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Impact of AI development on green total factor productivity

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The improvement of GTFP has become an important guarantee to change China's development mode and achieve long-term stable economic growth, while the development of AI is of great significance to the development of GTFP. This paper adopts the SBM-GML method to calculate the GTFP of 30 regions in China from 2011 to 2020, and manually collects AI data to study the impact of AI on GTFP, and systematically analyze the relationship between AI and GTFP using a panel double-fixed model with a faceted threshold model. The experimental results show that: (1) There is a positive and significant effect of AI on GTFP, which increases GTFP productivity by 0.3654% for every 1% increase in AI, which still holds after a robust type test. (2) The development of AI in China's eastern region has a greater promoting effect on GTFP. (3) Further mechanism analysis reveals that RIS and ER are two important channels through which AI influences the improvement of GTFP. (4) Threshold regression shows that AI has a single threshold effect on GTFP based on TI and LNPGDP. The promotion of GTFP by AI is higher when technological innovation is less than the threshold value of 29.95, and the promotion of GTFP by AI is insignificant when the level of economic development is less than the threshold value of 85.45. This paper deepens the knowledge and understanding of the role played in the development of AI at the macro level and provides suggestions for improving GTFP at the provincial level in China.

Keywords AI, GTFP, System GMM model, Threshold model

Abbreviations

AI	Artificial intelligence
GTFP	Green total factor productivity
RIS	Industrial structure
ER	Environmental regulation
TI	Technological innovation level
LNPGDP	Economic development level

In 2010, China's economy surpassed Japan to become the world's second-largest economy. By 2019, China's per capita GDP exceeded $10,000, indicating significant economic development. However, this growth was historically reliant on low labor costs and environmentally damaging energy supplies[1]. The extensive economic model remained unchanged for a long time, posing a significant challenge to China's new normal of economic development. Therefore, there is a need to transform the mode of economic development—improving total factor productivity in China's economy is imperative[2]. An increase in total factor productivity signifies an enhancement in social production efficiency and resource allocation efficiency, reflecting technological progress, improved organizational management, and optimized system elements. However, traditional total factor productivity fails to consider resource constraints, leading to environmental issues. Deteriorating environmental quality can profoundly impact China's economy, making it an essential element in studying China's economic development[3]. GTFP integrates economic benefits with environmental benefits, aligning with contemporary economic practices while embodying green development concepts. Enhancing China's GTFP has become an urgent issue requiring resolution for the country's long-term stable economic growth, and AI, seen as the driving force of a new round of industrial transformation, offers effective approaches to improve it.

As a significant outcome of the Fourth Industrial Revolution, AI has emerged as a new engine for economic development[4]. Expert forecasts suggest that AI will contribute to more than a 10% increase in global economic growth over the next 15 years and that by 2030, over 70% of companies will adopt AI technologies[5]. With the continuous development of AI, it has shown many significant advantages. On the one hand, AI technology utilizes smart terminals and modern digital technologies such as cloud computing to break through the time limit and space limit, and promote the sharing and interoperability of information and resources, which is in line with the demand for high-quality economic development. On the other hand, the advantages of AI, such as

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high efficiency and wide coverage, have stimulated the innovation vitality of micro-principals, and brought new opportunities for boosting the transformation of the economic growth mode and enhancing the region's GTFP. In this context, it is of great significance to clarify the relationship between AI development and GTFP, and to further examine the contributions and positive and negative effects of AI at different levels, so as to find out how AI can better drive China's GTFP.

China's transition from pollution-intensive growth to sustainable development necessitates improving GTFP, yet the role of AI—a cornerstone of the Fourth Industrial Revolution—remains underexplored. Existing research lacks comprehensive metrics for AI and overlooks its environmental-economic dual benefits. This study aims to fill these gaps by systematically analyzing how AI drives GTFP, leveraging China's provincial data (2011–2020) to address critical questions: Can AI enhance GTFP? Through what mechanisms? And under what conditions? The findings are vital for policymakers seeking to align technological advancement with green growth goals.

The purpose of this paper is to systematically analyze and explore the specific impact of the development of AI on GTFP. By constructing a multi-dimensional research model, it seeks to comprehensively assess the actual effect of AI in enhancing GTFP. This paper also hopes to provide empirical support for the field of AI and GTFP in the context of relatively weak related research. Compared with the existing literature, this paper has the following three main innovations: in terms of research content, this paper constructs a comprehensive measure of the current level of AI in China based on the manual collection of AI data in three dimensions, covering the three dimensions of the construction of intelligent infrastructure, the level of development of the AI industry, and the ability of AI technology products. In terms of research methodology, this paper comprehensively analyzes the impact of AI on GTFP by using a combination of a multi-system GMM model and a threshold model in the field of AI and GTFP research. The GMM model investigates the impact of AI on GTFP from a dynamic perspective, which reduces the problems of endogeneity and estimation bias. The introduction of the threshold model clarifies that there is variability in the promotion of AI development on GTFP at different stages, and differentiated development strategies should be adopted. In terms of research data, this paper uses the complete Chinese provincial area data. The dataset covers the period 20,011 – 2020, which makes the data in this paper cover the widest and most representative data interval and ensures a long-period analysis of the impact of GTFP. Finally, threshold effects associated with technological innovation and economic development are found, revealing non-linear relationships that inform region-specific policies. By combining systematic GMM modeling and threshold modeling, this paper provides reliable empirical evidence while taking into account endogeneity and dynamic effects, distinguishing it from previous studies that narrowly focused on traditional total factor productivity or the manufacturing sector.

Literature review

As the "new engine" of high-quality development, the rapid development of AI will profoundly change human society and the world. The current research on AI by scholars mainly has the following two aspects, one of which is about the measurement of Ai, there is no unified standard in the academic world yet, and there are mainly the use of single-indicator method[6], the construction of indicator system[7] and policy effects instead of[8,9]. Compared with the single-indicator method and policy effects, constructing an indicator system can comprehensively measure China's AI level. The second is about the impact of AI on the economy. Most of the studies show that AI increases productivity and promotes economic growth. Lu[10] shows that the development of Ai increases economic growth. Qin, Xu[11] also draws similar results.

