the core explanatory variable AI technology empowerment level is significantly positive at the 5% confidence level. Columns (2)-(4) indicate the changes in the impact between the level of AI technology empowerment and the level of rationalization of industrial upgrading, respectively, after the sequential addition of control variables. The results in column (4) show that after controlling for the three human capital, firm size and foreign direct investment simultaneously, the regression coefficient is 0.891, which is significant at the 10% level of significance. Among the control variables, enterprise scale plays the most significant role in promoting industrial upgrading. According to columns (2) and (3), after controlling enterprise size, the regression coefficient of AI technology empowerment level increases from 0.752 to 0.929, and is significant at the significance level of 10%, which indicates that enterprise size has a positive promoting effect on industrial rationalization level, thus verifying the research hypothesis 1 proposed above. The regression results in column (4) show that the capability of foreign-funded enterprises does not pass the significance test, which may be due to the low development level of China's equipment manufacturing industry and its weak absorption capacity for foreign advanced technologies, which makes it difficult to exert the spillover effect of foreign-funded enterprises.

The regression results of AI technology empowerment on the upgrading of equipment manufacturing industry are listed in (5)-(8). According to the regression results, at the significance level of 1%, artificial intelligence technology empowerment has a significant positive impact on the upgrading of

equipment manufacturing industry. The regression conclusion verifies the research hypothesis 2. Column (5) shows the direct impact of AI technology empowerment on the upgrading of equipment manufacturing industry, indicating that every unit of AI technology empowerment increases, the degree of industrial upgrading increases by 1.055 units. Column (8) shows that after controlling human capital, enterprise scale and OFDI, the regression coefficient of AI technology empowerment is 0.905, which passes the test at the significance level of 1%. Among the control variables, human capital has the highest impact on industrial upgrading, and the regression coefficient is 0.636, which is significant at the significance level of 1%. The regression coefficients of enterprise size and OFDI are negative and fail to pass the significance test.

Table 2. The Benchmark Regression Results

| 变量 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-----------------------|---------------------|---------------------|--------------------|-------------------|--------------------|--------------------|--------------------|--------------------|
| <i>fu</i> | 0.922** (1.99) | 0.752 (1.60) | 0.929* (1.96) | 0.891* (1.81) | 1.055*** (7.01) | 0.923*** (6.59) | 0.889*** (6.24) | 0.905*** (6.10) |
| <i>hr</i> | | 0.862* (1.74) | 1.035** (2.08) | 1.038** (2.08) | | 0.670*** (4.55) | 0.637*** (4.26) | 0.636*** (4.23) |
| <i>gm</i> | | | 0.174* (1.86) | 0.176* (1.87) | | | -0.033 (-1.18) | -0.034 (-1.20) |
| <i>fc</i> | | | | 0.788 (0.29) | | | | -0.326 (-0.40) |
| <i>c</i> | 0.604*** (11.41) | 0.583*** (10.86) | 0.436*** (4.57) | 0.381* (1.83) | 0.036** (2.11) | 0.020 (1.25) | 0.048* (1.67) | 0.071 (1.13) |
| <i>Obs</i> | 119 | 119 | 119 | 119 | 119 | 119 | 119 | 119 |
| <i>R</i> ² | 0.629 | 0.641 | 0.654 | 0.654 | 0.722 | 0.772 | 0.775 | 0.776 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>F</i> | 9.491 | 9.325 | 9.250 | 8.705 | 14.51 | 17.69 | 16.90 | 15.92 |

Note. Values in parentheses are *t* values, *, ** and *** represent statistical significance at the level of 1%, 5% and 10% respectively.

