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Does artificial intelligence promote industrial upgrading? Evidence from China

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ABSTRACT

Based on the panel data of 285 cities in China from 2000 to 2019, this paper searches the number of patent applications related to urban artificial intelligence from five dimensions: algorithm, data, computing power, application scenario and related technology. Combining the two perspectives of industrial upgrading and rationalization, we analyze the internal influence theory of the research topic from the theoretical and empirical perspectives. The results show that artificial intelligence is not only conducive to industrial upgrading, but also significantly inhibit the deviation of industrial structure from equilibrium, which is conducive to industrial rationalization. In addition, the conclusion of this paper is still valid after a series of robustness tests, such as eliminating the samples of central cities, winsorize treatment and instrumental variables method. Through the heterogeneity test, it is found that the promoting effect of artificial intelligence on industrial upgrading is more obvious in big cities and cities with high level of industrial upgrading. The internal mechanism test results show that artificial intelligence promotes industrial upgrading by promoting technological innovation. In cities with a high degree of marketization and Internet development, the role of artificial intelligence in promoting industrial upgrading can be strengthened. The research conclusions of this paper will be conducive to accelerating the development of artificial intelligence to promote industrial upgrading, and provide a useful reference for realizing high-quality development.

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1. Introduction

Since China's reform and opening-up, relying on "demographic dividend" and "policy dividend", China has gradually grown into a world factory and created a miracle in human economic history (Yuan & Gao, 2020). However, at this stage, China is facing an extremely severe economic situation. On the one hand, the traditional profit

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model has been seriously impacted by the expiration of domestic factor dividends. On the other hand, COVID-19 has repeatedly blocked the economic development, shrinking demand for production, investment, consumption and export, and increasing downward pressure on economic development. In this context, a new round of scientific and technological revolution and industrial reform is both an opportunity and a challenge to China. Industrial transformation and upgrading has become a key variable leading China's future sustainable economic development. However, where is the direction and driving force of China's industrial upgrading? The report of the 19th National Congress of the Communist Party of China pointed out that the deep integration of artificial intelligence and the real economy should be promoted. This is the advance planning and strategic prediction of industrial upgrading.

China's artificial intelligence is developing rapidly and gradually takes the lead in the world. According to the "China Internet Development Report 2020", the number of artificial intelligence patent applications in China surpassed the United States for the first time and became the first in the world. Artificial intelligence is gradually penetrating into all walks of life, and the scale of core industries continues to expand. Moreover, the "China Artificial Intelligence Industry White Paper 2020" pointed out that China's industrial financing scale is 140.2 billion yuan, and the market scale of the industry's core industries exceeds 150 billion yuan, of which manufacturing accounts for 57.3%. Artificial intelligence promotes the development of production automation and intelligence, and greatly liberates the productive forces. However, some scholars pointed out that machine replacement reduces the role of labor force, and profits are seized and concentrated in the hands of capitalists. Artificial intelligence has changed the coupling degree of production factors and technical factors (Grimshaw, 2020), resulting in "production paradox" (Raisch & Krakowski, 2021), "baumol disease" (Aghion et al., 2019) and "wage polarization" (Mellacher & Scheuer, 2021). So, does artificial intelligence have a significant impact on industrial upgrading? What is the direction and mechanism of its influence? Clarifying the above problems can clarify the significant effects and channels between the two. This provides policy enlightenment for China to promote the development of artificial intelligence and realize industrial upgrading.

The existing literature lays a theoretical foundation and a logical starting point for this study. Based on this, our research makes valuable contributions to the literature from the following aspects. First, research perspective. Due to the limitations of data, how to effectively quantify artificial intelligence still creates great difficulties for research topics. This paper solves the problem of data availability from the perspective of artificial intelligence patent for the first time. We use the keyword retrieval method to obtain the number of patent applications related to urban artificial intelligence in China from five dimensions: algorithm, data, computing power, application scenarios and related technologies. This will help to improve the comprehensiveness and rationality of the empirical research results and open up a new horizon of research. Second, research methods. Combined with theoretical mechanism and empirical analysis, this paper discusses the impact of artificial intelligence on industrial upgrading. Meanwhile, we comprehensively consider the endogeneity, robustness and heterogeneity of the model. Among them, the robustness of the model is tested by eliminating the influence of central cities, winsorize treatment and instrumental variable method. And the heterogeneity of the model is investigated by dividing cities of different sizes and using quantile regression method. Third, research mechanism. What are the specific channels for artificial intelligence to promote industrial upgrading? The existing research lacks the discussion on the internal mechanism of this topic. Therefore this paper further investigates the influence channels of research topics by introducing the mechanism of intermediary and regulatory effect. We examine the intermediary effect mechanism from the perspective of technological innovation and the regulatory effect mechanism from the perspectives of marketization and Internet popularity.

The remaining chapters of this paper are organized as follows. The second chapter puts forward the theoretical hypothesis of artificial intelligence and industrial upgrading. The third chapter describes the use of empirical analysis methods, including measurement model setting, index measurement and data sources. The fourth chapter introduces the empirical estimation results. Empirical test the relationship between artificial intelligence and industrial upgrading, including robustness test and heterogeneity test. The fifth chapter discusses the internal mechanism of the relationship between the two, including intermediary effect mechanism and regulatory effect mechanism. The sixth chapter summarizes the research of this paper, puts forward relevant policy suggestions and the shortcomings of this research.

2. Theoretical mechanism and research hypothesis

As a new factor of production, artificial intelligence uses emerging technologies to reshape productivity and lead the transformation of production relations (Bogachov et al., 2020). From a macroeconomic perspective, artificial intelligence has a profound impact on technological progress and productivity growth. Artificial intelligence improves management efficiency and resource allocation efficiency, from improving the efficiency of specialized division of labor to improving the efficiency of diversified division of labor, and expanding the boundaries of production possibilities (Wu et al., 2020). From the perspective of meso industry, intelligent technology forms an economic environment of economies of scale, economies of scope and long tail effect. Artificial intelligence promotes the intelligent upgrading and transformation of the upstream, midstream and downstream of the industrial chain, and realizes incremental output through continuous penetration into industrial development. The upstream industry increases the supply of raw materials and intermediate products for the midstream industry through intelligent technology research and development, and the downstream industry obtains timely feedback on product application (Ge et al., 2020). From the perspective of micro enterprises, artificial intelligence helps enterprises reduce costs, increase efficiency and expand business benefits. Big data technology and intelligent platform realize the integration, processing and analysis of data, which not only promotes the intelligent transformation of enterprise production mode, business process and product service, but also improves the management level, product and service quality of enterprises.