Modern economic growth theory posits that the driving force behind a country's continuous economic growth is total factor productivity. There is debate over whether AI can improve total factor productivity. Most scholars believe that AI promotes the improvement of total factor productivity. Wang, Sun[12] examine of the impact of AI technology on the total factor productivity (TFP) of Chinese manufacturing enterprises revealed that AI can enhance enterprise TFP. However, there exists heterogeneity depending on the geographical location, industry sector, ownership structure, and life cycle stage of the enterprises. Shen and Zhang[13] used the number of AI applications as a proxy for measuring AI and found that AI could replace manual labor through human-machine integration and the expansion of the AI industry chain, thereby promoting economic development, improving market efficiency, and enhancing production efficiency. They also discovered that in regions with a strong AI foundation, the effects of AI are more pronounced. Zhang and Wu[14], by calculating the level of intelligent development of Chinese manufacturing enterprises over nine years, concluded that intelligent development significantly improves enterprise total factor productivity without any paradox of production due to intelligent development. Enterprises can combine intelligent manufacturing and service innovation to enhance total factor productivity. Zhong, Xu[15], using the number of industrial robots to represent AI, examined the impact of industrial robot application in Chinese manufacturing on total factor productivity and found that the use of AI in the production process increases total factor productivity, with a greater enhancement in medium and high technology industries than in low technology industries. They also identified that the main pathway through which AI affects total factor productivity is by improving technical efficiency. A minority of scholars believe that AI hinders the improvement of total factor productivity. Brynjolfsson, Hitt[16] found that applying AI technology to improve total factor productivity is complex; when fully reliant on AI technology, it can lead to a slowdown in the growth of total factor productivity. Hunt[17] argued that when enterprises over-automate, they may experience resource wastage and labor mismatch, leading to reduced productivity and indirectly lowering the improvement of total factor productivity. Fan and Liu[18] studied the impact of AI on industrial structure through static and dynamic panel models, showing that based on the static panel, the rationalization of industrial structure is not significantly affected by AI, indirectly reducing productivity. Some scholars consider the impact of AI on total factor productivity to be uncertain. Cheng, Luo[19], by constructing a multi-sector dynamic equilibrium model, suggested that whether AI positively affects and improves production efficiency after upgrading an industry depends on the difference between AI's output elasticity and the substitution elasticity between AI and traditional production methods. However, Wang, Wang[20] argue that traditional total factor productivity primarily considers the impact of capital and labor inputs on output but does not incorporate resource and environmental capacity into its scope. Traditional total factor productivity fails to reflect changes in socio-economic welfare and evaluate economic performance adequately. Xia and Xu[21] found that traditional total factor productivity has shortcomings as it does not account for resource consumption, leading to potential biases in industrial policy. Therefore, Jiakui, Abbas[22] believe that considering environmental factors when studying productivity and measuring GTFP aligns with China's new economic norm development. Li, Han[23] contend that GTFP can more accurately calculate the level of economic development compared to traditional total factor productivity. The enhancement of GTFP contributes to China's high-quality development and meets the requirements for sustainable development of both the economy and the environment. Thus, it is necessary to further analyze the factors affecting China's GTFP. Lyu, Wang[24] discovered that the digital economy promotes GTFP through regional innovation efficiency and reducing factor mismatches, with a greater impact on regions with lower productivity and industrial structures. Tian and Feng[25] found that environmental regulations affect the change in GTFP, thereby influencing China's industrial development, and there exists a threshold effect of environmental regulations. Jiang, Jiang[26] studied the impact of the internet on GTFP across 255 prefecture-level cities and above in China, categorizing GTFP into green technology efficiency and green technological progress. They found that internet development promotes green technology efficiency while suppressing green technological progress, but overall enhances GTFP.

The research on GFTP is more in-depth, and the current literature explores the effects of FDI, climate change, and environmental regulations on GTFP. Wang, Xie[27] found that FDI investment boosts agricultural GTFP but has an inverted U effect in the long run .Feng, Zhao[28] studied to improve GTFP from the perspective of climate change, and the results of the study found that reducing CO2 emissions and maintaining temperature were the key factors to improve GTFP. Fan, Yang[29] explore how to improve GTFP from the perspective of environmental regulation and find that there is a spatial autocorrelation between environmental regulation and GTFP, and that environmental regulation not only improves local GTFP, but also allows neighboring regions to improve GTFP.

Finally, there has been a wealth of research on the measurement of GTFP, which will not be repeated in this paper. These include the following three methods: DEA, SFA and SBM models with non-expected outputs. As the DEA method ignores the random error term which may lead to the underestimation of GTFP, the SFA model ignores the spatial spillover effect in the efficiency measurement process which may lead to the bias in the efficiency estimation. Therefore, SBM models with non-expected outputs are usually more systematic and scientific and can reflect GTFP more comprehensively.

In summary, through a review of existing research results, it is found that there is room for expansion in this field. Firstly, most scholars typically quantify AI indicators using the number of industrial robot installations or AI patent applications. This paper argues that using the number of industrial robot installations to quantify AI only considers the industrial impact on AI and fails to account for the influence on agriculture and services. When using AI patents, it only considers one aspect of AI achievements and does not provide a comprehensive measure of AI. Secondly, current research on the factors affecting GTFP mainly focuses on the digital economy, environmental regulations, and the internet. Most literature considers the impact of AI on total factor productivity, particularly in manufacturing, without fully exploring its relationship with GTFP. Thirdly, most of the research on AI is about economic development, ignoring research on GTFP. Based on this, the SBM-GML method is used to calculate the GTFP of 30 provinces (cities, districts) in China from 2011 to 2020, empirically revealing the impact and mechanisms of AI development levels on China's GTFP.

Mechanism analysis

The impact of AI on GTFP is analyzed in this paper from the following aspects.