5.2 Robustness Analysis

5.2.1 Sample Size Change

The 2010 China Statistical Yearbook redefined the assets of large and medium-sized enterprises, resulting in a difference in the definition of large and medium-sized enterprises before and after 2010. In order to circumvent the impact of this statistical difference on the regression results, the sample data are here divided into two periods, i.e., 2001-2010 and 2011-2017, using 2010 as the boundary, and the regressions are conducted separately, and the specific regression results are shown in Table 3, The regression results are presented in columns (1) and (3) for the sample period 2001-2010, and in columns (2) and (4) for the sample period 2011-2017. The explanatory variable in columns (1) and (2) is industrial rationalization and the explanatory variable in columns (3) and (4) is industrial sophistication. The regression results in Table 4 show that AI empowerment has a significant positive impact on the upgrading of the equipment manufacturing industry in both time periods. This finding is consistent with the conclusion obtained from the benchmark regression, which indicates that the conclusion obtained from the benchmark regression is robust.

Table3. The Sample Size Change Regression Results

| 变量 | (1) | (2) | (3) | (4) |
|------------------|--------------------|--------------------|--------------------|--------------------|
| <i>fu</i> | 1.288*** (2.70) | 0.901*** (2.83) | 0.408*** (3.27) | 1.183*** (4.40) |
| Control Variable | Control | Control | Control | Control |
| Industry FE | Control | Control | Control | Control |
| Year FE | Control | Control | Control | Control |
| <i>Obs</i> | 70 | 49 | 70 | 49 |

Note. Values in parentheses are t values, *, ** and *** represent statistical significance at the level of 1%, 5% and 10% respectively.

5.2.2 Endogenous Analysis

Artificial intelligence technology empowerment and equipment manufacturing upgrading between the possible existence of reverse causation, that is, the higher the value chain position of the equipment manufacturing enterprises, usually the stronger the application of artificial intelligence technology will be willing to use active intelligent transformation to achieve the purpose of continuing to occupy the high-end of the value chain. In order to avoid the problem of endogeneity caused by reverse causality, this paper uses the lag phase empowered by artificial intelligence technology as the instrumental variable and uses 2SLS method to estimate the model parameters. Therefore, it can be considered that

one stage lag of AI empowerment is an instrumental variable, and there is no problem of unrecognized and weak recognition. The empowerment of artificial intelligence technology has a significant positive impact on the rationalization and upgrading of the upgrading of equipment manufacturing industry at the significance level of 1%, which is consistent with the conclusion obtained from the benchmark regression, which further indicates that the research conclusions obtained from the benchmark regression are robust.

Table 4. The Endogenous Analysis Results

| 变量 | (1) | (2) | (3) | (4) |
|-----------------------|--------------------|--------------------|--------------------|--------------------|
| <i>fu</i> | 1.008*** (6.98) | 1.039*** (5.36) | 0727*** (10.81) | 0.643*** (8.49) |
| Control Variable | | Control | | Control |
| Industry FE | Control | Control | Control | Control |
| Year FE | Control | Control | Control | Control |
| Weak correlation test | 1.1e+0.4 | 7453.363*** | 1.1e+0.4 | 7453.363*** |
| Unidentified test | 111.042 | 110.634*** | 111.042 | 110.634*** |
| <i>Obs</i> | 112 | 119 | 112 | 119 |

Note. Unidentified test refers to the unidentified test Kleibergen-Paaprk LM statistic, which tests the original hypothesis that there is an unidentified problem with the regression of instrumental variables; weakly identified test refers to the weakly identified test Kleibergen-Paaprk Wald F statistic, which tests the original hypothesis that there is a weakly identified problem with the regression of instrumental variables. Values in brackets are t , *, ** and *** represent statistical significance at the level of 1%, 5% and 10% respectively.

5.3 Industry Heterogeneity Analysis

Due to the differences in the input factor structure of various equipment manufacturing industries, the impact of AI empowerment on the upgrading of the equipment manufacturing industry may be different. Therefore, this part refers to the classification method of Fu, Y. H. etc. (2016) and divides the equipment and equipment manufacturing industry into two categories: mid-end industry and high-end industry. The middle-end equipment manufacturing industry includes metal products industry, general equipment manufacturing industry, transportation manufacturing industry, electrical machinery and equipment manufacturing industry. High-end equipment manufacturing industries include specialized equipment manufacturing, computer, communication and other electronic equipment manufacturing, instrument and meter manufacturing.