H1. Artificial intelligence improves the advanced level of industry.

Artificial intelligence realizes a high degree of adaptation between the industrial supply side and the consumer demand side, and effectively corrects the problem of unbalanced and insufficient development. At the supply side level, artificial intelligence has derived new ways of division of labor and cooperation among industries to improve resource utilization efficiency through rational allocation and integration of production factors. Artificial intelligence can make full use of big data, cloud computing and other technologies to collect information and accurately predict changes in market supply and demand (Ruiz-Real et al., 2020). The supply side is constantly upgraded to adapt to the demand side, so as to realize the intellectualization of production links. This will not only enhance the industrial operation capacity, but also alleviate the problems of production inventory backlog and capital turnover difficulties (Acemoglu & Restrepo, 2018). At the demand side level, artificial intelligence is widely used in various service scenarios, and intelligent technology is deeply integrated into innovation chain and industrial chain. For instance, enterprises promote the construction of smart platform, smart payment and smart logistics system. By realizing the seamless connection of information flow, capital flow and real logistics, the consumption development environment is optimized (Feizabadi, 2022). Intelligent technology efficiently matches the market demand, and promotes the extension of the industry to the high-end value chain by improving the utilization efficiency of industrial scarce resources and the sharing degree of high-quality resources (Chen, 2020).

H2. Artificial intelligence promotes industrial rationalization.

Artificial intelligence leads the second machine revolution, promotes the leap-forward development of technology, and realizes industrial upgrading driven by innovation diffusion. Artificial intelligence can realize human mental work and creative activities. For instance, it is widely used in scientific research activities such as material identification, biomedicine and so on. In the fields of digital modeling and emergency rescue, artificial intelligence is widely endowed with the right to analyze, make decisions and create innovations (Galaz et al., 2021). As a general technology, artificial intelligence improves the process of technological innovation and performance. By promoting complementary innovation, it has a great impact on technological innovation and economic development, thus bringing about a multiplier effect (Kromann et al., 2019). Intelligent technology promotes the rational flow and efficient agglomeration of highly skilled talents, and improves R&D efficiency by shortening R&D cycle and saving R&D cost (Alrowwad et al., 2020). Artificial intelligence attracts technological innovation "clusters". The technology promotion and commercial operation of complementary innovation will give birth to more emerging industries. Furthermore, artificial intelligence accelerates the transformation of industrial technology paradigm and continuously improves the adaptability to changes in the external environment, so as to obtain the market competitive advantage of disruptive innovation (Liu et al., 2020).

H3. Artificial intelligence promotes the upgrading of industrial structure by promoting technological innovation.

The market mechanism can stimulate the enthusiasm of producers, and the market price can reasonably reflect the scarcity of resources and the supply and demand of products, so as to provide reasonable guidance for production allocation (Geng et al., 2021). An effective market is conducive to cross regional competition and cooperation, and cities with higher degree of marketization have less repetitive construction. Form economies of scale through mergers, acquisitions, and new market development, improving the efficiency of technological innovation (Chen et al., 2021). A high level of marketization indicates that the product and factor markets are well developed. The more perfect the development of factor market, the more it can promote the transfer efficiency of talents, capital, innovation and other factors among industries. The resource allocation among industries is improved by reducing production costs (Jiang et al., 2020). Product marketization reduces the threshold for international intelligent products to enter the local market and promotes fair competition in the domestic market. The entry of high-level intelligent enterprises will bring advanced intelligent technology imitation opportunities and management experience to local enterprises, and promote the intelligent development of regional industries (Hao et al., 2021).

H4. Regions with a higher degree of market development can strengthen the role of artificial intelligence in promoting industrial upgrading.

The Internet promotes the formation of new technologies, new industries and new business models, and is an important driving force for modern industrial upgrading. Artificial intelligence makes use of the connection, calculation and analysis capabilities of the Internet to improve the quality and efficiency of the industrial supply system and promote the development of production in the direction of flexible manufacturing and green manufacturing (Wang et al., 2020). Intelligent environment requires network communication technology to connect control systems, industrial equipment and production line robots to create production information. In the automation system, whether data can be obtained and transmitted in time depends on the development level of the Internet (Zheng et al., 2018). The wide application and development of Internet technology has accelerated the integration, dissemination and diffusion of information in regional intelligent systems (Arthur, 2007). The Internet can realize the interconnection of people, machines and things, build a new industrial production and service system with comprehensive connection of the industrial chain, and promote the high-end intelligence of production equipment (Glavas & Mathews, 2014). The Internet has the characteristics of increasing "marginal effect" on technological innovation. By providing high-end and high-quality network technology services to application departments, it can lower the threshold for enterprises to obtain market information and provide a good network information foundation for industrial upgrading (Cassetta et al., 2020).

H5. The more developed regions of the Internet can strengthen the role of artificial intelligence in promoting industrial upgrading.

3. Research design

3.1. Measurement model construction

Based on the above theoretical analysis, in order to explore the impact of artificial intelligence on industrial structure upgrading, this paper constructs the following basic test model:

$$\ln is_{it} = \alpha_0 + \beta_0 \ln ai_{it} + \delta_0 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{1}$$

Among them, $\ln is_{it}$ is the explained variable, indicating industrial upgrading, which is divided into industrial advancedization $\ln isu_{it}$ and industrial rationalization $\ln isr_{it}$. $\ln ai_{it}$ is the core explanatory variable, representing the artificial intelligence level of city i in year$t$. β_0 is the action coefficient of artificial intelligence to promote industrial upgrading. $\ln control_{it}$ is the control variable, indicating the relevant variables affecting industrial upgrading. δ_0 is the estimation coefficient of the control variable. σ_i is urban fixed effect, and ε_{it} is the random error term of the model. Subscripts i and t are city and year respectively.