First, AI, as a representative technology of the fourth industrial revolution, is leading human societal development and transformation through its technological economic characteristics such as permeability, substitutability, synergy, and innovation[30]. On one hand, AI can change the original development model, assist users in decision-making and monitor other equipment during use, or replace humans in performing some complex tasks in certain fields, improving labor sector productivity and factor utilization rates[31]. This allows enterprises to reduce factor inputs while increasing output to some extent, promoting the growth of GTFP. On the other hand, AI promotes value addition through complementary innovation at various stages of production, and with technologies like big data and cloud computing, makes the production process transparent[32]. It guides industries to shift from high pollution and high energy consumption production methods to those with advanced production techniques and clean and efficient processes. Based on this, the paper proposes the following hypothesis:

H1: AI promotes the improvement of China's GTFP.

Against the backdrop of China's high-quality economic development, optimizing industrial structure and rational layout have become urgent requirements for building a modern economic system. AI technology, as a leading force for innovation-driven development, relies on digital technology and data resources to break information exchange barriers, accelerating the impact on traditional industrial structures[33]. Intelligent production as a new way of industrial innovation and transformation is reshaping the global industrial ecosystem, profoundly affecting the overall industrial structure. As AI technology penetrates from the consumer to the production end, Chinese industries enter a golden stage of development[34]. However, the integration level of AI in production and consumption fields is extremely uneven, with stronger penetration in the consumption field but not fully realized in the production field. From the consumer perspective, AI has driven the prosperity of downstream industries such as online consumption and logistics services, where a significant portion of profits comes from replacing and squeezing out traditional industries and jobs, causing certain shocks to traditional industries and hindering inter-industrial coordinated development, thus reducing the efficiency of AI in enhancing total factor productivity. From the production perspective, the current value creation capability of AI in the manufacturing process remains low, limited to typical, demonstrative parts of manufacturing links, making the promotion effect of AI on reasonable industrial structure layout not obvious. Meanwhile, the weak industrial foundation in China means that existing organizational structures and production equipment cannot bear the comprehensive industrialized innovation brought by AI in the short term, causing imbalance in rational industrial structure and weakening the enhancement of GTFP. Based on this, the paper proposes the following hypothesis:

H2: The inhibitory effect of AI on industrial structure reduces the improvement of China's GTFP.

With the improvement of laws and regulations and the increase in environmental awareness among residents in various provinces, governments pay more attention to environmental control and raise enterprise emission review standards. Enterprises with high pollution and high emissions face hefty fines, forcing them to adopt cleaner technologies[35]. Widely adopted AI technology significantly enhances GTFP only when it is used. Additionally, good environmental regulations provide protection for AI innovation activities, encouraging enterprises to apply AI in the production process, achieving green technological innovation, and causing low efficiency and pollution-intensive enterprises to exit[36]. Based on this, the paper proposes the following hypothesis:

H3: AI promotes the improvement of China's GTFP through environmental regulation.

The actual situation varies across provinces, making the mechanism of AI's impact on GTFP quite complex. The relationship between technological innovation levels and AI development is relatively relevant. Only by continuously achieving breakthroughs in AI technology and innovating industries can productivity be improved[37]. Therefore, when AI technology is at a lower level, it limits its effect on GTFP. At the same time, technological innovation in other non-intelligent industries promotes coordination and matching between local original technologies and AI-related technologies. In the production process, the promotion effect of AI technology on GTFP will be greatly enhanced. Additionally, the level of economic development also becomes an important factor for AI to promote total factor productivity. The development of AI has characteristics such as large investment scale, high investment risk, and lagging economic benefits, facing high overall costs[38]. Therefore, the regional level of economic development will directly affect the breakthrough and diffusion of AI. Regions with higher economic development levels have sound financial information disclosure systems and financial development platforms. In such an environment, it is conducive to reducing the degree of information asymmetry between transaction parties, expanding financing channels for AI technology innovation, motivating continued innovation activities, and accelerating the growth of GTFP.

H4: Controlling for other influencing factors, the impact of AI on GTFP exhibits threshold effects related to technological innovation and economic development levels.

Research design
Model building
Baseline regression model

This paper uses provincial-level panel data to study the impact of AI on GTFP. The following econometric model is constructed:

$$GTFP_{it} = a_0 + a_1 AI_{it} + a_j X_{it} + u_i + u_t + \epsilon_{it} \tag{1}$$

In this model, $GTFP_{it}$ represents the GTFP of province i in period t, AI denotes the level of AI in province i at time t, X_{it} are control variables that have an impact on the GTFP of province i at time t, u_i indicates regional fixed effects, u_t represents time fixed effects, and ε_{it} is the error term.

Furthermore, to examine the indirect channels through which AI affects GTFP, the following model is constructed:

$$RIS_{it} = a_0 + a_1 AI_{it} + a_j X_{it} + u_i + u_t + \epsilon_{it} \tag{2}$$

$$ERN_{it} = a_0 + a_1 AI_{it} + a_j X_{it} + u_i + u_t + \epsilon_{it} \tag{3}$$

In this model, RIS and ERN represent the two mediating variables of industrial structure and environmental regulation, respectively.

GMM model regression

This paper studies the impact of AI on GTFP. Since the change in GTFP is a dynamic process, the lagged value of GTFP from the previous period is included in the model for analysis. The system GMM estimation method is employed to address the potential correlation between the lagged dependent variable and the disturbance term in the dynamic panel data.

$$GTFP_{it} = a_0 + a_1 GTFP_{it-1} + a_2 AI_{it} + a_j X_{it} + u_i + u_t + \varepsilon_{it} \tag{4}$$

Dynamic panel threshold model
This paper refers to the research findings of Duffield, Bowers[39] and constructs a threshold effect model for the impact of AI on GTFP, using technological innovation level and economic development level as threshold variables. Equation (1) is further revised as follows:

$$\begin{aligned} GTFP_{it} &= a_0 + a_2 AI_{it} \cdot I\left(TV_{it} \leq\ y_1\right) + a_3 AI_{it} \cdot I\left(y_1 \leq\ Tv_{it} \leq\ y_2\right) \\ &+ a_n AI_{it} \cdot I\left(TV_{it} \geq\ y_2\right) + a_j X_{it} + u_i + u_t + \epsilon_{it} \end{aligned} \tag{5}$$

.

