Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3, 228-242
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i3.5183

How artificial intelligence narrows the productivity gap between enterprises: A regional technological spillover perspective

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Abstract: This study aims to investigate the mechanisms through which artificial intelligence (AI) contributes to the reduction of productivity disparities among enterprises, specifically through regional technology spillover effects. We constructed a regression model based on the relationship between AI integration and productivity convergence of the listed firms in China from 2001 to 2021. The empirical results, derived from a β-convergence model, reveal a pronounced trend of both absolute and conditional convergence in productivity, signifying that lower-efficiency firms are progressively aligning with their higher-efficiency counterparts. The findings underscore that AI serves as a pivotal driver of productivity enhancement, facilitating not only the catch-up potential of lower-efficiency enterprises but also the speed of productivity convergence across the sector. Our analysis indicates that the deployment of AI significantly elevates production efficiency and fosters overall regional R&D output, thereby creating conducive conditions for mitigating the productivity gap between enterprises. Additionally, the elevation of regional R&D levels further amplifies the growth trajectory of lower productivity firms. The research conclusions of this paper demonstrate the positive significance of applying artificial intelligence in promoting the development of small and medium-sized enterprises.

Keywords: *Artificial Intelligence, TFP, Productivity.*

1. Introduction

Artificial Intelligence (AI) has built a multi-layered infrastructure through innovations in computer technology, algorithms, and technical aspects. This infrastructure enables machines to engage in deep learning, leveraging knowledge accumulation and big data analysis to mimic human physical and intellectual capabilities. Currently, AI has become a core driving force behind the technological revolution and a significant guiding power in industrial transformation. It is fundamentally changing human economic models and social lifestyles across various domains, including manufacturing, services, and the intelligence of daily life [1]. The development of AI is receiving high attention from economies worldwide, particularly the United States, the European Union, Japan, China, and India, viewing it as a key element in global strategic competition [2].These countries are also continuously increasing their investment and support for AI technologies through policy initiatives. For instance, the Chinese government has formulated the "New Generation Artificial Intelligence Development Plan," emphasizing seizing the strategic opportunities of AI development to gain a competitive advantage in this field. Additionally, complementary policy documents such as the "Three-Year Action Plan to Promote the Development of the New Generation of Artificial Intelligence Industry (2018-2020)," the "Guiding Opinions on Promoting the Deep Integration of Artificial Intelligence and the Real Economy," and the "Ethical Norms for the New Generation of Artificial Intelligence" provide institutional safeguards for the application and development of AI.As a critical engine driving a new round of technological revolution and industrial transformation, AI has a profound impact on enhancing

History: Received: 27 December 2024; Revised: 21 February 2025; Accepted: 24 February 2025; Published: 4 March 2025
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productivity and promoting the upgrading of industries [3, 4]. Undoubtedly, the introduction of AI technologies has made enterprises more efficient in processes such as production flow, resource allocation, and market responsiveness. However, a specific focus should be placed on how AI, while promoting productivity growth in Chinese companies, affects the productivity gap between enterprises. Is it possible that technological advancements can promote convergence in productivity and bridge the gap between different companies?

To address these questions, this paper will first explore the relationship between the dynamics of AI development and enterprise productivity by comprehensively reviewing relevant research literature and achievements, analyzing the theoretical and empirical contributions of existing studies in this area. Building on this foundation, the article will construct a total factor productivity convergence model and conduct empirical testing using data from Chinese publicly listed companies between 2001 and 2021. Additionally, from the perspective of regional technological spillovers, this study will delve into how AI can positively impact the narrowing of productivity gaps among enterprises through mechanisms such as technology diffusion, knowledge sharing, and industrial linkage. Ultimately, this paper aims to provide theoretical support and practical guidance for understanding the role of AI in fostering economic development and social progress.

2. Literature Review

2.1. Productivity Convergence

The theory of productivity convergence primarily investigates the dynamic trends of disparities in efficiency indicators, largely based on assumptions such as diminishing marginal returns and constant returns to scale [5]. Productivity convergence needs to be distinguished from industrial convergence. Industrial convergence refers to the dynamic process in which different industries gradually form new industries through mutual penetration and intersection, while productivity convergence reflects the changing trend of productivity gaps among enterprises [6].

