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Research article

Impact of artificial intelligence technology innovation on total factor productivity: an empirical study based on provincial panel data in China

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Abstract: As the focus of the new round of technological revolution, it is crucial to explore the role of artificial intelligence (AI) technology innovation in improving total factor productivity (TFP). Based on the data from 30 Chinese provinces from 2003 to 2021, this article measured AI innovation using the number of patent applications and empirically investigated the effects of AI technology innovation on TFP. The results demonstrated that AI technology innovation exerts significantly positive influences on the TFP. The mechanism analyses revealed that AI technology innovation improves TFP by upgrading industrial structures and promoting human capital. The subsample results indicated that the promotion effect of AI technology innovation on TFP is significant only in areas with high levels of marketization, financial development, and digital infrastructure. The panel quantile regression results indicated that as the TFP increases, the promoting effect of AI technology innovation on TFP gradually strengthens. This study offers comprehensive empirical evidence for understanding the impacts of AI technology innovation on TFP, giving a reference for further enhancing the level of AI development and promoting a sustainable economic development.

Keywords: Total factor productivity; artificial intelligence technology innovation; sustainable economic development; industrial structure upgrading; human capital

JEL Codes: O1, O3

1. Introduction

Improving total factor productivity (TFP) is crucial for sustainable economic development (Zeng et al., 2022); how to improve TFP has received considerable attention from the academic circle. Based on macroeconomic theory, technology innovation is one of the key drivers of TFP. Technology innovation inputs and outputs, as well as the spillover and diffusion of new technologies, have a direct impact on the improvement of regional TFP (Acemoglu et al., 2014). Different from the general technology innovation, as a strategic technology of the new round of technological revolution, artificial intelligence (AI) has profound effects in every aspect of the economy and society (Wang et al., 2023); so, will TFP be affected by the level of AI technology innovation? If AI technology innovation contributes to the improvement of TFP, what are the influential mechanisms behind it? How does AI technology innovation affect TFP heterogeneously under different conditions? A thorough discussion of the above issues is essential in promoting AI technology innovation to drive the high-quality development of the economy.

Correspondingly, the literature on the impact of AI on TFP is growing, but the relevant research has not yet reached a consensus, with two different views, as follows. One view is that AI technology innovation promotes TFP. At the micro level, Ren et al. (2023) empirically examined the impact of AI technology innovation on enterprises' TFP based on data from listed companies in China. Their study showed that AI technology innovation improves production efficiency by reducing costs and increasing efficiency in production, marketing, and management processes. Also based on firm-level data, Zhai and Liu (2023) argued that AI technology innovation improves firms' TFP through cost reduction, increased utilization of high-skilled labor, facilitated digital transformation, and enhanced innovation efficiency. At the macro level, Jiang and Li (2022), using data from 258 cities in China, examined the impact of AI technology innovation on the TFP of surrounding areas from the perspective of spatial economics. According to their study, the development of AI in central cities has promoted the TFP of peripheral cities through a spatial spillover effect, resulting in a "technology dividend".

Another viewpoint is that AI technology has not brought about TFP growth, and there is a "productivity paradox". Since Solow put forward the productivity paradox of information technology in 1987, academic circles have been discussing it continuously; with the breakthrough of AI technology, the Solow paradox in the era of AI has become an emerging research topic. According to Brynjolfsson et al. (2019), despite the continuous development of AI technology, measured productivity growth has declined by half in the past decade. In this regard, they put forward four possible explanations, namely false hopes, mismeasurement, redistribution, and implementation lags. Among them, implementation lags are considered to be the most important reason. However, Acemoglu and Restrepo (2019) believed that excessive automation may be the reason why the development of robots and AI has not contributed to the ideal growth of productivity.

In summary, the academic discussion on whether there is a productivity paradox in AI technology is not yet clear, and further in-depth research is necessary. Based on this, this article takes 30 provinces in China from 2003 to 2021 as samples and studies the core theme of the TFP improvement effect of AI technology innovation. This paper found that AI innovation has a promoting effect on China's TFP as a whole. The mechanism analysis results show that AI technology innovation enhances the TFP through two paths: promoting industrial structure upgrading and enhancing human capital. Additionally, we find that the promoting effects of AI technology innovation on TFP exist solely in the regions with high levels of marketization, financial development, and digital infrastructure.

The marginal contributions of the current study are as follows. First, this paper provides a more accurate and complete measure for AI technology innovation. In the measurement of AI technological progress, the existing literature generally selected the number of industrial robots as the proxy variable (Chang et al., 2023; Liu et al., 2020). However, this may lead to significant measurement bias, as industrial robots only represent a small portion of AI technologies. A small number of scholars consider using AI patents for measurement, but their recognition of AI patents is mostly based on simple keywords, which makes it difficult to comprehensively and accurately measure AI technology innovation. Given this, this paper used the identification method of the World Intellectual Property Organization (WIPO) combined with the Cooperative Patent Classification (CPC) code, International Patent Classification (IPC) code, and AI keywords to identify AI patents in a more accurate manner, to conduct a more scientific measurement of regional AI innovation level. Moreover, considering the lagging effect of AI innovation, and different from the existing studies that rely on the flow of AI patents to measure AI technology innovation, this paper uses the stock of AI patents to capture the impact of AI technology innovation on TFP in a more reasonable way.

Second, few studies have explored the supporting mechanism of the effect of AI technology innovation on TFP. Thus, this paper comprehensively explores the supporting mechanism from three aspects of marketization, financial development, and digital infrastructure. By doing so, we further clarify the inconsistency of results and reveal the potential reasons behind the Solow paradox in the era of AI.

Third, this paper also adopts the mediating effect model to examine how AI technology innovation affects TFP and the panel quantile regression model to study the impact of AI technology innovation on TFP under the difference of TFP. This is not only beneficial for supplementing related studies but also conducive to a better understanding of the impact of AI technology innovation on TFP.

2. Research hypotheses

2.1. Direct impact of AI technology innovation on TFP

According to Schumpeter's theory of innovation and endogenous growth, technological progress generated by innovative activities is an important endogenous factor in promoting economic growth, and digital technology innovation is the most powerful radiation-led field of innovation (Aghion et al., 2009; Aghion and Howitt, 1992). As a new generation of digital technology, AI has four characteristics: substitutability, creativity, synergy, and permeability, and the impact of AI technology innovation on TFP is as follows.