3.2. Variable selection

In the study samples, because some cities such as Turpan and Nyingchi lack many data values, this part of the samples is excluded. In this context, this paper selects 5700 sample data from 285 cities in China from 2000 to 2019. Relevant data come from "China Urban Statistical Yearbook", Statistical Yearbook of prefecture-level cities, EPS database, SRTM database, CNRDS database, Baiteng.com patent search and the State Intellectual Property Office. Meanwhile, the missing phenomenon of individual data is filled by interpolation method. In order to reduce heteroscedasticity and other problems, the measurement indicators are treated with logarithm.

3.2.1. Explained variables

Industrial structure advancedization (*lnisu*). The industrial form from low-level to high-level is the process of the industry evolving from low value-added to high value-added and low-tech to high-tech. Referring to the method of Fu (2010), GDP is divided into three parts according to the three industries, and the industrial added value of each part accounts for the proportion of GDP as the component of the space vector, and a set of three-dimensional vector $X_0 = (x_{1,0}, x_{2,0}, x_{3,0})$ is constructed. Calculate the included angles θ_1, θ_2 and θ_3 between X_0 and vectors $X_1 = (1,0,0)$, $X_2 = (0,1,0)$ and $X_3 = (0,0,1)$ arranged from low to high in the industrial level respectively:

$$\theta_j = \arccos\left(\frac{\sum_{i=1}^{3}(x_{i,j}\cdot x_{i,0})}{\sum_{i=1}^{3}\left(x_{ij}^2\right)^{1/2}\cdot\sum_{i=1}^{3}\left(x_{i,0}^2\right)^{1/2}}\right), j = 1,2,3 \tag{2}$$

Finally, the formula of the industrial advanced value *ISU* is as follows:

$$ISU = \sum_{k=1}^{3}\sum_{j=1}^{k}\theta_j \tag{3}$$

Industrial advancedization is a positive indicator. The greater the *ISU* value, the higher the level of industrial advancedization. The closer the *ISU* value is to 0, the lower the level of industrial advancedization.

(2) Industrial structure rationalization (*lnisr*). The improvement of inter industry coordination ability and correlation level is conducive to promoting the dynamic balance of industrial structure and improving industrial quality. Industrial rationalization mainly discusses how to solve the problem of mutual adaptation of supply and demand structure. The formula is:

$$ISR' = \sum\nolimits_{i=1}^{n} \left| \frac{Y_i/L_i}{Y/L} - 1 \right| = \sum\nolimits_{i=1}^{n} \left| \frac{Y_i/Y}{L_i/L} - 1 \right| \tag{4}$$

In the above formula, ISR' represents the degree of structural deviation. Y is the output value, L is the employment, i is the industry, and n is the number of industrial sectors. However, the deviation degree of industrial structure "equates" all industries, ignores the important degree of each industry in the economic weight, and the calculation of absolute value also brings inconvenience to the research. Therefore, the Theil index introduced by Gan et al. (2011) is used for reference to measure industrial rationalization. The formula is as follows:

$$ISR = \sum\nolimits_{i=1}^{n} \left(\frac{Y_i}{Y}\right) \ln\left(\frac{Y_i}{L_i} / \frac{Y}{L}\right) \tag{5}$$

The degree of industrial deviation is a reverse index. The greater the *ISR* value, the greater the deviation of industrial structure and the lower the level of industrial rationalization. The closer the *ISR* value is to 0, the closer the industrial structure is to an equilibrium state, and the higher the level of industrial rationalization.

3.2.2. Core explanatory variables

Academic circles often use computer software industry fixed asset investment (Borland & Coelli, 2017), robot installation density (Liu et al., 2020) and related composite index system (Sun & Hou, 2019) to measure artificial intelligence. However, the above methods have great limitations. It is not only difficult to accurately cover and measure the development of artificial intelligence, but also difficult to effectively quantify the data to the urban level. Many scholars propose to use keyword retrieval method to identify the number of patent applications related to artificial intelligence (Joung & Kim, 2017; Kim et al., 2018). This provides new ideas for relevant issues at the urban level. Inspired by this, we take the patent database of baiting website[1] as the data source and identify the number of patent applications[2] containing artificial intelligence related keyword information such as patent titles or abstracts by setting specific periods and cities as constraints. This paper selects 27 keywords from 5 dimensions such as algorithm, data, computing power, application scenario and related technology (Table 1). In order to avoid double counting, we deleted the duplicate values with the same patent application number, and finally obtained the panel data of 285 cities from 2000 to 2019. The patent search method has the following three advantages. First, scientific. It can avoid the measurement error of artificial intelligence and evaluate the development level of artificial intelligence more comprehensively. Second, rationality. It is beneficial to eliminate the endogeneity problem caused by the mutual influence and reverse causality between economic variables and

Table 1. Retrieval of patent applications of relevant keywords of artificial intelligence.

N	Dimension	Keyword retrieval
1	algorithm	deep learning, machine learning, genetic algorithm, neural network
2	data	big data, natural language processing, machine vision, computer vision
3	computing power	expert system, complex system, cloud computing
4	application scenario	intelligent robot, industrial robot, intelligent manufacturing, intelligent control, automatic driving, UAV, speech recognition, image recognition, face recognition, fingerprint recognition, biometrics
5	related technology	artificial intelligence, intelligent technology, robot technology, automation technology, human-computer interaction

Source: The Authors.

reduce the model estimation error. Third, creativity. Bring more micro data for the study of artificial intelligence related issues at the urban level.

3.2.3. Mediating and moderating variables

What is the specific path of artificial intelligence affecting the level of industrial structure? This paper focuses on examining the intermediary effect mechanism from the perspective of technological innovation, and uses the number of patent applications to measure the level of technological innovation (*lntech*). The regulation effect mechanism is investigated from the perspectives of marketization and Internet. The marketization level is measured by the proportion of private and individual employment in the total employment (*lnmarket*). Internet penetration is measured by the proportion of Internet broadband access users in the total resident population (*lnnet*).

3.2.4. Instrumental variables

This paper looks for appropriate instrumental variables to reduce the endogenous problems caused by mutual causality and missing variables in the model. In this context, artificial intelligence mean and terrain relief are used as instrumental variables respectively. Among them, China altitude data (DEM) is used to measure topographic relief, which is from SRTM database. Using ArcGIS 10.5 software analysis tools and overlaying Chinese city shp basemap files to extract raster data. The selection basis and calculation method of instrumental variables are reflected in the chapter of empirical analysis.