In recent years, international scholars have commonly employed two testing methods—σ convergence and β convergence—to study productivity convergence in China [7]. σ convergence refers to the decreasing dispersion of individual indicators over time, which can be assessed by analyzing the trend in the standard deviation of productivity among individuals. A declining standard deviation over time indicates the presence of σ convergence, while an increasing standard deviation suggests divergence [8]. The results of σ convergence can be visually represented in graphs, effectively illustrating changes in the standard deviation of productivity over time. In addition to standard deviation, past studies have also utilized coefficients of variation, Theil index, or Gini coefficients for measurement [5, 9].

In contrast to σ convergence testing, β convergence requires the establishment of a parametric regression model. It can be divided into absolute convergence and conditional convergence based on the inclusion of control variables in the regression model [10]. The presence of β convergence implies that productivity growth rates are faster for lagging entities compared to leading ones [5]. Absolute β convergence emphasizes that individual productivity will ultimately reach identical steady-state growth rates and levels, sharing the same growth paths and equilibrium states. Its regression model is simpler, primarily examining the correlation between productivity growth and initial values; a significantly negative regression coefficient indicates absolute β convergence [11]. Conditional convergence, on the other hand, takes into account other controlling factors, suggesting that individual entities are approaching their respective steady-state levels, each with distinct growth paths and equilibrium states. The regression model for conditional convergence is similar to that of absolute convergence, with the addition of a series of control variables [12]. It is important to note that conditional convergence does not imply that productivity indicators will converge absolutely among individuals. Instead, recognizing the different foundational conditions among individuals, productivity evolves along respective steady-state paths, ultimately achieving stable growth rates and levels, while disparities may persist [8].

The factors influencing the spatial distribution and evolutionary patterns of total factor productivity can be considered from both internal factors within firms, such as management practices, factor inputs, and R&D, and external environmental influences like market competition, levels of openness, and government intervention Syverson [13]; Wang, et al. [14] and He, et al. [15]. Dieppe and Matsuoka [16] used an industry-level database to study the impact of industry internal structure on β convergence. They believe that sector reallocation and sector reconfiguration have become important driving forces for the β convergence of labor productivity. Eder, et al. [17] found that industrial robots can promote labor productivity growth and cross-border economic convergence. Hu [18] found that the main driving force behind China's agricultural GTFP growth comes from technological progress, and the convergence of agricultural GTFP has both phased and regional characteristics, and the convergence of agricultural GTFP has been significantly improved. Yiğiteli and Şanlı [19] analyzed the total factor productivity (TFP) growth in 26 regions of Türkiye and explored the possible role of technological efficiency.

Research indicates that industry-level and policy-level factors could be significant drivers of total factor productivity convergence [20]. Incentive policies and moderate administrative interventions often favor the emergence of convergence trends in productivity. For instance, the "benchmark competition" behavior formed under the "Chinese-style decentralization" system is conducive to spatial convergence of total factor productivity [21]. Economic policies promoting infrastructure construction and income growth can facilitate convergence in regional industrial labor productivity [22]. Additionally, the implementation of forestry property rights reform has significantly accelerated the convergence speed of regional forestry labor productivity [23]. However, some studies have pointed out that improper or excessive administrative intervention may lead to resource misallocation, negatively impacting productivity convergence [24]. Furthermore, increased openness to foreign investment and easing of restrictions may accelerate the polarization of total factor productivity among enterprises, hindering convergence trends [25, 26]. Additionally, disparities in technological advancement rates across cities are a major reason behind the divergence in total factor productivity [27].

In recent years, there has been a notable spatial dependency in technological innovation and efficiency improvements among regions in China, suggesting the potential for spatial correlations in analyses of indicators like productivity. Some scholars have noted that the acceleration of inter-provincial total factor productivity convergence from 1978 to 2012, as well as a shortening of the cycles, is primarily due to spatial convergence in scale efficiency and technical efficiency [28]. Spatial effects have also resulted in a faster convergence of green total factor productivity in agriculture from 2011 to 2016 [29]. In empirical research focused on assessing the impact of influencing factors, some scholars have added interaction terms to examine moderating effects Yang and Zhao [30] while other literature has incorporated variable factors directly into convergence equations for a more intuitive observation of changes in convergence coefficients and speeds [21, 31].