First, innovation in AI technology can reduce labor input in the production process and improve TFP. On the one hand, AI can become new virtual labor replacing humans in executing programmatic tasks, achieving intelligent automation of complex tasks, and directly improving production efficiency (Acemoglu et al., 2018). On the other hand, AI now has the ability to self-learning. AI technology has achieved a "dual" substitution effect for physical or mental workers, reducing the demand for medium- and low-skilled workers to a certain extent, and helping to improve labor production efficiency and overall economic growth rate (Graetz and Michaels, 2015).

Second, innovation in AI technology can promote the deep integration of AI technology with traditional production factors, enhance factor mobility, improve factor quality and allocation efficiency, and ultimately increase TFP (Purdy et al., 2017). The application of AI can supplement or enhance the productivity of other production factors, improve production factor mobility and utilization, and thus promote the TFP. Meanwhile, due to the fast iteration speed and short innovation cycle of AI technology, the application of AI can increase productivity by one or more orders of magnitude (Purdy et al., 2017). Besides, AI technology has high penetration and is applied to various aspects of the economy and society, promoting complementary innovation and development (Nordhaus, 2021). At present, AI technology has been widely applied in fields such as autonomous driving, disease diagnosis and treatment, facial recognition, and personalized product recommendation, promoting innovative development in different industries.

Following the above theoretical analyses, we have the following research hypothesis:

H1: The improvement of AI technology innovation will directly promote the improvement of TFP.

2.2. Indirect impact of AI technology innovation on TFP

As a new generation of information technology, AI technology facilitates the mobility and aggregation of skilled professionals in innovation factors (Alrowwad et al., 2020). Therefore, AI has the role of attracting the agglomeration of technology innovation elements and will also give rise to more emerging industries. AI technology innovation can empower the real economy, so that resources are transformed in the direction of high technology industries, and continuously promote the industrial structure upgrading. At the same time, the industrial structure upgrading will also promote the improvement of TFP. First, industrial structural upgrading helps to steer the flow of innovative factors. Thus, industrial structure upgrading can promote TFP by increasing the level of digitization and intelligence among industries. Second, as factors of production flow to more efficient sectors, the scale of operations in the sector can be expanded and economies of scale can be realized, thus contributing to the increase in TFP (Valli and Saccone, 2009). Based on these analyses, we propose the following hypothesis:

H2a: AI technology innovation raises the TFP by promoting industrial structure upgrading.

From the substitutability of AI, with the continuous innovation and development of AI technology, its substitution effect on the middle and low-skilled labor force is increasing (Lei and Wang, 2023). Therefore, the innovation of AI technology promotes the shift of labor structure from physical labor demand to mental labor demand, which is conducive to the high-end development of labor factors and thus improves human capital. From the creativity of AI, innovation in AI technology will lead to a large number of production tasks containing cutting-edge technology, and a labor demand that can form a good fit with AI technology emerges, forcing the labor force to learn AI-related technologies, improve skill levels, and drive the improvement of human capital level (Galor and Moav, 2002). Meanwhile, human capital is regarded as a significant factor in improving TFP (Xiong and Chen, 2022). Human capital affects the ability to absorb and learn new technologies in regions with high technology levels (Kijek and Kijek, 2020). The investment of high-skill human capital can promote the use of new technologies by enterprises, adjust their existing production and operation models, thereby improving their production and operation efficiency, and promote the improvement of regional TFP (Lei and Wang, 2023).

Thus, we propose this research hypothesis:

H2b: AI technology innovations contribute to the TFP by raising the level of human capital.

2.3. Moderating effects of marketization, financial development, and digital infrastructure

First, a higher level of regional marketization means that the government's intervention is smaller, which is more conducive to competition and cooperation among enterprises, thus improving innovation efficiency. With the gradually weakening impact of government regulation on AI innovation, the competition between enterprises is greater, and factor flow is freer (You and Xiao, 2022), which can better promote the differentiated development of AI technology and promote the realization of AI technology innovation to enhance TFP. Second, the higher the degree of regional marketization, the more developed the product and factor markets are. By reducing production costs and improving resource allocation between industries (Jiang et al., 2021), innovation factors will flow and allocate towards high-tech industries represented by intelligent technology, thereby promoting the realization of the productivity improvement effect of AI technology innovation to a greater extent.

Thus, we propose the following research hypothesis:

H3a: The contribution of AI technology innovation to TFP is moderated by the level of marketization.

First of all, in the process of commercialization of AI technology, the financial market plays a key role in financial support. The higher the level of regional financial development, the more financial support it can provide for innovation entities and related enterprises, to provide a good financial environment for innovation activities (Wang et al., 2022). Meanwhile, the lower the level of financial development, the more unfavorable the commercialization and development of AI technology. Second, there are certain risks in the commercialization of AI technology. Financing constraints and distortion of credit allocation will seriously restrict technology research and development (Hopenhayn, 2014). The improvement of the financial market level can significantly improve market transparency, restrain the imbalance of credit allocation (Lee et al., 2019), effectively reduce the R&D risk and innovation investment risk of AI innovation, and thus improve the efficiency of AI technology innovation in promoting TFP. Finally, the core technology of AI, as the main driving force, empowers the participating subjects and business links of the financial industry, which can help the real economic sector overcome problems such as information asymmetry (Tang et al., 2020) and help to enhance resource allocation efficiency, thus providing internal impetus for the improvement of quality and efficiency of the economy (Tang et al., 2019).

Thus, this study proposes the following research hypothesis:

H3b: The contribution of AI technology innovation to TFP is moderated by the level of financial development.

First, digital infrastructure is a series of new types of infrastructures based on information networks and centered around data collection, storage, processing, computation, transmission, application, and security, playing a significant role in the convergence and diffusion of data elements and digital technologies. From this point of view, the higher the level of digital infrastructure in the region, the more conducive to the integration and complementarity of AI and cloud computing, blockchain, and other new-generation information and communication technologies, which is more conducive to the promotional effect of AI innovation on TFP. Second, digital infrastructure can break through geographic location limitations, dramatically increase the scope and popularity of data and knowledge dissemination, and reduce the cost of data and knowledge acquisition (Tang et al., 2021), which helps to promote the growth of the digital economy scale, enhance the openness of the innovation ecosystem, and create a more inclusive and open environment for enterprise innovation (Wang et al., 2022). Therefore, the higher the level of digital infrastructure, the more innovative resources will be attracted to the cluster, reducing the cost and risk of AI technology innovation, and providing a more convenient channel for AI innovation.