3.2.5. Control variables

In order to more accurately evaluate the impact of artificial intelligence on urban industrial upgrading, this paper controls other factors that may affect industrial upgrading. Population density level (*lnpop)* is measured by dividing the population by the administrative area. Infrastructure level (*lninstra*) is measured by highway mileage. The level of human capital (*lnedu*) is measured by the number of students per 10000. The level of openness (*lnfdi*) is measured by the proportion of foreign direct investment in GDP. Government intervention (*lngov*) is measured by the proportion of fiscal expenditure in GDP. Economic growth (*lnpgdp*) is measured by per capita GDP. According to the "EKC" curve hypothesis, there is a nonlinear relationship between economic development level and industrial structure. Therefore, we add the square term of per capita GDP to the empirical regression. Enterprise size (*lncomp*) is measured by the number of industrial enterprises above designated size.

Table 2. Stability test.

	Original value				First-order difference value			
Variable	LLC test	P value	IPS test	P value	LLC test	P value	IPS test	P value
lnisu	−8.52	0.00	−6.90	0.00	−34.08	0.00	−46.31	0.00
lnisr	−2.50	0.00	−2.97	0.00	−67.39	0.00	−55.33	0.00
lnai	−3.91	0.00	−2.92	0.00	−39.57	0.00	−39.08	0.00
lnpop	−19.66	0.00	−13.51	0.00	−53.68	0.00	−58.58	0.00
lninstra	−31.18	0.00	−51.87	0.00	−81.59	0.00	−55.14	0.00
lnedu	−24.50	0.00	−17.28	0.00	−50.54	0.00	−49.09	0.00
lnfdi	−20.89	0.00	−15.69	0.00	−48.38	0.00	−48.92	0.00
lngov	−14.59	0.00	−8.68	0.00	−13.35	0.00	−27.20	0.00
lnpgdp	−54.06	0.00	−6.90	0.00	−32.95	0.00	−11.65	0.00
lncomp	−9.93	0.00	−3.67	0.00	−36.87	0.00	−31.34	0.00

Source: The Authors.

4. Empirical research

4.1. Stability analysis

The panel data contains two dimension information: time series and cross section. Panel data can provide comprehensive, comprehensive and dynamic information for research, which is helpful to solve the measurement problems such as missing variables. However, due to the problems of deterministic trend, structural change or random trend, panel data also has the possibility of unit root. Therefore, in order to measure the effectiveness of the model and avoid the pseudo regression problem, we need to test the stationarity of the panel data. In order to improve the reliability of the inspection, we use both the LLC inspection and the IPS inspection. The panel unit root test results of the measurement indicators and their first-order difference values in this paper are shown in Table 2. The results show that the results of the two unit root test methods are both significant at the 1% confidence level, that is, the null hypothesis containing the unit root is rejected. The test results show that the quantitative index data in this paper have good stationarity.

4.2. Empirical analysis

4.2.1. Benchmark regression

The benchmark regression of the impact of artificial intelligence on industrial upgrading is shown in Table 3. Among them, columns (1) and (2) are listed as static and dynamic panel regression models of the impact of artificial intelligence on industrial advancedization. The empirical results show that artificial intelligence can significantly promote industrial upgrading in both short-term and long-term ($\beta = 0.0082$, $p < 0.01$, Model 1; $\beta = 0.0044$, $p < 0.01$, Model 2). Therefore, H1 is supported. On the one hand, artificial intelligence gathers resources quickly across time, space and industries through intelligent technology. By cultivating new forms of human-computer collaboration and data-driven, resource factors drive the development of knowledge and technology, and accelerate the innovation, transfer and transformation of industrial achievements. On the other hand, intelligent technology is increasingly infiltrating key links such as product R&D, design and manufacturing. New technologies give birth to new business formats, accelerate industrial branding and high-end

Table 3. Benchmark regression.

Variable	Model (1) *lnisu*	Model (2) *lnisu*	Model (3) *lnisr*	Model (4) *lnisr*
lnisu (-1)		0.4970***		
		(0.0530)		
lnisr (-1)				0.5250***
				(0.0288)
lnai	0.0082***	0.0044***	−0.0144***	−0.0110***
	(0.0008)	(0.0006)	(0.0027)	(0.0015)
lnpop	0.0130**	0.0050	−0.0369*	−0.0092
	(0.0056)	(0.0040)	(0.0215)	(0.0108)
lninstra	−0.0132***	−0.0083***	0.0203***	0.0176***
	(0.0023)	(0.0018)	(0.0074)	(0.0044)
lnedu	0.0031	0.0003	−0.0037	0.0027
	(0.0030)	(0.0019)	(0.0047)	(0.0030)
lnfdi	0.0035*	0.0058***	−0.0124**	−0.0151***
	(0.0020)	(0.0013)	(0.0053)	(0.0032)
lngov	0.0126***	0.0138***	−0.0168***	−0.0179***
	(0.0019)	(0.0015)	(0.0048)	(0.0034)
lnpgdp	0.1390***	0.0434**	−0.2530***	−0.1140***
	(0.0274)	(0.0168)	(0.0831)	(0.0420)
lnpgdp^2	−0.0059***	−0.0018**	0.0134***	0.0060***
	(0.0014)	(0.0008)	(0.0042)	(0.0021)
lncomp	−0.0018	−0.0014	−0.0134***	−0.0023
	(0.0019)	(0.0012)	(0.0051)	(0.0029)
Constant	1.0560***	0.6860***	1.6150***	0.6120***
	(0.1390)	(0.1060)	(0.4250)	(0.2180)
Fixed effect	YES	YES	YES	YES
Observations	5,700	5,415	5,700	5,415
R-squared	0.608	0.702	0.110	0.300

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

development, and enhance industrial operating efficiency and comprehensive competitiveness (Spencer, 2017). Columns (3) and (4) are listed as the static and dynamic panel regression model of artificial intelligence on industrial rationalization (Deviation index of industrial structure). The empirical results show that artificial intelligence can significantly inhibit the deviation of industrial structure from equilibrium in both short-term and long-term, which is conducive to industrial rationalization ($\beta = -0.0144$, $p < 0.01$, Model 3; $\beta = -0.0110$, $p < 0.01$, Model 4). Therefore, H2 is supported. On the supply side, artificial intelligence accurately grasps the needs of customers and realizes the optimal allocation of production factors through intelligent services. On the demand side, artificial intelligence improves the efficiency of industrial resource utilization and high-quality resource sharing, and realizes the efficient matching between intelligent technology supply and market demand (Rainnie & Dean, 2020).