In this model, TV represents the threshold variable, I (·) denotes the indicator function, which takes the value 0 when the condition inside the parentheses is not met and 1 otherwise, and y is the threshold value.

Variable description

Explained variable
Green total factor productivity (GTFP) is the explanatory variable in this paper, and the super-efficient SBM model has become the mainstream evaluation method of GTFP because it can not only consider variable slack and non-desired outputs in the production process, but also solve the sorting problem of effective decision-making units. In this paper, based on the DEA method, using Matlab software, the desired output, non-desired output and a variety of inputs are simultaneously included in the measurement framework, and the GML indexes of 30 provinces in China are calculated on the basis of the comprehensive consideration of the non-desired output super-efficiency (SBM) model and combined with the global Malmquist productivity index. The main years of GTFP are shown in Fig. 1.

The data used are shown in Table 1. This paper adopts the research method of Wang, Xie[27], setting the GTFP of the base period as 1, and then multiplying it by the GML index of the following year to obtain the green total factor productivity (GTFP) for each province over a 10-year period. Due to space constraints, the exact calculation process and formulas are shown in Appendix I.

Explain variable
The core explanatory variable in this paper is AI. From the current research findings, there is no unified standard for measuring AI, and it is difficult to obtain a direct indicator of AI measurement. Therefore, this paper refers to the findings of Mhlanga[40] and constructs an AI index system for each province from three dimensions: intelligent infrastructure construction, AI industry development level, and AI technology product capability, involving 8 secondary indicators, all of which are positive indicators. The entropy method is used to calculate the index weights and then build the AI index system for each province, for specific indicators, see Table 2. The AI levels of the main years are shown in Fig. 2 radar chart. Due to space constraints, the exact calculation process and formulas are shown in Appendix II.

Intelligent infrastructure construction. Infrastructure construction is a necessary condition for the development of AI. Without well-developed infrastructure, such as the construction of 5G, the application of Internet of Things technology, and the preparation of computer terminals, AI cannot function effectively. Therefore, fixed investment in information transmission, computer services, and software industry, the length of long-distance optical cable lines, the number of internet broadband access ports, and the number of computers at the end of the period are adopted.

AI technology product capability. The capability of AI technology products can only be widely applied when used by enterprises, promoting the development of the AI industry. Therefore, the level of AI basic research achievement transformation and the development of the AI industry itself can well represent the capability of AI technology products. Thus, in this paper, we refer to the research results of Miric, Jia[41] and manually collect the number of AI patent applications in China by region to portray the level of transformation of AI basic research results, and also use the revenue of the software and information technology service industry to portray the output capacity of AI technology products.

Mediating variable
This study refers to the research results of Li, Wang[42], where the Industrial Structure (RIS) is represented by the ratio of the output value of the secondary industry to the GDP of each province.

For Environmental Regulation (ER), this paper synthesizes formal and informal environmental regulation indicators using the entropy method for each province. Formal environmental regulation is a composite of industrial pollution control investment completed amount/value-added of the secondary industry and environmental protection expenditure/GDP. Informal environmental regulation adopts the method proposed by Pargal and Wheeler[43], which includes income level, education level, population density, and age structure.

Threshold variable
The Technological Innovation Level (TI) in this study follows the methodology of De Noni and Ganzaroli[44], utilizing the logarithm of the annual patent grant applications per province to represent the level, encompassing invention patents, utility model patents, and design patent applications granted.

The Economic Development Level (LNAGDP) adopts the approach of Xie, Zhang[45], which reflects the regional economic development status through the annual per capita GDP of each province. A higher per capita GDP indicates a more advanced level of economic development.