The specific results of industry heterogeneity analysis are shown in Table 5. (1)-(4) as artificial intelligence technology assignment can affect the regression results for the equipment manufacturing industry rationalization, among them, the first column (1) and (2) as artificial intelligence technology can assign for high-end equipment manufacturing industry upgrading of rationalization affect the regression results, the regression results show that the artificial intelligence can assign for high-end equipment manufacturing industry rationalization has significant positive influence. Columns (3) and (4) show the regression results of the impact of artificial intelligence technology empowerment on the rationalization of middle-end equipment manufacturing industry. The regression results show that the impact of artificial intelligence empowerment on the rationalization of middle-end equipment manufacturing industry is not significant. It can be concluded that there is industry heterogeneity in the impact of AI empowerment on the rationalization of equipment manufacturing industry.

Columns (5)-(8) are regression results of the influence of artificial intelligence technology empowerment on the upgrading of equipment manufacturing industry, where columns (5) and (6) are regression results of artificial intelligence empowerment on the upgrading of high-end equipment manufacturing industry, and columns (7) and (8) are regression results of artificial intelligence empowerment on the upgrading of mid-end equipment manufacturing industry. According to the regression results in columns (5)-(8), AI empowerment has a significant positive effect on the upgrading of both mid-end and high-end equipment manufacturing, but AI empowerment has a strong positive effect on the upgrading of high-end equipment manufacturing.

Based on the above analysis, it can be concluded that there is industry heterogeneity in the impact of AI empowerment on the upgrading of equipment manufacturing industry, and AI empowerment has a stronger role in promoting the upgrading of high-end equipment manufacturing industry. The conclusion of this study verifies the research hypothesis 3 proposed above.

Table 5. Industry Heterogeneity Regression Results

| 变量 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-----------------------|--------------------|--------------------|---------------------|-------------------|---------------------|----------------------|--------------------|---------------------|
| <i>fu</i> | 2.665*** (5.05) | 3.058*** (7.02) | -0.119 (-0.18) | -0.133 (-0.13) | 1.426*** (10.49) | 1.690*** (14.03) | 0.910*** (3.59) | 0.294*** (2.93) |
| <i>hr</i> | | 3.230*** (7.82) | | 0.714 (0.90) | | 0.768*** (6.72) | | 0.815*** (3.41) |
| <i>gm</i> | | 0.109* (1.71) | | 0.116 (0.61) | | 0.017 (0.95) | | -0.128** (-2.22) |
| <i>fc</i> | | -2.134 (-1.20) | | 1.583 (0.09) | | -1.517*** (-3.07) | | -4.947 (-0.93) |
| <i>c</i> | 0.408*** (5.37) | 0.260** (2.32) | 0.653*** (10.50) | 0.434 (0.33) | -0.012 (-0.62) | 0.008 (0.27) | 0.046* (1.96) | 0.505 (1.28) |
| <i>Obs</i> | 51 | 51 | 68 | 68 | 51 | 51 | 68 | 68 |
| <i>R</i> ² | 0.875 | 0.963 | 0.573 | 0.582 | 0.925 | 0.974 | 0.642 | 0.775 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>F</i> | 12.78 | 36.31 | 3.709 | 3.069 | 22.43 | 52.96 | 4.963 | 7.564 |

Note. Values in parentheses are *t* values, *, ** and *** represent statistical significance at the level of 1%, 5% and 10% respectively.