4.2.2. Robustness test

In order to test the robustness of the benchmark regression results, this paper tests the robustness from three aspects: eliminating the central city, winsorize treatment and instrumental variable method.

(1) Excluding central cities. The sample data of this paper include 285 cities, including municipalities directly under the central government, provincial capital cities, sub provincial cities and ordinary prefecture level cities. Generally speaking,

Table 4. Robustness test I: Elimination of central cities and Winsorize treatment.

Variable	Model (1) *lnisu* Excluding central cities	Model (2) *lnisu* Winsorize	Model (3) *lnisr* Excluding central cities	Model (4) *lnisr* Winsorize
lnai	0.0089***	0.0083***	−0.0159***	−0.0136***
	(0.0009)	(0.0008)	(0.0029)	(0.0027)
Constant	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES
Observations	4,980	5,700	4,980	5,700
R-squared	0.606	0.630	0.113	0.109

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

central cities such as municipalities directly under the central government, provincial capital cities and sub provincial cities have advantages over ordinary cities in resource allocation, location conditions and preferential policies. If these cities are included in the empirical regression at the same time, there may be some deviation in the results. Therefore, this paper deletes the samples of municipalities directly under the central government, provincial capital cities and sub provincial cities, and only investigates the samples of ordinary prefecture level cities. The results show that after excluding the samples of central cities, artificial intelligence can still significantly promote industrial advancedization ($\beta = 0.0089$, $p < 0.01$, Model 1). At the same time, AI significantly inhibits the deviation of industrial structure, which is conducive to industrial rationalization ($\beta = -0.0159$, $p < 0.01$, Model 3).

(2) Winsorize treatment. When the selected sample size is large enough, in order to prevent the influence of outliers on the research results, we usually need to shrink the tail of continuous variables. Based on this, we deal with the extreme values of the variables of the benchmark regression at the 1% and 99% quantiles. Numbers less than 1% are assigned a value of 1%, and numbers greater than 99% are assigned a value of 99%. The results show that artificial intelligence still significantly promotes industrial advancedization ($\beta = 0.0083$, $p < 0.01$, Model 2) and significantly inhibits the deviation of industrial structure, which is conducive to industrial rationalization ($\beta = -0.0136$, $p < 0.01$, Model 4). Therefore, we have reason to believe that the above conclusion is robust. (Table 4)

(3) Instrumental variable method. There are still endogenous problems in the model due to two-way causality and measurement error. On the one hand, the higher the economic level of the city, the higher the degree of industrial upgrading and productivity in general, and the local people are more willing and able to promote the development of artificial intelligence. Therefore, there may be a causal relationship between artificial intelligence and industrial upgrading. On the other hand, due to the availability of data or factors that cannot be measured, the variables cannot be measured, resulting in model errors. For example, artificial intelligence infrastructure layout, urbanization process (Beladi et al., 2020), urban attraction, cost of living (Cramer-Greenbaum, 2021), industrial development policies and other factors in different regions are difficult to accurately quantify and be incorporated into the empirical model as economic variables. In this paper, the instrumental variable method is used to further solve the endogenous problem of the model. Referring to the practices

Table 5. Robustness test II: Instrumental variable method.

Variable	Model(1) *lnisu*	Model(2) *lnisu*	Model(3) *lnisr*	Model(4) *lnisr*
lnisu (-1)	0.3900***	0.3700***		
	(0.1270)	(0.1060)		
lnisr (-1)			−0.5150**	0.1120
			(0.2150)	(0.6820)
lnai	0.0081**	0.0096***	−0.0450***	−0.0471***
	(0.0034)	(0.0036)	(0.0133)	(0.0180)
Constant	YES	YES	YES	YES
Controls	YES	YES	YES	YES
AR(2)	1.02	1.10	1.14	1.20
Sargan test-P	0.694	0.277	0.500	0.254
Hansen test-P	0.322	0.558	0.308	0.184

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

of Fisman and Svensson (2007) and Liu et al. (2020), the mean value of artificial intelligence and topographic relief are used to construct tool variables respectively (Table 5). Generalized moment estimation (GMM) is commonly used to solve the endogenous problem of models. It is divided into differential GMM and system GMM. Since the system GMM combines the differential model and the horizontal model, the estimation efficiency can be improved compared with the differential GMM Estimation (Liu & He, 2019). Therefore, this paper uses the systematic GMM method for further regression to solve the endogenous problem.

Columns (1) (2) and (3) (4) take AI mean and terrain relief as tool variables respectively. The average value of artificial intelligence in different cities can not be directly affected by the behavior of a single enterprise. At the same time, the average level of artificial intelligence in cities is correlated with explanatory variables. Therefore, as a tool variable, the mean value of artificial intelligence meets the exogenous and correlation conditions of tool variable selection. Topographic relief affects the installation, commissioning and efficiency of equipment related to intelligent technology. At the same time, topographic relief is not affected by relevant intelligent economic variables. Thence, as a tool variable, topographic relief meets the exogenous and correlation conditions of tool variable selection. Considering that the topographic relief has a negative impact on the installation, commissioning and efficacy of intelligent infrastructure equipment, we take the reciprocal of the urban topographic relief variable to obtain a positive index. Therefore, it is reasonable to take the average value of artificial intelligence and topographic relief as the instrumental variables of the measurement model in this paper. Because the average value of artificial intelligence and topographic relief are in the form of section data, they can not be directly used for econometric analysis of panel data. Referring to Nunn and Qian (2014), the dummy variable of each year is introduced as an intersection and multiplication term with the section tool variable to construct the panel tool variable. The results show that the estimation results further confirm the robustness of the model. And the sequence correlation test did not reject the original hypothesis of second-order autocorrelation. In addition, combined with the sargan test and the hansen test, it can be seen that the model does not have the problem of over-identification, and

Table 6. Heterogeneity test I: Heterogeneity of urban scale of industrial upgrading.