H3c: The effect of AI technology innovation on TFP is moderated by digital infrastructure.

3. Research design

3.1. Econometric model

We mainly use the panel fixed-effects model to examine the impact of AI technology innovation on TFP. First, we construct the following model:

$$\mathrm{lnTFP}_{it} = \beta_0 + \beta_1 \mathrm{lnAI_{it}} + X_{it}^{T}\gamma + \lambda_1 T + \mu_i + \varepsilon_{it} \tag{1}$$

$$X_{it} = (\mathrm{FIN_{it}}, \mathrm{GOV_{it}}, \mathrm{URB_{it}}, \mathrm{OPEN_{it}}, \mathrm{lnPRGDP_{it}}, \mathrm{INF_{it}}) \tag{2}$$

$$\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6) \tag{3}$$

In Equation (1), LNTFP is the logarithm of TFP; lnAI is the logarithm of AI technology innovation; the control variables are FIN, GOV, URB, OPEN, lnPRGDP, and INF, which denote the financial development, government intervention, urbanization, opening up, economic development, and the level of informatization, respectively. Furthermore, i and t refer to the province and year, respectively; u_i represents the provincial individual fixed effects; T represents time trend term; and ε_{it} is random disturbances.

The theoretical hypothesis part points out that industrial structure upgrading and human capital are two paths through which AI technology innovation affects TFP. This article adopts the mediation effect test method to study the mechanism. The selected mediating variables in this article have a clear and intuitive causal relationship with the dependent variable TFP. The focus is on AI technology innovation on the mediating variable. Therefore, building upon the foundation of the baseline regression Equation (1), this paper sets Equation (4) to test the mediating effect:

$$M_{it} = \alpha_0 + \alpha_1 \mathrm{lnAI_{it}} + X_{it}^{T}\gamma + \lambda_2 T + \mu_i + \varepsilon_{it} \tag{4}$$

where M_{it} denotes the mechanism variable tested, which contains industrial structural upgrading (IS) and human capital level (HC).

The panel data regression model focuses on the impact of the explanatory variables on the conditional expectations of the explanatory variables, which is in fact mean regression. Conditional expectation is only an indicator that portrays the concentration trend of the conditional distribution; if the conditional distribution is not symmetrically distributed, portraying the entire conditional distribution is difficult. Moreover, the objective function estimated by least squares regression is susceptible to extreme values. Therefore, this study further adopts panel quantile regression to examine the effect of AI innovation on TFP, and the model is shown in Equation (5):

$$Q_{\mathrm{LNTFP}}(\tau_k | u_i, X_{it}) = u_i + D + X_{it}^{T}\beta(\tau_k) \tag{5}$$

where τ represents the quantile; $Q_{\mathrm{GTFP}}(\tau_k | u_i, X_{it})$ represents the conditional distribution function of TFP at a given τ quantile of the control variable; X is the vector consisting of the independent variables; and $\beta(\tau_k)$ is the regression parameter under the τ quantile.

3.2. Variable measurement

The selection and measurement of TFP, AI technology innovation, and the control variables are described below.

3.2.1. Dependent variable: TFP

Among the methods for calculating TFP, the non-parametric type does not require the production function model setting compared with the parametric type, to avoid the bias of the model setting. Thus, we first use the non-parametric DEA-Malmquist index to measure it. The output value used in the calculation selects the actual GDP of each province, and we choose 2003 as the base year; the input value is measured by the capital and labor input value, in which the capital input is expressed by the capital stock of each province. Using the practice of Wang and Fan (2000) for reference, the total fixed assets investment index of the whole society is selected, and the capital stock is calculated using the perpetual inventory method. The depreciation rate is 9.6%, as measured by Zhang et al. (2004); labor input is calculated based on the total number of employed persons.

Meanwhile, we also adopt the parametric method to measure TFP. For the specific method chosen, drawing on prior research (Zhang and Sun, 2015), we utilize the classical Solow residual method to estimate TFP.

3.2.2. Key explanatory variable

When measuring AI, due to the availability of data, existing studies mostly use industrial robots, but these are only a small part of AI. Therefore, there may be a large deviation in measurement through industrial robots. Some scholars use patent data to measure AI technology innovation, but there are large differences in the identification of AI patents. There are two main types of identification of AI patents. One is the use of patent classification codes (CPC or IPC). The CPC and IPC information contained in patent data lists the technical field categories to which the patent belongs, which is conducive to identifying patented AI technology innovation activities. For example, Zhai and Liu (2023) used the relevant IPC codes to identify AI patents. Another approach, such as the Jiang and Li (2022) approach, selects AI-related keywords to identify AI patents. However, considering the complexity and wide range of AI technologies, it is difficult to comprehensively capture AI technology innovation activities using either simple patent classification codes or keywords alone. In view of this, this paper refers to the WIPO's analysis of the concept, characteristics of AI, and the construction of an AI patent search formula and tries to build a search formula from three levels: CPC code, IPC code, and the keywords of related AI technologies; we acquire related patents using Incopat database. Then, the patent data obtained is summarized to the provincial level. In this way, we build a more comprehensive measurement of the provincial AI technology innovation index.

In addition, considering the lagged effect of technology innovation, using patent stock to measure technology innovation will be more scientific. Referring to Lin and Zhu (2019), this article intends to use patent stock to measure AI technology innovation. The specific formula is shown in Equation (6):

$$\mathrm{Stock}_{it} = \sum_{j=0}^{t} \mathrm{Patent}_{ij} e^{-\alpha_1 (t-j)} [1 - e^{-\alpha_2 (t-j+1)}] \tag{6}$$

where Stock_{it} is the AI patent stock of province i in year t; Patent is the number of AI patent applications; α_1 and α_2 represent the depreciation rate and diffusion rate, respectively, and take the values of 0.36 and 0.03 as in Yan et al. (2020). Meanwhile, in order to make the innovation capabilities of AI technology in provinces of different scales more comparable, the per capita AI patent stock in each region is used for measurement.