5.4 Intermediary Mechanism Analysis

Technological innovation is an important means to promote the value creation of the equipment manufacturing industry upward leap, based on the aforementioned analysis, artificial intelligence empowerment through cross-border innovation resource integration, reshape the paradigm of technological innovation and other paths to help accelerate the iteration of technological innovation, thereby promoting the equipment manufacturing industry to accelerate the upgrading. Therefore, technological innovation plays a mediating role in the process of upgrading of the equipment manufacturing industry enabled by artificial intelligence. In order to verify the mediating mechanism, the Bootstrap test is used to test the mediating mechanism of technological innovation. The specific test results are shown in Table 6. The mediating effect of technological innovation is significant at the 5% significance level for the rationalization of the equipment manufacturing industry, with a mediating effect of 0.294, accounting for 0.397 of the total effect; for the advanced equipment manufacturing

industry, the mediating effect of technological innovation is also significant, with a mediating effect of 0.286, accounting for 0.491 of the total effect. In other words, technological innovation has a mediating role in the process of artificial intelligence empowerment to promote the upgrading of the equipment manufacturing industry, and this finding verifies research hypothesis 4.

Table 6. Intermediary Effect Analysis

| Variable | Effect type | Path | Effect size | Standard error | confidence interval |
|-----------------|-----------------|--------------------------------------|-------------|----------------|---------------------|
| Rationalization | Direct effect | $fu \rightarrow rea$ | 0.4452 | 0.1252 | [0.1252,0.7787] |
| | Indirect effect | $fu \rightarrow ti \rightarrow rea$ | 0.2937 | 0.0907 | [0.1292,0.4812] |
| Advance | Direct effect | $fu \rightarrow high$ | 0.2973 | 0.03498 | [0.2263,0.3637] |
| | Indirect effect | $fu \rightarrow ti \rightarrow high$ | 0.2864 | 0.06420 | [0.1577,0.4134] |

Note. Values in brackets are 95% confidence intervals; *, ** and *** represent statistical significance at the level of 1%, 5% and 10% respectively; Values in the table are for a sample of 5000.

6. Conclusion

In this paper, enterprises applying artificial intelligence are identified and screened through Qichacha, and the proportion of the number of enterprises applying artificial intelligence in the number of enterprises in the whole industry is calculated to measure the empowerment level of artificial intelligence to the industry. Then, the panel data of China's equipment manufacturing industry from 2001 to 2017 were used to empirically test the effect and mechanism of AI empowerment on the upgrading of China's equipment manufacturing industry. The specific conclusions of the study are as follows: First, AI empowerment has a significant positive impact on the upgrading of equipment manufacturing industry, but the impact exists in industry heterogeneity, and AI empowerment has a stronger role in promoting the upgrading of high-end equipment manufacturing industry. Second, technological innovation is the channel through which artificial intelligence enables the upgrading of equipment manufacturing industry. That is, artificial intelligence enables the upgrading of equipment manufacturing industry through technological innovation channels.