Variable	Model(1) Big cities *lnisu*	Model(2) Small-Medium cities *lnisu*	Model(3) Big cities *lnisr*	Model(4) Small-Medium cities *lnisr*
lnai	0.0081***	0.0073**	−0.0136***	−0.0147
	(0.0008)	(0.0027)	(0.0029)	(0.0110)
Constant	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES
Observations	5,520	180	5,520	180
R-squared	0.616	0.686	0.112	0.176

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

the construction of instrumental variables is effective. The results of this part provide further support for the benchmark regression results.

4.2.3. Heterogeneity test

(1) Heterogeneity of urban scale. Urban scale is closely related to labor employment, capital agglomeration level, technological innovation transfer and transformation and other factors. In cities of different scales and levels, there may be differences in the promotion of industrial upgrading by artificial intelligence. Facing the upsurge of artificial intelligence development, what policies and plans should cities at different levels formulate? In order to answer these questions, we test whether there are differences in the impact of artificial intelligence on industrial upgrading for different city sizes. According to the city scale classification standard issued by the State Council in 2014, the sample classification in this paper is based on the following: cities with a permanent population of less than one million are small and medium-sized cities; cities with a population of more than one million are large cities[3].

Columns (1) (3) are listed as the results of heterogeneity regression for large cities, and columns (2) (4) are listed as the results of heterogeneity regression for small cities (Table 6). The results are as follows. On the one hand, in large-scale cities, artificial intelligence plays a great role in promoting industrial advancedization ($\beta = 0.0081$, $p < 0.01$, Model 1). In medium and small-scale cities, artificial intelligence plays a significant role in promoting industrial advancedization, but the estimation coefficient decreases compared with large cities ($\beta = 0.0073$, $p < 0.05$, Model 2). On the other hand, in large-scale cities, artificial intelligence helps to restrain the deviation of industrial structure and has a positive impact on industrial rationalization ($\beta = -0.0136$, $p < 0.01$, Model 3). However, in medium and small-scale cities, artificial intelligence has no significant inhibitory effect on the deviation of industrial structure ($\beta = -0.0147$, $p > 0.10$, Model 4). The possible reason is that large cities have a sound industrial structure system, more high-quality large enterprises and a large number of highly skilled labor force, which is conducive to accelerating the agglomeration of intelligent industrial resources and playing a "leading role" (Zhou et al., 2021). Due to the lack of intelligent basic elements in small and medium-sized cities, the construction of high-end intelligent facilities needs a lot of capital to maintain. There is no doubt that it has increased the pressure of industrial upgrading in small and medium-sized cities. Therefore, compared with large cities, artificial

Table 7. Heterogeneity test II: Heterogeneity of industrial upgrading.

Variable	Model (1) *lnisu* Q25	Model (2) *lnisu* Q 50	Model (3) *lnisu* Q 75	Model (4) *lnisr* Q 25	Model (5) *lnisr* Q 50	Model (6) *lnisr* Q 75
lnai	0.0059***	0.0072***	0.0070***	−0.0113***	−0.0065***	−0.0058***
	(0.0005)	(0.0004)	(0.0004)	(0.0019)	(0.0023)	(0.0026)
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Observations	5,700	5,700	5,700	5,700	5,700	5,700
R-squared	0.425	0.432	0.420	0.172	0.205	0.210

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

intelligence in small and medium-sized cities plays a relatively small role in the upgrading of industrial structure.

(2) Heterogeneity of industrial upgrading. Quantile regression is a weighted least square method based on different quantiles. This method can fully reflect the information of each part of the whole sample distribution, and fully consider the influence of sample extreme value. Therefore, this paper uses quantile method to investigate the heterogeneous impact of artificial intelligence on industrial upgrading in different quantiles. Table 7 reports the results of measuring the impact of artificial intelligence on industrial upgrading under different industrial upgrading levels with 25%, 50% and 75% as representative quantiles. A higher quantile indicates a higher degree of industrial advancedization, but also a higher degree of industrial deviation and a lower degree of industrial rationalization. It can be seen from the results that the maximum action coefficient of artificial intelligence on industrial advancedization appears at 50% quantile, and the action coefficient at 75% quantile is greater than that at 25%. It shows that artificial intelligence plays a greater role in promoting cities with high industrial advancedization level. In cities with low-level industrial advancedization, the force of artificial intelligence to promote industrial advancedization has been reduced. The maximum effect coefficient of artificial intelligence on industrial deviation appears at the 25% quantile. Compared with cities with low industrial rationalization, artificial intelligence plays a greater role in promoting cities with high industrial rationalization level. In cities with high industrial upgrading, the positive role of artificial intelligence is obvious. The possible reason is that cities with high industrial upgrading level have complete industrial systems, clear gradients and prominent cluster effects. Due to the good foundation of industrial coordinated development, cities with high level of industrial upgrading are more conducive to expand the role of artificial intelligence in promoting industrial upgrading (Li & Wang, 2019).

5. Further analysis

In order to deeply explore the influence relationship between artificial intelligence and industrial upgrading, we still need to analyze the internal mechanism and principle. Based on the idea of Peng et al. (2021), this paper discusses the action mechanism of artificial intelligence on industrial upgrading from two methods: intermediary mechanism and regulatory effect mechanism. The model is constructed as follows:

Table 8. Intermediary effect test: Technological innovation mechanism.