3.2.3. Control variables

Aside from the AI technology innovation that this article focuses on, there are also other factors that can affect the TFP. Referring to established studies (Meng et al., 2023; Zou et al., 2024), the specific control variables selected in this paper are: financial development, government intervention, urbanization, opening up, economic development level, and information technology level. The measurement of each variable is shown in Table 1.

Table 1. Variable measurement methods.

Type	Name	Symbol	Method
Dependent variable	Total factor productivity	LNTFP_M	Malmquist index method for non-parametric methods
		LNTFP_S	Solow residual value method
Explanatory variable	AI technology innovation	lnAI	Logarithm of per capita stock of AI patents by province
Control variable	Financial development	FIN	The proportion of RMB loans from financial institutions to regional GDP
	Government intervention	GOV	The ratio of general budget expenditures of local finance to regional GDP
	Urbanization	URB	The proportion of urban population
	Opening up	OPEN	The ratio of total imports and exports to regional GDP
	Economic development	LNPGDP	Logarithm of regional GDP per capita
	Information level	INF	Total postal and telecommunications operations divided by total population

3.3. Data sources

Considering that AI patent data at the provincial level has been increasing since 2003, and relevant data is severely missing since 2022, this article sets the sample interval as 2003–2021. In addition, considering the serious lack of data in some regions, we selected 30 provinces, autonomous regions, and municipalities in China as the research objects (Tibet, Hong Kong, Macao, and Taiwan are excluded from our sample due to a lot of missing values). AI patents are from the Incopat database, and the remaining data is from the National Bureau of Statistics, CNRDS, and EPS databases.

4. Empirical results and analysis

4.1. Unit root tests and cointegration tests

To prevent spurious regression in model analysis, this paper initially performs panel unit root examinations for all variables. To guarantee the robustness of the test results, we simultaneously use five commonly used first-generation panel unit root tests as well as the second-generation panel unit root test, the CIPS test, which takes into account cross-sectional dependence. As shown in Table 2, among the above six test statistics, basically more than two statistics for each variable cannot reject the hypothesis of the existence of a unit root. However, after first-order differencing, almost all statistics rejected the hypothesis of the existence of unit root in the variables. Out of prudential considerations, the variables are considered to be first-order integrated sequences, and further panel cointegration tests are conducted to examine the existence of cointegration.

Table 2. Results of unit root tests.

Variables		ADF-Fisher	HT	Breitung	LLC	CIPS	IPS
LNTFP	Level	2.3473	6.3590	9.1454	−1.1880	−1.199	1.0158
	difference	-2.5946^{***}	-1.7462^{**}	-2.0590^{**}	-1.9905^{**}	-3.078^{***}	-1.4908^{*}
LNAI	Level	-2.9154^{***}	-2.8639^{***}	2.8722	3.4679	−2.031	−0.4921
	difference	-4.9865^{***}	-14.2885^{***}	-2.2985^{**}	0.7653	-3.162^{***}	-4.0954^{***}
FIN	Level	2.5560	2.7043	4.5507	5.2653	−1.523	4.6865
	difference	-5.6449^{***}	-12.9348^{***}	-3.7767^{***}	0.6173	-3.543^{***}	-3.0877^{***}
GOV	Level	5.2947	5.5831	5.8544	4.0517	−2.003	3.5703
	difference	-4.0506^{***}	-9.0346^{***}	-1.8895^{**}	-3.4746^{***}	-3.617^{***}	-3.4524^{***}
URB	Level	-1.8297^{**}	2.2310	2.6793	-3.2087^{***}	−2.096	−0.9563
	difference	-4.5537^{***}	-1.3577^{*}	-7.7649^{***}	-4.7058^{***}	-2.604^{***}	-2.2506^{**}
OPEN	Level	-3.0717^{***}	-2.0488^{**}	-1.7250^{*}	2.4690	−1.775	-1.3952^{*}
	difference	-5.7912^{***}	-12.5761^{***}	-4.6838^{***}	-5.0358^{***}	-3.645^{***}	-5.4572^{***}
LNPRGDP	Level	−0.9501	6.6651	5.8296	2.5005	−2.332	1.9092
	difference	-3.1558^{***}	1.8373	-2.9972^{***}	-3.9163^{***}	-3.260^{***}	-2.4595^{***}
INF	Level	2.8577	9.0634	8.9958	12.1995	−2.334	5.0413
	difference	-5.5320^{***}	-2.2382^{**}	-2.6985^{***}	1.8933	-2.58^{***}	−0.1886

Note: The numbers in the table are the corresponding test statistic values. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3. Results of panel cointegration test.

Types	Test statistics	Statistic
Pedroni test	Modified Phillips-Perron t	8.7674***
	Phillips-Perron t	−4.7433***
	Augmented Dickey-Fuller t	−4.4060***
Westerlund test	Variance ratio	1.6128*

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Following Yao et al. (2019) and Zheng and Walsh (2019), the Pedroni test and the Westerlund test are selected for panel cointegration test; the results obtained are shown in Table 3. It can be found that at the 10% significance level, the test results based on the four statistics reject the hypothesis that there is no cointegration relationship between the variables. Therefore, it can be assumed that a long-run stable cointegration relationship exists and further econometric analyses can be carried out.

4.2. Benchmark regression analysis

This paper first conducts a full sample estimation of the impact of AI innovation on TFP in Equation (1). The results are in Table 4, where columns (1)–(3) utilize the DEA-Malmquist index to evaluate TFP and columns (4)–(6) employ the Solow residual method for TFP assessment. Columns (1) and (4) display the results of the pooled OLS regression; columns (2) and (5) are the results estimated via the fixed-effects model in order to control the provincial individual fixed effects; columns (3) and (6) are the estimates obtained from the random effects model. From Table 4, we find that regardless of which model is used for estimation and which method is used to measure TFP, lnAI coefficients are consistently positive at a significance level of 1%. It clearly suggests that enhancing China's TFP is directly linked to AI technology innovation. It is consistent with economic theory expectations and also echoes the research outcomes of Wang et al. (2023). Thus, we validate H1.