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References

- Chen, A. Z., & Zhong, G. Q. (2014). Whether International Trade in China's Equipment Manufacturing Industry Has Contributed to Its Technological Development—Based on Analysis of Panel Data and DEA. *Economist*, 2014(05), 43-53.
- Chen, Y. W. (2018). Artificial Intelligence and Economics: A Review of Recent Literature. *Journal of Dongbei University of Finance and Economics*, 2018(03), 6-21.
- Duan, Y. Q., Li, D., & Li, L. S. (2009). Analysis of The Effect of The Financial Support on China's Equipment Manufacturing. *Studies in Science of Science*, 27(03), 388-392.
- Fu, W. Y., Li, Y., & Zhao, J. F. (2020). How does Artificial Intelligence Affect the Optimization and Upgrading of Regional Manufacturing Industry?—Research Based on the Dual Mediation Effect. *Reform of Economic System*, 2020(04), 187-193.
- Gao, Y. (2019). Intelligent Model Selection for the Deep Integration of Artificial Intelligence and Manufacturing in China's high-quality Economic Development. *Journal of Northwest University (Philosophy and Social Sciences Edition)*, 49(05), 28-35.
- Jiang, B., Ma, S. L., & Tang, X. H. (2019). The Impact of Industrial Integration on the Innovation Efficiency of China Equipment Manufacturing Industry: Adjustment Perspective Based on Structural Embedding. *Science & Technology Progress and Policy*, 36(09), 77-86.
- Jiang, H. (2004). The Meaning and Countermeasure of Quickening The Development of Equipment Manufacturing in China. *The Border Economy and Culture*, 2004(11), 47-51. <https://doi.org/10.1360/03yb0228>
- Mi, J. H., Jiang, L. W., & Li, Z. T. (2020). Research on the Application of Artificial Intelligence Technology to Promote the Upgrading of China's Manufacturing Industry. *The Journal of Humanities*, 2020(09), 46-55.
- Niu, Z. D., & Zhang, Q. X. (2012). An Analysis of Technological Innovation Efficiency of Manufacturing Equipment Industries in China. *Journal of Quantitative & Technological Economics*, 29(11), 51-67.
- Qi, L. Q., Wang, C. D., & Cai, Y. Y. (2014). Research on the Evaluation of R&D Efficiency in China's Equipment Manufacturing Industry and its Influencing Factors. *R&D Management*, 26(01), 111-118.

- Ren, B. P., & Song, W. Y. (2019). Effects and Pathways of the Deep Integration of Next-generation Artificial Intelligence and the Real Economy for High-quality Development. *Journal of Northwest University (Philosophy and Social Sciences Edition)*, 49(05), 6-13.
- Shen, G. R. (2006). Industry transition: The Discussion of Development Strategy of Equipment Manufacturing in Shanghai. *Shanghai Journal of Economics*, 2006(11), 111-116.
- Shi, B. (2020). An Explanation of the Mechanism of AI Promoting Economic High-quality Development. *Reform*, 2020(01), 30-38.
- Shi, X. A., Ji, L. Y., & Cheng, Z. H. (2017). Influence of “Internet+” on Transformation Upgrading of Chinese Manufacturing Industry—Based on the National 2003-2014 Provincial Panel Data. *Science & Technology Progress and Policy*, 34(22), 64-71.
- Wang, H. S., & Sheng, X. Y. (2020). The Comparative Study on the International Competitiveness of China’s High-tech Equipment Manufacturing Industry. *Journal of Dalian University of Technology (Social Sciences)*, 41(01), 8-18.
- Wang, Z. Y., Liu, J. B., & Zhang, X. H. (2013). The Financial Support for the Development of Equipment Manufacturing Industry—A Case Study of Shenyang Branch, ICBC. *Finance Forum*, 18(06), 72-79.
- Yang, L. G., Gong, S. H., Wang, B., & Chao, Z. S. (2018). Human Capital, Technology Progress and Manufacturing Upgrading. *China Soft Science*, 2018(01), 138-148.
- Zhang, L. P., & Zhang, S. Z. (2020). Technology Empowerment: The Effect of Technological Innovation on the Integrated Development of Artificial Intelligence and Industry. *Finance & Economics*, 2020(06), 74-88.
- Zhang, Q. S., & Liu, M. (2001). Strategic Thinking on Realizing Leapfrog Development of China’s Equipment Manufacturing Industry. *China Soft Science*, 2001(10), 121-122.
- Zhao, Y. L., & Pei, C. C. (2019). Technological Innovation, Industrial Convergence and Manufacturing Upgrading. *Science & Technology Progress and Policy*, 36(11), 70-76.
- Zhu, W., Chen, H. H., Tian, S. Y., & Wang, H. W. (2016). Artificial Intelligence: New Blue Ocean from a Scientific Dream—Analysis and Countermeasures of the Development Situation of AI Industry. *Science & Technology Progress and Policy*, 33(21), 66-70.