Variable	Model(1) *lnisu*	Model(2) *lntech*	Model(3) *lnisu*	Model(4) *lnisr*	Model(5) *lnisr*
lnai	0.0082***	0.2500***	0.0073***	−0.0144***	−0.0139***
	(0.0008)	(0.0191)	(0.0008)	(0.0027)	(0.0028)
lntech			0.0039***		−0.0019
			(0.0015)		(0.0051)
Bootstrap test			0.0078***		−0.0267***
			(0.0006)		(0.0025)
Constant	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES	YES
Observations	5,700	5,700	5,700	5,700	5,700
R-squared	0.608	0.888	0.610	0.110	0.110

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

$$\ln is_{it} = \alpha_0 + \beta_0 \ln ai_{it} + \delta_0 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{6}$$

$$M_{it} = \alpha_1 + \beta_1 \ln ai_{it} + \delta_1 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{7}$$

$$\ln is_{it} = \alpha_2 + \beta_2 \ln ai_{it} + \beta_2' M_{it} + \delta_2 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{8}$$

$$\ln is_{it} = \alpha_3 + \beta_3 \ln ai_{it} + \beta_3^{'} Adj_{it} + \delta_3 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{9}$$

$$\ln is_{it} = \alpha_4 + \beta_4 \ln ai_{it} + \beta_4' Adj_{it} + \beta_4'' \ln ai_{it} \times Adj_{it} + \delta_4 \ln control_{it} + \sigma_i + \varepsilon_{it} \tag{10}$$

Among them, equations (6) - (8) are the test steps of mediation mechanism, and equations (9) - (10) are the test steps of regulation mechanism. M_{it} represents the intermediate variable, Adj_{it} represents the adjustment variable, and the other formula variables are consistent with the benchmark model mentioned above. Among them, the judgment rules of mediation mechanism are as follows: if β_0, β_1 and β_2 are significant, and β_2 becomes smaller or significantly lower than β_0, it indicates that there is a partial mediating effect in the model. If β_0, β_1 are significant and β_2 is not significant, it indicates that the model has a complete mediating effect. If at least one of β_1 and β_2' is not significant, bootstrap shall be used for further inspection.

5.1. Analysis of intermediary mechanism

Following the test steps of mediating effect (Table 8), columns (1) (4) are listed as the benchmark regression, column (2) is listed as the regression model of artificial intelligence for mediating variables, and columns (3) (5) are listed as the model that incorporates mediating variable *lntech* into the benchmark regression. The results show that artificial intelligence significantly promotes technological innovation ($\beta = 0.2500$, $p < 0.01$, Model 2). Technological innovation plays a significant role in promoting industrial advancedization ($\beta = 0.0039$, $p < 0.01$, Model 3). For every 1% unit increase in artificial intelligence, technological innovation increases by 0.2500% unit, and industrial advancedization increases by 0.0039% unit. That is, artificial

Table 9. Regulatory effect test I: Market mechanism.

Variable	Model(1) *lnisu*	Model(2) *lnisu*	Model(3) *lnisr*	Model(4) *lnisr*
lnai	0.0082***	0.0072***	−0.0142***	−0.0115***
	(0.0008)	(0.0008)	(0.0027)	(0.0028)
lnmarket	0.0025**	0.0030**	−0.0077*	−0.0090**
	(0.0012)	(0.0012)	(0.0042)	(0.0043)
lnai × lnmarket		0.0022***		−0.0062***
		(0.0005)		(0.0017)
Constant	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES
Observations	5,700	5,700	5,700	5,700
R-squared	0.609	0.613	0.112	0.118

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

intelligence promotes industrial advancedization by promoting the level of technological innovation. Technological innovation has a certain inhibitory effect on the deviation degree of industrial structure ($\beta = -0.0019$, $p > 0.10$, Model 5). Since the estimation coefficient here is not significant, in order to improve the reliability of the mediation effect results, this paper further uses the bootstrap test, and we set the sampling times to 500. The results show that the estimated coefficient of the mediation effect of the bootstrap test is −0.0267, and it passes the 1% confidence level, which indicates that the model has mediation effect. That is, artificial intelligence can further restrain the industry from deviating from the equilibrium state by promoting the level of technological innovation, which is conducive to industrial rationalization. For every 1% unit increase in artificial intelligence, technological innovation increases by 0.2500% unit, which can restrain the deviation of the industrial structure by 0.0019% unit. At the same time, in columns (3) and (5), the estimation coefficient of artificial intelligence are smaller than that of benchmark regression. That is, technological innovation plays a partial intermediary effect in the influence process of artificial intelligence promoting industrial upgrading. To sum up, artificial intelligence promotes industrial upgrading by promoting technological innovation. Conclusions validate H3.

5.2. Analysis of regulation mechanism

5.2.1. Market-oriented mechanism

Columns (1) - (4) of Table 9 report the regression results of the regulatory effect of marketization. The results show that: Column (1) includes the adjustment variable marketization level, and marketization has a positive impact on industrial advancedization ($\beta = 0.0025$, $p < 0.05$, Model 1). Column (2) is a combination of artificial intelligence and marketization($lnai \times lnmarket$) based on column (1). The cross multiplication term has a positive regulatory effect on industrial advancedization ($\beta = 0.0022$, $p < 0.01$, Model 2). It shows that cities with a high degree of marketization strengthen the role of artificial intelligence in promoting industrial advancedization. On the contrary, it weakens the role of artificial intelligence in promoting industrial advancedization. Column (3) includes the level of marketization of regulatory variables, indicating that marketization is conducive to restraining the deviation

Table 10. Regulatory effect test II: Internet mechanism.

Variable	Model(1) *lnisu*	Model(2) *lnisu*	Model(3) *lnisr*	Model(4) *lnisr*
lnai	0.0076***	0.0064***	−0.0127***	−0.0069***
	(0.0008)	(0.0008)	(0.0026)	(0.0026)
lnnet	0.0051***	0.0057***	−0.0142***	−0.0168***
	(0.0014)	(0.0014)	(0.0043)	(0.0043)
lnai × *lnnet*		0.0008**		−0.0038***
		(0.0003)		(0.0011)
Constant	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES
Observations	5,700	5,700	5,700	5,700
R-squared	0.610	0.612	0.114	0.119

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.
Source: The Authors.

degree of industrial structure and promoting industrial rationalization ($\beta = -0.0077$, $p < 0.10$, Model 3). Column (4) is the intersection of artificial intelligence and marketization (*lnai* × *lnmarket*) based on column (3). Marketization helps to restrain the degree of industrial deviation and has a positive regulatory effect on the rationalization of industrial structure ($\beta = -0.0062$, $p < 0.01$, Model 4). It shows that cities with a high degree of marketization enhance the role of artificial intelligence in promoting industrial rationalization. On the contrary, it weakens the role of artificial intelligence in promoting industrial rationalization and verifies H4. The higher the degree of marketization, the more we can avoid the phenomenon of blind production and waste of resources caused by imperfect market mechanism, and improve productivity. In addition, factors such as demand, cost and profit in the market economy are used to force industrial upgrading (Zhang, 2021).