Table 4. Results of benchmark regression.

	LNTFP_M			LNTFP_S		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	FE	RE	OLS	FE	RE
lnAI	1.108***	0.561**	0.842***	0.190***	0.469***	0.329***
	(0.234)	(0.207)	(0.193)	(0.0563)	(0.153)	(0.0942)
FIN	0.0101	0.0962**	0.129***	0.0237***	0.0679***	0.0466***
	(0.0153)	(0.0361)	(0.0336)	(0.00717)	(0.0188)	(0.0129)
GOV	−0.459***	−1.049**	−1.021**	−0.869***	−0.704**	−0.694***
	(0.143)	(0.459)	(0.425)	(0.0652)	(0.272)	(0.223)
URB	0.00228	−0.0164*	−0.0100*	−0.00198*	0.00622	0.00239
	(0.00199)	(0.00851)	(0.00526)	(0.00119)	(0.00585)	(0.00422)
OPEN	0.462***	−0.211	−0.193	0.247***	0.0597	0.0541
	(0.0507)	(0.154)	(0.135)	(0.0203)	(0.0676)	(0.0697)
lnPRGDP	−0.224***	0.143	0.300**	0.354***	0.505***	0.453***
	(0.0337)	(0.146)	(0.126)	(0.0198)	(0.136)	(0.105)
INF	−0.606**	0.515*	0.556**	−0.0592	0.255*	0.276**
	(0.239)	(0.263)	(0.278)	(0.108)	(0.145)	(0.138)
T	NO	−0.0263	−0.0519***	NO	−0.0342**	−0.0228***
		(0.0180)	(0.0131)		(0.0132)	(0.00779)
_cons	1.782***	−0.606	−2.401**	−3.187***	−4.952***	−4.267***
	(0.257)	(1.342)	(1.066)	(0.153)	(1.209)	(0.853)
Region FE	NO	YES	YES	NO	YES	YES
N	570	570	570	570	570	570
R2	0.603	0.711		0.877	0.766	

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

4.3. Robustness tests

To validate the robustness of the estimation results, we conduct robustness tests using the reconstruction of core indicators, the adjustment of control variables, and the instrumental variable regression.

1. Change the core explanatory variable measurement method. The differences in measurement methods for AI technology innovation may also influence the results. In the benchmark regression above, AI patent applications were used to measure AI technology innovation, and alternative measurement of patent grants was used for the robustness test. The results are presented in Column (1) of Table 5, where the coefficient of lnAISQ is positive, aligning consistently with the above results. Besides, this study also changes the depreciation rate in calculating patent stock from 0.36 to 0.22 to measure AI technology innovation. The results are shown in column (2), which also supports the findings of this paper.
2. Control variables lagged one year. Considering that the impact of each control variable on TFP may be lagged, to further guarantee the robustness of the results, with reference to Liang and Dong (2023), this paper lags all the control variables by one period and then tests them again. As illustrated in column (3), the results affirm the robustness of the conclusion.
3. Instrumental variable regression. In addition, both the possible bidirectional causality and the issue of omitted variables will bring the endogeneity problem, which will cause inconsistency in the parameter estimation results. In this regard, we refer to Song et al. (2021), taking the independent variable with one year of lag (i.e., one period of lagged AI technology innovation as the instrumental variable) as the first instrumental variable and then further conducting parameter estimation with the help of 2SLS. The results in column (4) indicate that the positive impact of AI technology innovation on TFP remains highly significant. This suggests that the findings are robust and reliable. Meanwhile, this paper takes third-order moments of the logarithm of AI technology innovation as the second instrumental variable (Lewbel, 1997). According to the results in column (5) of Table 5, the estimated coefficient of AI innovation is still positive, which further verifies the robustness of the estimation results.

Table 5. Robustness test.

	(1)	(2)	(3)	(4)	(5)
lnAISQ	1.418**				
	(0.566)				
lnAIDR		0.480**			
		(0.175)			
lnAI			0.546***	0.530***	0.363***
			(0.175)	(0.109)	(0.0714)
Control variable	YES	YES	YES	YES	YES
T	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES

Continued on next page

	(1)	(2)	(3)	(4)	(5)
N	570	570	540	540	570
R^2	0.708	0.712	0.699	0.701	0.709

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

4.4. Mechanism tests

The above analyses demonstrate that AI technology innovation can significantly improve TFP, and the mechanism behind this promotion needs to be further investigated. The theoretical analysis points out that AI technology innovation can promote TFP through promoting industrial structure upgrading and enhancing human capital level, and this paper will test these two mechanisms next.

4.4.1. Mechanism test for industrial structure upgrading

We adopt the ratio of value added of the tertiary industry to the value added of the secondary industry to evaluate the upgrading of industrial structure (Dong et al., 2022; Ren et al., 2023). The results of the test are displayed in columns (1)–(3) on Table 6. Column (1) presents the evaluation of AI innovation, which is measured by the number of patent applications. The innovation of AI technology in column (2) is measured using the number of patents authorized. In column (3), the measurement of AI technology innovation is also based on the patent application number, but a depreciation rate of 0.22 is used for patent stock measurement. It can be found that no matter what measure of AI technology innovation is selected, the AI technology innovation coefficient is positive. This indicates that AI innovation can facilitate industrial structure upgrading. The theoretical analysis above indicates that enhancing industrial structure can greatly enhance TFP.

Thus, AI technology innovation promotes the TFP by promoting industrial structure upgrading. As a result, H2a is verified.

Table 6. Results of the mechanism test.