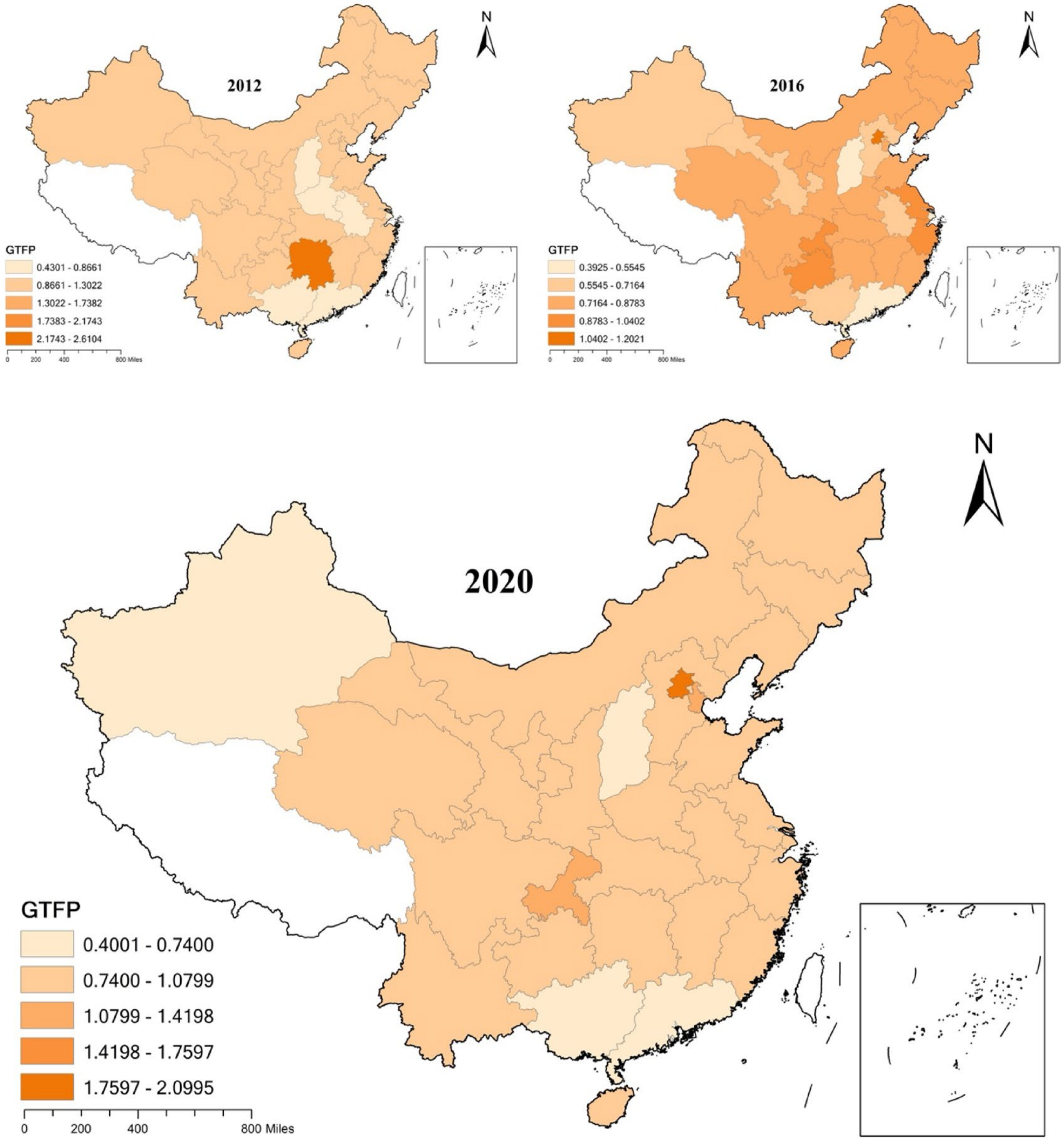

Fig. 1. China's GTFP in main years. (This figure is based on the standard map of the National Natural Resources Ministry's Standard Map Service System. Http://bzdt.ch.mnr.gov.cn).

	Indicators	Formula
Output	Expected output	GDP of each province from 2011 to 2020
	Unexpected output	Using the entropy method, we generate a single undesirable output indicator from the industrial wastewater discharge, sulfur dioxide emissions, and nitrogen oxides emissions of each province. Limited to space constraints, the specific calculation process and formulas are shown in Appendix I.
Input	Capital input	Using the perpetual inventory method for estimation, the capital stock of period t is calculated using the formula $K_t = K_{t-1}(1\text{-}\delta) + I_t$, where K_t and K_{t-1} represent the capital stock of year t and year t-1 respectively, δ represents the depreciation rate of 10.96%, and I_t represents the fixed asset investment of year t. The initial capital stock is obtained by dividing the fixed capital formation total of each province in 2001 by the sum of the average depreciation rate of 10.96% and the average growth rate of investment between 2001 and 2005.
	Labor input	Year-end employment number
	Energy input	total energy consumption of each province

Table 1. GML index output and input Indicators.

Control variable

GTFP can be influenced by various factors. Drawing from the research outcomes of Zhang, Zhu[46] and Wang, Wu[47], we select the following six control variables: Government intervention (GOV): This is represented by the ratio of each province's fiscal expenditure to its GDP. Foreign direct investment (FDI): The annual actual amount

Total indicators	Level 1 indicators	Level 2 indicators
AI	Intelligent infrastructure construction	Fixed Asset Investment in Information Transmission, Computer Services, and Software Industry
		Length of Long-Distance Optical Cable Lines
		Number of Internet Broadband Access Ports
		End-of-Period Number of Computers
	AI industry development level	Installed Number of Industrial Robots in China
		Number of Software Developers
	AI technology product capability	Number of AI Patent Applications
		Income from Software and Information Technology Services

Table 2. AI evaluation Indicator system.