5.2.2. Internet mechanism

Columns (1) - (4) of Table 10 report the regression results of the regulatory effect of the Internet. Columns (1) and (3) are included in the moderating variable Internet penetration, and the results show that the Internet has a positive impact on industrial advancedization ($\beta = 0.0051$, $p < 0.01$, Model 1), and has a significant inhibitory effect on the deviation of industrial structure ($\beta = -0.0142$, $p < 0.01$, Model 3). Columns (2) and (4) are the results obtained by incorporating the multiplication term of artificial intelligence and Internet popularity (*lnai* × *lnnet*) based on columns (1) and (3). The Internet not only strengthens the role of artificial intelligence in promoting industrial advancedization ($\beta = 0.0057$, $p < 0.01$, Model 2), but also strengthens the inhibitory effect of artificial intelligence on the deviation of industrial structure ($\beta = -0.0168$, $p < 0.01$, Model 4). That is, cities with a high degree of Internet development are conducive to enhancing the role of artificial intelligence in promoting industrial upgrading. On the contrary, it weakens the role of artificial intelligence in promoting industrial upgrading. The H5 in this paper is verified. On the one hand, the Internet accelerates the information integration and diffusion of urban intelligent systems, and promotes the spillover of cutting-edge technologies. On the other hand, the Internet improves the use efficiency of innovative resources, widens the breadth and depth of intelligent technology activities, and speeds up industrial transformation and upgrading (Li & Cao, 2020).

6. Conclusion and recommendations

6.1. Conclusion

Under the background of accelerating the two-way integration of artificial intelligence and real economy, the promoting effect of artificial intelligence on industrial upgrading is gradually emerging. Based on the panel data of 285 cities in China from 2000 to 2019, this paper theoretically and empirically analyzes the impact of artificial intelligence on industrial upgrading. The results show that artificial intelligence is not only conducive to industrial advancedization, but also significantly inhibit the deviation of industrial structure from equilibrium, which is conducive to industrial rationalization. In addition, after adopting robust analysis methods such as excluding central city samples, winsorize treatment and instrumental variables method, the results of the study are still valid. Meanwhile, through the heterogeneity test, it is found that artificial intelligence plays a "leading role" in big cities. Relying on its superior resources, location and policy support, big cities take the lead in promoting the upgrading of industrial intelligence. Artificial intelligence plays a greater role in promoting cities with a higher level of industrial upgrading. Cities with a high level of industrial upgrading have a complete industrial system and a good foundation for coordinated development. The intermediary mechanism shows that technological innovation has a significant intermediary effect. Artificial intelligence promotes industrial upgrading by promoting technological innovation. The regulation mechanism shows that marketization and Internet have significant regulation effects. In cities with a high degree of marketization and Internet development, the role of artificial intelligence in promoting industrial upgrading can be strengthened.

6.2. Policy recommendations

In order to better promote the development of artificial intelligence and realize industrial transformation and upgrading, this paper puts forward the following policy suggestions. First, we should use artificial intelligence technology to realize industrial transformation and upgrading. On the one hand, it is necessary to strengthen the research and development of core technologies and key devices related to artificial intelligence, and deepen the integrated development of artificial intelligence and traditional manufacturing industry. On the other hand, there is a need to strengthen the dynamic tracking and monitoring of the development of artificial intelligence industry, build a statistical system of artificial intelligence industry, and provide high-quality data support for the development of artificial intelligence industry. Second, through the heterogeneity test of this paper, we get the following enlightenment: local governments should improve the policy system and create a favorable environment for innovation. Service systems such as AI standards, assessments, and intellectual property rights in big cities should be accelerated. In addition, the construction of industry training resource libraries, standard test data sets, and open platforms should be promoted. The government should promote the improvement of relevant preferential policies in big cities, especially the policies on talents, finance and taxation, and finance. Moreover, it makes sense to encourage large cities to carry out pilot and demonstration construction of smart cities, and provide experience and reference for the promotion of smart technologies in small and medium-sized cities. Third, through the mechanism analysis in this paper, we get the inspiration as follows: the government should encourage and support enterprises to establish artificial intelligence and intelligent manufacturing innovation centers, focusing on the research and development and promotion of common technologies in the application of artificial intelligence in manufacturing. Besides, industry associations should take the market as the driving force and enterprises as the main body to actively promote the cooperation of enterprises, universities and scientific research institutions in artificial intelligence area. Moreover, leading enterprises should play an exemplary and leading role, and support small and medium-sized enterprises to carry out all kinds of intelligent innovation development and application. At the same time, the government needs to help enterprises to speed up the construction of Internet big data centers, identification analysis systems, industrial Internet platforms, Internet internal and external networks and other infrastructure constructions, use the industrial Internet to achieve information and technology sharing, and achieve accurate matching and efficient connection of cross-regional and cross-industry resources.

6.3. Limitations and future research prospects

Up to now, this study still has several shortcomings. Firstly, the empirical sample needs to be expanded. The positive effect of artificial intelligence on industrial upgrading will be more obvious during the pandemic, but due to the availability of data, the latest data can not be used for further research in the demonstration. Future research can expand the time dimension, and the research objects can go deep into China's county-level cities or other industries, so as to improve the effectiveness of our research. Secondly, the internal mechanism of research needs to be enriched. This paper analyzes the internal mechanism only from the perspectives of technological innovation, marketization and Internet popularity, but there may be other influencing factors as mechanism variables. In the future research, we can explore the impact of institutional variables such as industrial agglomeration, institutional environment and inclusive finance, so as to enrich the theoretical mechanism framework. Finally, the endogeneity problem still has room for improvement. Although this paper adopts the instrumental variable method to reduce the endogenous problem of the model, there are still other methods to reduce the endogenous problem that can be applied to this paper. In the future research, we can try to find the exogenous policy impact and use the differences-in-differences method to do the quasi natural experiment of the pilot policy.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. Baiteng website: https://www.baiten.cn/
2. The number of patent applications includes the number of patents for invention, utility model, design and WIPO certification.
3. Divide city size according to source: http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm.

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