	Industrial structure upgrading			Human capital		
	(1)	(2)	(3)	(4)	(5)	(6)
lnAI	0.904***			0.131***		
	(0.212)			(0.0260)		
lnAISQ		1.731***			0.322***	
		(0.626)			(0.107)	
lnAIDR			0.733***			0.111***
			(0.180)			(0.0207)
FIN	0.146***	0.143***	0.145***	0.00497	0.00497	0.00481
	(0.0451)	(0.0464)	(0.0452)	(0.00417)	(0.00422)	(0.00417)
GOV	−0.0886	−0.201	−0.0741	−0.0559*	−0.0669**	−0.0523*
	(0.618)	(0.585)	(0.622)	(0.0289)	(0.0318)	(0.0283)
URB	−0.0172	−0.0204*	−0.0171	−0.000606	−0.000907	−0.000539
	(0.0103)	(0.0109)	(0.0103)	(0.000662)	(0.000758)	(0.000646)

Continued on next page

	Industrial structure upgrading			Human capital		
	(1)	(2)	(3)	(4)	(5)	(6)
OPEN	0.00162	−0.0622	0.000846	−0.0123	−0.0193	−0.0117
	(0.177)	(0.184)	(0.176)	(0.0159)	(0.0156)	(0.0158)
lnPRGDP	−0.777***	−0.801***	−0.776***	−0.0150	−0.0167	−0.0145
	(0.239)	(0.249)	(0.238)	(0.0205)	(0.0215)	(0.0203)
INF	−0.481	−0.442	−0.484	−0.0384	−0.0337	−0.0392
	(0.427)	(0.423)	(0.428)	(0.0269)	(0.0269)	(0.0267)
T	0.112***	0.121***	0.112***	0.00876***	0.00950***	0.00858***
	(0.0284)	(0.0307)	(0.0283)	(0.00243)	(0.00270)	(0.00240)
_cons	8.439***	8.833***	8.429***	0.216	0.247	0.208
	(2.264)	(2.398)	(2.255)	(0.198)	(0.212)	(0.196)
Region FE	YES	YES	YES	YES	YES	YES
N	570	570	570	570	570	570
R^2	0.731	0.722	0.731	0.876	0.872	0.877

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

4.4.2. Mechanism test for human capital

As with (Pan et al., 2022), we use the proportion of the population with college education or above to assess the human capital. We then examine the role of human capital in the relationship between AI innovation and TFP. The results are in columns (4)–(6) of Table 6. In column (4), the measure of AI technology innovation capacity relies on the number of patent applications; in column (5), it is measured by patents granted; and in column (6), in the measure of patent stock, a depreciation rate of 0.22 is chosen.

It can be found that no matter what measure of AI technology innovation is selected, the coefficient is significantly positive, which fully demonstrates that AI technology innovation can significantly improve human capital. Drawing from the theoretical analysis provided earlier, it is evident that human capital has the potential to greatly improve TFP. Thus, it can be said that AI technology innovation promotes the TFP through the enhancement of the human capital. H2b is verified.

5. Further analysis

This paper next discusses the heterogeneous effects from three perspectives: marketization, financial development, and digital infrastructure.

5.1. Analysis under differences in marketization, financial development, and digital infrastructure

5.1.1. Analysis under differences in marketization

Theoretical analysis suggests that the relationship between AI innovation and TFP is affected by marketization. To verify the validity of this hypothesis, this article uses the marketization index compiled by Wang et al. (2021) to measure marketization. This index comprehensively and objectively measures the marketization level of various provinces in China from five aspects, having been extensively utilized in academic circles (Ge et al., 2023; Zhou et al., 2023). Given that this data is currently only published until 2019, this study computes the mean marketization index for every province between 2003 and 2019, while the top 15 and bottom 15 provinces are then classified as high and low marketization regions, respectively. The results of the analysis can be found in Table 7.

Columns (1) and (2) of Table 7 are the TFP measured based on the DEA-Malmquist index method; columns (3) and (4) are the TFP measured based on Solow Residual method; columns (1) and (3) are the estimation result of low marketization region; and columns (2) and (4) are the result of high marketization region. It can be seen that, no matter which method is based on to measure TFP, the impact of AI innovation on TFP in low-marketization regions is not significant, while it is significantly positive in high-marketization regions. This illustrates the significant difference in the effect of AI technology innovation on TFP in regions with different marketization. This difference fully explains that the role of AI innovation on TFP requires the support of marketization. Thus, we validate H3a.

Table 7. Results under differences in marketization.

	LNTFP_M		LNTFP_S	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
lnAI	1.333	0.328*	0.742	0.261*
	(0.96)	(1.97)	(1.07)	(2.10)
FIN	0.0693	0.0927***	0.0586**	0.0608***
	(1.15)	(3.12)	(2.51)	(3.36)
GOV	−0.0707	−1.481**	0.0224	−1.532***
	(−0.14)	(−2.44)	(0.16)	(−3.24)
URB	−0.00257	−0.0260**	0.0111*	0.00326
	(−0.42)	(−2.86)	(2.01)	(0.60)
OPEN	−0.116	−0.0488	0.525*	0.0945*
	(−0.23)	(−0.28)	(1.95)	(1.86)
lnPRGDP	0.00553	0.190	0.430**	0.516***
	(0.04)	(1.04)	(2.22)	(3.60)
INF	1.029***	0.0559	0.593***	0.0425
	(4.25)	(0.16)	(5.13)	(0.23)
T	−0.0491***	−0.00590	−0.0451**	−0.0212
	(−3.31)	(−0.29)	(−2.34)	(−1.52)
_cons	−0.126	−0.538	−4.560**	−4.902***
	(−0.10)	(−0.31)	(−2.61)	(−3.73)
Region FE	YES	YES	YES	YES
N	285	285	285	285

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

5.1.2. Analysis under differences in financial development

To determine if variances exist in the effects of AI technology innovation on TFP based on varying levels of financial development, referring to Cao et al. (2022), we adopt the total of deposits and loans of financial institutions as a share of GDP to measure the level of financial development. Similarly, by calculating the average value of the financial development of each province in 2003–2021, 30 provinces are categorized into regions with lower and higher financial development levels and then estimated separately, with the results presented in Table 8.

In particular, the estimated results of measuring TFP using the DEA-Malmquist index method are presented in Columns (1) and (2). Column (1) presents the estimated outcomes for areas with low financial development. It is evident that the estimated AI technology innovation coefficient is negative and insignificant. The results in Column (2) reveal the positive effect of AI technology innovation in regions that have high levels of financial development. It indicates that the role of AI technology innovation on TFP differs between regions with low and high levels of financial development, further suggesting that regional financial development plays a crucial role in supporting the effects of AI technology innovation on TFP; the results validate H3b.

Table 8. Results under differences in financial development.