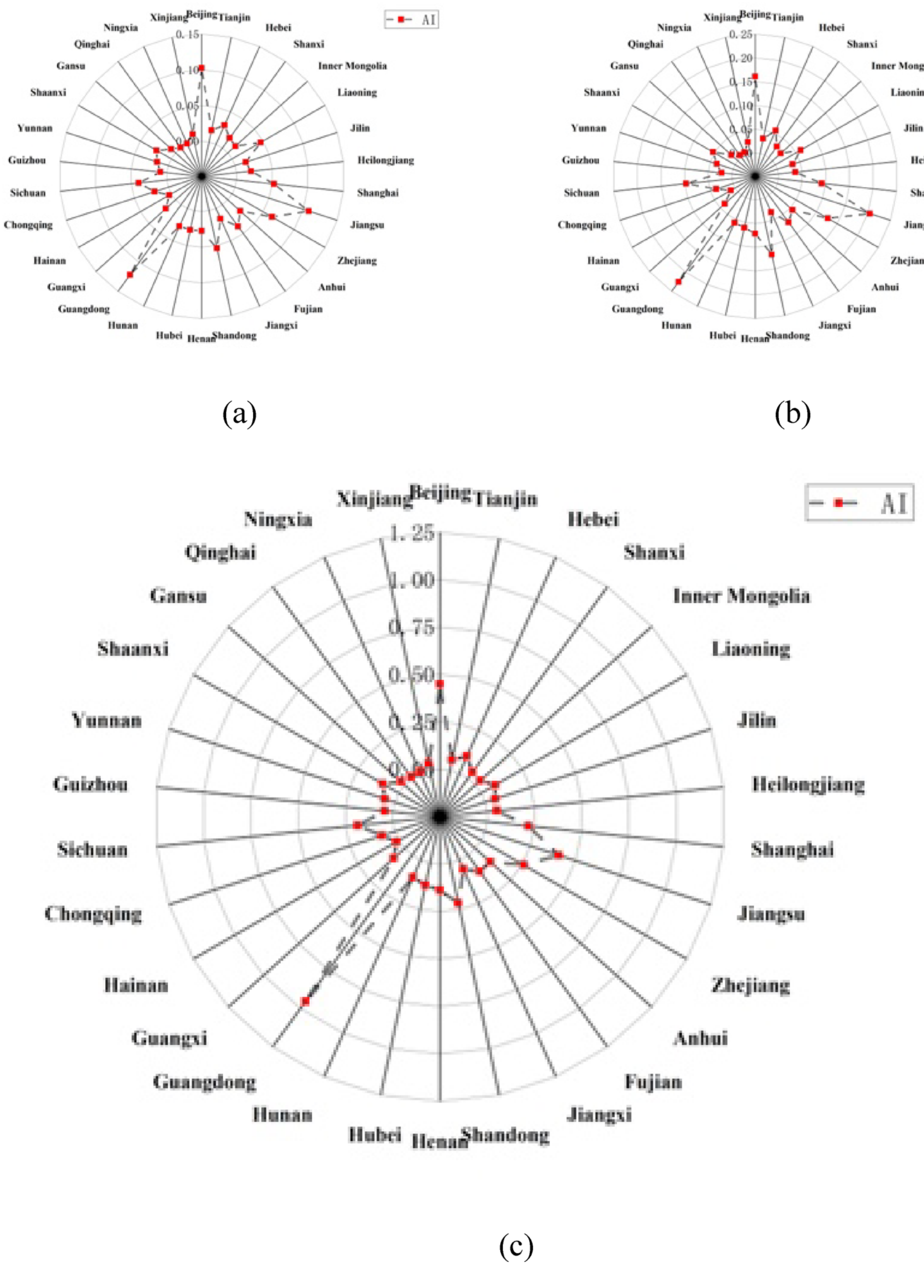

Fig. 2. China's AI Level in 2011 (**a**), 2016 (**b**), and 2020 (**c**).

Variable	Mean value	Standard deviation	Minimum value	Maximum value
GTFP	0.8485	0.2014	0.3887	2.6104
AI	0.0658	0.0855	0.0005	0.9531
HC	0.0260	0.03321	0.0052	0.2264
GOV	0.3227	0.3476	0.1196	2.2093
FDI	5.3872	1.6347	-1.2203	7.4947
MD	1.8736	0.3174	0.8458	2.4849

Table 3. Descriptive statistics of variables.

	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
L.GTFP				0.3250***
				(9.6670)
AI	0.3286*	0.3225*	0.3654**	0.1890***
	(1.9265)	(1.8698)	(2.1015)	(2.7460)
GOV		-1.1185***	-1.0218***	0.1791*
		(-3.0887)	(-2.7913)	(1.7049)
HC		-3.9720	-4.9906	4.9048
		(-1.2393)	(-1.5106)	(1.5034)
FDI			-0.9834	-0.0105**
			(-1.2992)	(-2.1268)
MD			-0.0298	0.0784***
			(-1.3355)	(9.2808)
_cons	0.9908***	1.4240***	1.6116***	-0.2196*
	(39.2797)	(9.5957)	(7.8784)	(-1.7557)
City	YES	YES	YES	YES
Year	YES	YES	YES	YES
AR(1)				0.2196
AR(2)				0.2357
Sargan				0.7285
R^2	0.2675	0.2945	0.3037	
N	300	300	300	270

Table 4. Baseline regression results of AI on GTFP. *z* statistics in parentheses, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

of foreign investment utilized in each province serves as a proxy variable for FDI. Human capital agglomeration (HC): The level of human capital agglomeration in each province is depicted using the logarithm of the number of students enrolled at or above the undergraduate level. Marketization degree (MD): The marketization index constructed by Fan Gang and others is used as a measurement indicator.

Data source and descriptive statistics
This paper employs panel data from 30 provinces (municipalities and autonomous regions) in China for the period 2011–2020. The data sources include the "China Statistical Yearbook," the "China Environmental Statistical Yearbook," and the official website of the National Bureau of Statistics of China. Some data were manually collected from the China Patent Network. Additionally, this paper standardizes certain variables to facilitate analysis. Descriptive statistics for the above variables are presented in Table 3.

Empirical analysis
Baseline regression
This paper first conducts a FE fixed-effects regression on AI and GTFP. The results are presented in Table 4. Column (1) shows the regression results without any control variables, while columns (2) and (3) show the regression results with control variables added step by step. The coefficients of AI are significantly positive at the 1% level in all cases. In the results from column (3), the coefficient of AI is 0.3654, meaning that a 1% increase in AI leads to a 0.3654% increase in total factor productivity, indicating that the development of AI is beneficial for improving GTFP, thus preliminarily proving Hypothesis 1.

Due to potential endogeneity and estimation bias issues in the static panel model setting, this paper includes the lagged dependent variable and constructs a dynamic panel model using system GMM for regression, as shown in column (4). To ensure the consistency of GMM estimates, an autocorrelation test is conducted on its residual series. According to the AR (2) test results, all models pass the autocorrelation test, showing no second-order serial correlation, which proves the validity of the estimation. The Sargan test results are all above 0.1, indicating that there is no over-identification problem with the instrumental variables. As seen in column (4), the regression coefficient of AI on GTFP is 0.1890 and is significant at the 1% level, demonstrating that the development of AI technology has a significant positive effect on GTFP, thereby confirming the validity of Hypothesis 1.

Heterogeneity analysis

China has a vast territory, and due to the influence of both natural conditions and policies, there are significant developmental disparities among different regions. The eastern regions, being coastal, have taken advantage of their superior geographical locations to open up to the outside world early on. As a result, their foreign trade is highly developed. Additionally, influenced by early policy preferences, factors such as talent, capital, and technology have gathered extensively in these areas. Consequently, their development far surpasses that of the central and western regions. This paper aims to verify the varying impacts of regional differences on the GTFP caused by artificial intelligence. It divides the country into eastern and central-western regions based on geographical location, thereby conducting an in-depth exploration and analysis of the different effects produced by these divisions. According to the regression results in Table 5, the eastern region has a more significant promoting effect on GTFP. The reason lies in the fact that the eastern regions are mostly coastal and developed areas with an earlier start and stronger overall strength. For example, Zhejiang Province has already become a demonstration zone for socialism with Chinese characteristics, outperforming the central and western provinces in terms of infrastructure construction and cultural education. The manufacturing industry in the eastern region is well-developed, and many emerging industries are concentrated there, so the momentum of green finance development in the eastern region is stronger than in the central and western regions.