	LNTFP_M		LNTFP_S	
	(1)	(2)	(3)	(4)
	Low regions	High regions	Low regions	High regions
lnAI	−0.122	0.450**	0.512	0.400**
	(−0.15)	(2.26)	(0.97)	(2.96)
FIN	0.145**	0.0629	0.0602**	0.0651**
	(2.21)	(1.75)	(2.94)	(2.66)
GOV	−2.035**	−0.728*	−1.278***	−0.564**
	(−2.27)	(−1.77)	(−3.07)	(−2.44)
URB	−0.00591	−0.0348***	0.0122	−0.00459
	(−0.64)	(−4.80)	(1.35)	(−0.96)
OPEN	−0.710***	0.0632	−0.0174	0.117*
	(−4.18)	(0.68)	(−0.16)	(1.77)
lnPRGDP	0.188	0.216	0.340*	0.717***
	(1.08)	(0.91)	(1.87)	(5.51)
INF	0.639**	0.623*	0.153	0.373*
	(2.78)	(1.84)	(0.74)	(1.94)
T	−0.0434*	−0.00582	−0.0235	−0.0390***
	(−1.87)	(−0.31)	(−1.05)	(−3.29)
_cons	−1.344	−0.475	−3.507*	−6.528***
	(−0.84)	(−0.23)	(−2.05)	(−5.59)
Region FE	YES	YES	YES	YES
N	285	285	285	285

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

The estimation results of TFP based on the Solow Residual Method can be found in Columns (3) and (4) of Table 8. These indicate that there is a significant difference in the effect of AI innovation on TFP between regions with different financial development levels, that is, the effect is insignificant in regions with low financial development but significantly positive in regions with high financial development, which also verifies H3b.

5.1.3. Analysis under differences in digital infrastructure

To examine whether differences in digital infrastructure will affect the relationship between Al innovation and TFP, we employ the entropy method to measure digital infrastructure level. In accordance with the prior study conducted by Pan et al. (2021), we selected five indicators (internet penetration, telephone penetration rate, length of long-distance optical cable lines, internet broadband access port, and number of Internet domain names) to evaluate the digital infrastructure level. Following the previous analysis, the 30 provinces were categorized into regions with varying levels of digital infrastructure, determined by the assessed digital infrastructure level. Subsequently, the two subsets were analyzed independently, and the resulting estimates can be found in Table 9.

Table 9. Results under differences in digital infrastructure.

	LNTFP_M		LNTFP_S	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
lnAI	1.563	0.285*	0.856	0.214*
	(1.419)	(0.152)	(0.780)	(0.111)
FIN	0.0785	0.0783**	0.0695***	0.0479**
	(0.0554)	(0.0356)	(0.0233)	(0.0202)
GOV	−0.139	−2.124***	−0.0471	−1.502***
	(0.472)	(0.468)	(0.158)	(0.357)
URB	−0.00426	−0.0300***	0.0111*	−0.00109
	(0.00699)	(0.00867)	(0.00526)	(0.00546)
OPEN	−0.349	−0.103	0.547**	0.0736
	(0.473)	(0.167)	(0.229)	(0.0548)
lnPRGDP	−0.130	0.411*	0.366*	0.638***
	(0.170)	(0.226)	(0.203)	(0.159)
INF	0.796***	0.328	0.422***	0.327
	(0.207)	(0.410)	(0.0978)	(0.265)
T	−0.0339*	−0.0168	−0.0387*	−0.0260*
	(0.0169)	(0.0214)	(0.0199)	(0.0140)
_cons	1.180	−2.282	−4.001**	−5.804***
	(1.464)	(2.059)	(1.830)	(1.405)
Region FE	YES	YES	YES	YES
N	285	285	285	285

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses.

The estimated outcomes of the TFP measurement using the DEA-Malmquist index technique are presented in columns (1) and (2). It can be found that in regions with low digital infrastructure levels, AI technology innovation does not significantly boost TFP, while in regions with high digital infrastructure levels, AI technology innovation significantly promotes the TFP. This result indicates that the promotion of AI technology innovation on TFP requires the support of a well-developed digital infrastructure. Columns (3) and (4) display the results measured based on the Solow residual method. Similarly, the promoting effect of AI technology innovation on TFP is insignificant in regions with low digital infrastructure levels, but it exhibits positivity in regions characterized by high levels of digital infrastructure. Therefore, we validate H3a.

5.2. Analysis under TFP differences

In the previous study, the influence of AI technology innovation on China's TFP was analyzed using both the complete sample and sub-regional samples. Then, this paper aims to investigate whether variations in China's TFP levels result in differing effects of AI technology innovation on TFP. In this regard, this paper adopts the Markov Chain Monte Carlo (MCMC) estimation method and further performs parameter estimation using the fixed-effects panel quantile regression model. Table 10 presents the obtained estimation outcomes.

From Table 10 and Figure 1, it can be seen that, similar to the estimation outcomes for the entire sample, the estimated coefficients for AI technology innovation at quantile points 0.1, 0.25, 0.4, 0.55, 0.7, and 0.85 are all positive. It can also be found that the estimated coefficients of AI technology innovation generally show a gradual upward trend with the increase in the TFP quantile points. This indicates that the contribution of AI technology innovation to TFP is more prominent with high levels of TFP. This could be attributed to the fact that regions boasting elevated TFP levels offer a more conducive atmosphere for fostering AI advancement, thus establishing opportunities for the enhancement of TFP through the innovation of AI technology.

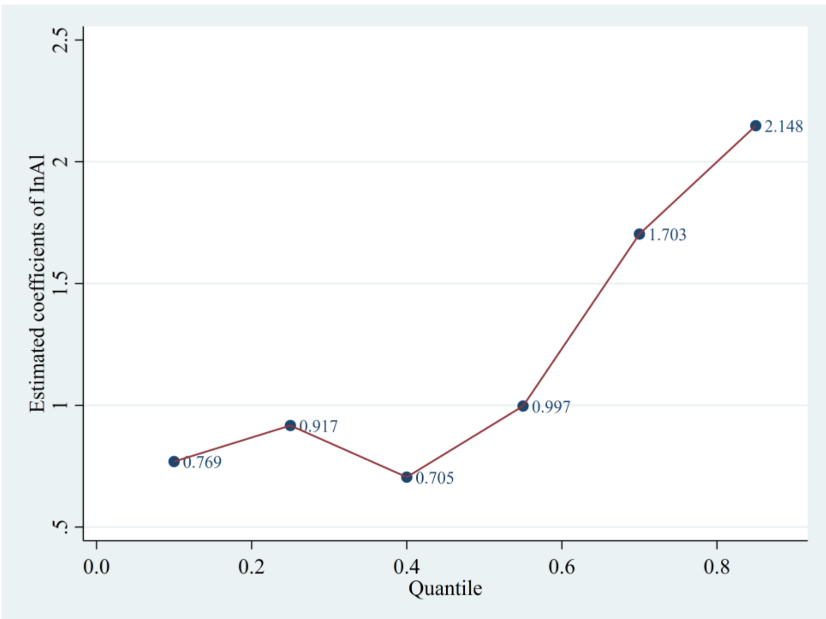

Figure 1. Estimation results of panel quantile regression.

Table 10. Estimation results of panel quantile regression.

	(1) 0.1	(2) 0.25	(3) 0.4	(4) 0.55	(5) 0.7	(6) 0.85
lnAI	0.769***	0.917***	0.705***	0.997***	1.703***	2.148***
	(7.75)	(22.90)	(33.28)	(17.89)	(78.11)	(16.63)
FIN	0.0594***	0.0669***	0.0909***	0.0346***	0.0275***	−0.00340
	(3.50)	(8.82)	(41.02)	(3.08)	(9.62)	(−1.20)
GOV	−1.777***	−1.340***	−1.021***	−0.527***	−0.423***	−0.0328**
	(−27.84)	(−20.25)	(−61.20)	(−6.10)	(−8.00)	(−2.26)
URB	0.000548	0.00948***	0.00186***	0.000600*	0.00166***	0.00154***
	(0.46)	(15.14)	(10.64)	(1.75)	(5.17)	(3.00)
OPEN	0.101*	0.140***	0.291***	0.446***	0.612***	0.419***
	(1.86)	(7.50)	(99.63)	(45.33)	(31.11)	(26.55)
lnPRGDP	−0.145***	−0.477***	−0.281***	−0.204***	−0.258***	−0.135***
	(−5.37)	(−35.81)	(−74.95)	(−23.09)	(−23.00)	(−12.30)
INF	−2.323***	−0.160***	−0.391***	−0.824***	−0.808***	−0.519***
	(−11.02)	(−9.30)	(−15.88)	(−12.83)	(−42.07)	(−11.40)
N	570	570	570	570	570	570

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

6. Conclusions and policy recommendations

Against the backdrop of China's increasing focus on enhancing TFP and attaining high-quality development, many scholars have keenly observed the influencing factors of TFP. This study focuses on the effect of AI innovation on TFP. Through the panel fixed-effect model and the mediation effect model, the direct impact and mechanism of AI technology innovation on TFP are tested. Besides, this article further examines whether the impact of AI innovation on TFP is related to the degree of marketization, financial development, digital infrastructure, and TFP level.

The conclusions obtained are as follows. First, AI innovation has a substantial positive influence on China's TFP, and this effect is highly robust. Second, AI technology innovation can promote TFP by industrial structure upgrading and human capital. Third, the impact of AI technology innovation on TFP is influenced by the degree of marketization, financial development, and digital infrastructure. Fourth, as TFP improves, the significance of AI technology innovation in enhancing TFP is progressively growing.

This article provides rich and detailed research findings and has the following significant policy implications:

First, increase the support for AI innovation and continue to play the role of AI innovation in promoting TFP. The findings of this paper demonstrate that AI innovation significantly promotes TFP. Therefore, the government should create a suitable environment for AI innovation and spare no effort to support AI innovation. Specifically, on the one hand, enterprises are the main body of technology innovation, and improving the ability of AI innovation must fully leverage the role of enterprises as the main body. The government should formulate and introduce scientific and effective policies, such as fiscal subsidies and tax incentives, to provide sufficient impetus for enterprises to perform AI technology innovation. On the other hand, we should leverage China's huge market size and diversified application advantages, encourage enterprises to establish various forms of cooperation with university research institutions, promote the accelerated integration of AI technology and diversified application scenarios, explore new areas of AI technology integration, and promote high-quality economic development through the scale and industrialization of emerging technology fields.

Second, explore the multi-dimensional path of AI technology innovation to promote TFP growth, focusing on the mechanism of industrial structure upgrading and human capital enhancement, and maximizing the role of AI technology innovation. On the one hand, each region should take into account its own development status, identify the strategic positioning of industrial functional zones, reasonably formulate the development plan for AI to promote industrial upgrading, strive to promote AI technology innovation to become a sustainable driving force to guide the upgrading of industrial structure, and smooth the path of industrial structure upgrading, in which AI technology innovation enhances TFP. On the other hand, it is necessary to clarify the significant role of human capital in the process of AI technology innovation to promote TFP, refine and implement policy research to promote the integration of AI and human capital, innovate the system and mechanism of the integration of AI and human capital, and consolidate advantages to form new momentum that drives the improvement of TFP. Specifically, it is necessary to focus on improving the comprehensive quality of the workforce, establishing a sound skill-training system, promoting effective collaboration between the workforce and AI, and promoting sustained productivity improvement. At the same time, it is also necessary to adjust and optimize the structure of university education, promote the effective connection between the supply of higher-education personnel and the AI industry so that university graduates can accurately meet the needs of the industry, release the human capital dividend of university graduates in a comprehensive manner, and further strengthen the synergy between AI and human capital to promote the enhancement of TFP.

Third, focus on the synergy between AI development policies and other policies. The results of this paper's subsample study show that the role of AI technology innovation in promoting TFP requires the effective support of the market mechanism, financial system, and digital infrastructure. Therefore, to maximize the potential of AI technology innovation in enhancing TFP while continuously improving the policy system to support AI development, China (especially in regions with relatively lagging market development, low financial development levels, and low digital infrastructure levels) should also accelerate the market reform, improve the financial development level, and enhance the construction of digital infrastructure, to cultivate more suitable conditions for the role of AI innovation in promoting the TFP.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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