Robustness test

To ensure the reliability of this study, on one hand, we adopted an alternative approach to measuring AI by using principal component analysis to calculate the AI index and replacing the AI variable value used in the baseline regression. As shown in column (1) of Table 6, the effect of AI on GTFP is significantly positive. We also constructed a dynamic panel model using GMM for regression, as shown in column (2). The regression results of AI on GTFP are consistent with the previous conclusions. On the other hand, we used a two-period lag approach, as shown in column (3), and found that the GTFP lagged by two periods is basically consistent with the results lagged by one period, both being significantly positive at the 1% level. This indicates that the estimation results of our regression model are robust and support the empirical research findings. Additionally, we performed a bilateral trimming treatment on continuous variables at the 1% and 99% levels, as shown in column (4).

From the robustness test results in Table 6, it can be seen that although the magnitudes of the coefficients for GTFP differ, their significance and signs are consistent with those in the baseline regression. Thus, the estimation results of our regression model are robust.

Mechanism analysis

The results in column (1) of Table 7 show that the regression coefficient of AI on industrial structure is significantly negative at the 1% level, indicating that the development of AI inhibits the improvement of industrial structure and reduces its promoting effect on GTFP. This also verifies Hypothesis H2 mentioned earlier. From column

	(1)	(2)
AI	0.4200***	-0.5787
	(-0.5537)	(-0.7471)
GOV	-1.4588*	-1.2769***
	(-1.9613)	(-3.0859)
HC	-11.1181***	7.6772
	(-2.7346)	(0.8174)
FDI	0.1157**	-0.0196
	(2.0435)	(-1.0118)
MD	-0.3920	-0.1297
	(-1.1769)	(-0.8452)
_cons	1.9867**	1.5483***
	(2.3096)	(4.6877)
City	YES	YES
Year	YES	YES
R^2	0.4042	0.3883
N	100.0000	200.0000

Table 5. Heterogeneity analysis.

	(1)	(2)	(1)	(2)
	GTFP	GTFP	GTFP	GTFP
L.GTFP		0.2984***	0.2633***	
		(7.3623)	(16.6186)	
L2. GTFP			0.1907***	
			(19.2598)	
AI	0.0228**	0.0209***	0.1615***	0.7185***
	(2.2766)	(3.8183)	(4.3667)	(3.7240)
GOV	-1.0867***	0.1238	0.3361**	-1.0330***
	(-2.9256)	(1.1377)	(2.0495)	(-4.1122)
HC	-4.6437	5.2372	8.4000***	-5.1276*
	(-1.3861)	(1.6160)	(2.5868)	(-1.8156)
FDI	-0.0043	-0.0128**	-0.0175***	-0.0056
	(-0.2237)	(-2.4396)	(-3.0602)	(-0.4258)
MD	-0.0294	0.0757***	0.0944***	-0.0202
	(-1.3097)	(10.4311)	(11.0382)	(-1.3474)
_cons	1.6494***	-0.1499	-0.5161***	1.5601***
	(7.7690)	(-1.1390)	(-3.5822)	(10.5824)
AR(1)		0.2474	0.5021	
AR(2)		0.1808	0.7826	
Sargan		0.6676	0.8716	
City	YES	YES	YES	YES
Year	YES	YES	YES	YES
R^2	0.3020			0.4758
N	300	270	240	300

Table 6. Robustness test results of AI on GTFP. *z* statistics in parentheses, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

	(1)	(2)
	RIS	ER
AI	-0.3168***	0.1653***
	(-2.6458)	(3.3012)
GOV	-0.1093	0.4759***
	(-0.4334)	(4.5143)
HC	-58.2819***	2.5543***
	(-25.6177)	(2.6848)
FDI	0.3279	-0.0969
	(0.6290)	(-0.4445)
MD	-0.0186	0.0118*
	(-1.2108)	(1.8426)
_cons	2.2129***	-0.1375**
	(15.7102)	(-2.3339)
City	YES	YES
Year	YES	YES
R^2	0.7715	0.2807
N	300.0000	300.0000

Table 7. Results on the mechanism of ai's impact on GTFP.

(2), it can be seen that environmental regulation promotes the development of AI, which in turn enhances the growth of GTFP. This also verifies Hypothesis H3 mentioned previously.

Threshold regression

Test for the existence of thresholds

As shown in Table 8, the threshold variable of technological innovation capability passed the single-threshold test but did not pass the double-threshold test. Similarly, the threshold variable of economic development level passed the single-threshold test but failed the double-threshold test. This indicates that the impact of AI on GTFP

Variable	Threshold number	F value	*P* value	threshold	Critical value		
					1%	5%	10%
TI	single threshold	29.95**	0.0000	12.1005	38.0148	24.2123	18.0758
LNPGDP	single threshold	85.45**	0.0300	11.7058	89.0994	49.3634	32.6898

Table 8. Test for the existence of thresholds.

	(1) TI	(2) LNPGDP
GOV	-1.6143***	-1.5911***
	(-6.3953)	(-5.8494)
HC	-4.1598	-1.3490
	(-1.6045)	(-0.8628)
FDI	-1.3210	-1.4921*
	(-1.2892)	(-1.7176)
MD	-0.0829***	-0.0551**
	(-2.8294)	(-2.3241)
AI_1	2.0974**	0.1523
	(2.2982)	(1.1552)
AI_2	0.5145**	2.4087***
	(2.1774)	(8.5620)
_cons	1.9561***	1.7774***
	(9.9087)	(11.1099)
R^2	0.2436	0.3413
N	300	300

Table 9. Regression results of the threshold model. AI_1 and AI_2 represent the estimated coefficients of AI in different threshold variable intervals.

exhibits a single-threshold effect with respect to both technological innovation level and economic development level. From the results, we can see that the threshold value for technological innovation capability is 12.1005. By 2020, only four provinces—Guangdong, Shandong, Jiangsu, and Hainan—had surpassed this threshold in terms of technology absorption capability, with other provinces falling short of the threshold value. The threshold value for economic development level is 11.7058, and by 2020, only Shanghai, Beijing, and Jiangsu had crossed this threshold in terms of economic development level.

Analysis of the regression results

After setting a single-threshold model for technological innovation level and conducting regression analysis, the results are shown in Column (1) of Table 9. When the technology absorption capability is less than or equal to 12.1005, the coefficient of AI is 2.0974, significantly positive at the 5% level, meaning that a 1% increase in AI leads to a 2.0974% increase in GTFP. However, when the technology absorption capability exceeds 12.1005, the coefficient of AI is 0.5145, significant at the 5% level, indicating that a 1% increase in AI results in a 0.5145% increase in GTFP. Overall, AI has a significant positive effect on GTFP. When the technological innovation level is below the first threshold value, its positive impact on the development of GTFP is more pronounced. At this stage, the development of technological innovation can promote the rapid development of AI, increase investment in core foundational technologies of AI, mature AI technology, integrate AI with other industries, and interact positively with other production factors in production, thereby improving production efficiency. When the technological innovation level crosses the threshold value, as the level of AI continues to improve, the cost of AI computing power also increases, raising the barriers for AI research and application. Meanwhile, China's chip design and manufacturing, high-end sensors, and other AI hardware developments cannot meet the demands of high-level AI development, which somewhat inhibits the promotion of GTFP. As a result, the positive effect of technological innovation level decreases after crossing the threshold value.

After setting a single-threshold model for economic development level and conducting regression analysis, the results are shown in Column (2) of Table 9. When the economic development level is less than or equal to 11.7058, the coefficient of AI is 0.1633, not significant. But when the economic development level exceeds 11.7058, the coefficient of AI is 2.4087, significant at the 1% level, meaning that only when the economic development level of provinces reaches the threshold does AI have a significant enhancing effect on GTFP. Overall, the development of AI technology requires a certain economic foundation. Only when the economy reaches a certain level will governments and enterprises increase their investment in research and development for AI technology, enabling its advantages to be fully realized and better promoting the improvement of GTFP.

Conclusions and policy implications

Conclusions

This paper selects panel data from 30 provinces (cities, districts) from 2011 to 2020, constructs a system GMM and threshold model to explore the impact mechanism of AI on GTFP. The research results show that artificial intelligence has a positive and significant effect on GTFP. When artificial intelligence increases by 1%, GTFP will increase by 0.3654%. The promoting effect of artificial intelligence is more pronounced in the eastern region. Furthermore, the mediation effect model reveals that as the industrial structure improves with the advancement of AI, it subsequently suppresses the increase in GTFP. An increase in environmental regulation enhances the extent to which AI boosts GTFP. Additionally, through threshold model regression, it is found that AI's effect on GTFP exhibits a single-threshold effect based on technological innovation capability and economic development level. When the technology absorption capacity crosses the threshold value, its impact on GTFP diminishes. Conversely, when the economic development level crosses the threshold value, its impact on GTFP intensifies.

Policy implications

To further promote the development of AI and enhance China's GTFP, this article proposes the following countermeasures and suggestions:

First, improve the relevant infrastructure to promote the development of artificial intelligence. As mentioned above, on the one hand, the development of artificial intelligence needs corresponding infrastructure support, such as support for sensors, chip manufacturing, if you can't continuously improve the infrastructure, the level of development of artificial intelligence will be limited, and lead to a reduction in the role of productivity improvement, and can't break through the core technology of artificial intelligence and lead to a decline in core competitiveness. Increase capital investment in artificial intelligence. On the other hand, we should pay attention to the development of big data technology and cloud computing technology, big data technology is the premise of artificial intelligence, mining value from massive data, cloud computing can save resources, save computing power, reduce computing power waste, greatly reduce the economic consumption of the enterprise, promote the development of artificial intelligence and promote the application of artificial intelligence, improve productivity.

Secondly, the contradiction between the development of AI technology and the development of the traditional economy is solved at the level of industrial structure. The government should select appropriate AI technology input efforts according to industrial factor endowments and development advantages, enhance the degree of data resource adaptation with traditional industries, and eliminate the development crisis of traditional economy. Secondly, it should vigorously promote the application scope of AI, deeply excavate industrial intelligence and other fusion development modes, force the research and development and fusion intensity of AI technology, further strengthen inter-industry interaction and collaboration, and realize the dynamic conversion of inter-industry stock. Secondly, it should actively guide the formation of AI value following and basic principles, and delineate specific boundaries for strict regulation; prudently control the scale of data element inflow, prevent and control the phenomenon of malicious monopoly, and reduce unreasonable fluctuations in the industrial structure.

Thirdly, the level of technological innovation and economic development as the level of development of artificial intelligence on the GTFP of the important hand, pay attention to the development of artificial intelligence technology research and development efforts, the development of solutions and products that benefit to enhance the GTFP. And focus on the development of regional economic level, in order to promote the sustainability of artificial intelligence development to provide a convenient economic foundation.

Fourth, improve relevant policies and systems, sound laws and regulations, the government should strengthen environmental supervision and governance. Only a sound legal system and good environmental regulation can stimulate the promotion of GTFP of existing AI technology.

Fifth, in the process of the new round of technological change and artificial intelligence development, each region can combine its own development characteristics. Especially for the central and western regions with backward economic level and backward marketisation, further policy inclination is needed, so as to realize green transformation by promoting the development of artificial intelligence.

Limitations

Our study examines the impact of AI technology on China's GTFP and investigates the intrinsic mechanisms by which AI technology affects China's GTFP. However, it must be recognized that there are certain limitations in this study. Firstly, due to the limitation of data acquisition, this study only selects the data at the provincial level in China during the period of 2011–2020 as the research object, and fails to conduct the study from the perspective of prefecture-level cities due to the difficulty of data acquisition. Second, the analysis in this paper only focuses on the development of AI technology in China, while the effect of this development varies in different countries. Future research could consider exploring the relationship between AI and GTFP in developed or other developing countries.

Data availability

The datasets used and analyzed during our study are available from the corresponding author on reasonable request.

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Author contributions
wenhao Ding: Project administration and conceptualization, Experimental work; Pan Hu: Characterization of the prepared materials, write first draft of manuscript, Review and edit. All authors read and approved the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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