2.2. The Role of Artificial Intelligence in Enterprise Productivity and Its Convergence

When discussing the impact of artificial intelligence (AI) on productivity, it is essential to address the "Solow Paradox." This paradox has attracted considerable attention from researchers and has sparked widespread academic debate. However, there is no consensus in the academic community regarding the actual existence of this phenomenon. Some scholars, such as Acemoglu and Restrepo [32] argue that advancements in AI, particularly through innovations and applications of technologies like industrial robots, can significantly enhance labor productivity. Their theoretical model suggests that by replacing low- to medium-skill workers, AI not only improves production efficiency but also potentially yields greater economic benefits for enterprises. Empirical research further supports this view; for example, Graetz and Michaels [33] analyzed industry data from 17 countries between 1993 and 2007 and found that the use of industrial robots not only increased labor productivity but also contributed to the growth of total factor productivity. In China, Li and Xu [34] examined robot usage data from 2000 to 2013 and highlighted a significant positive impact of increased robot utilization on labor productivity in the country's manufacturing sector. Additionally, Qu and Lü [35] emphasized that companies employing industrial robots often exhibit stronger innovation capabilities, which not only enhance productivity but also promote the long-term development potential of these firms. Tasheva and Karpovich [36] proposed that AI is already being used to automate routine tasks, freeing up employees to plan more strategically and create greater business value, and that the combination of human strengths and AI can lead to higher levels of innovation, efficiency, and output. Xie and Yan [37] found that AI can promote the agglomeration of producer services directly or by improving productivity.

Regarding the mechanisms involved, research by Li, et al. [38] shows that AI contributes to productivity improvements in the manufacturing sector by optimizing the structure of factor inputs and transforming production and management models. For instance, smart management and data analysis during production processes can enhance resource utilization efficiency, reduce waste, and enable more precise production scheduling. Furthermore, the application of AI reduces the need for low-end assembly line jobs and hazardous positions, which increases the demand for high-skilled labor. This shift not only accelerates the accumulation of human capital within enterprises but also significantly boosts production efficiency [39]. As a critical focus in this field, studies of publicly listed companies have revealed that the development of AI has substantially enhanced their productivity, influenced by factors such as labor quantity, the efficiency of material capital usage Fan, et al. [40] technological innovation output Zhong, et al. [41] as well as the convenience of information transfer and the flattening of management structures [42].

However, opposing views are increasingly gaining importance. Another group of researchers argues that the "Solow Paradox" has a valid basis in the relationship between AI development and productivity Cheng [43]. Filippucci, et al. [44] argue that AI has unique autonomous and self-improving capabilities, which may accelerate innovation and potentially restore sluggish productivity growth across industries, while also acknowledging the uncertainty of AI's impact on long-term productivity. Some studies indicate that, despite rapid growth in AI patent applications in certain regions, the growth rate of labor productivity in those regions remains unusually slow Hu, et al. [45]. Zhong, et al. [41] found that artificial intelligence can empower the real economy and promote the intelligent transformation and upgrading of enterprises, but whether the application of artificial intelligence has improved the total factor productivity (TFP) of enterprises in developing countries remains an unknown.

Furthermore, there are studies suggesting that between 2011 and 2020, the development of AI did not lead to an effective increase in productivity in China's manufacturing sector, particularly in high-tech manufacturing, where the phenomenon of the Solow Paradox is especially pronounced Li, et al. [38]. Jiang and Li [46] also found no significant advancements in total factor productivity in the pharmaceutical manufacturing, computer, and instrumentation sectors from 2001 to 2017, attributable to AI development. Regarding the reasons behind the "Solow Paradox" in the relationship between AI and productivity, Acemoglu and Restrepo [47] note that the application of technologies like AI should be closely tied to actual enterprise development; excessive or inappropriate use may lead to misallocation of capital and labor, thus hindering total factor productivity improvement. Chinese scholars have also conducted in-depth analyses; for instance, Guo and Fang [48] discussed the lag effect of technological innovation, while Cheng [43] emphasized the importance of prior accumulation of intangible capital. Simultaneously, Hu, et al. [45] highlighted productivity losses due to human-machine mismatches. Additionally, Li, et al. [38] pointed out that the lack of human capital and limitations in market scale adversely affect the role of AI in enhancing productivity.

In summary, researchers' views on AI's role in improving productivity exhibit opposing trends, reflecting the complexity and applicability of this technology in practice. Future research should continue to explore the effects of AI on various industries and regions to provide more accurate theoretical guidance and practical references for policy-making and enterprise management.

Current literature on the impact of AI on productivity has covered multiple aspects, yet studies regarding how AI affects productivity disparities between firms and their convergence remain relatively scarce. This scarcity is evident in several areas. Firstly, while explorations into the influence of AI on productivity among Chinese enterprises have been ongoing, particularly within the framework of the "Solow Paradox," no consensus has emerged to date. Most research has focused on the overall level, leading to a limited amount of empirical studies and verified evidence at the enterprise level. This gap poses challenges for academia in explaining the complex relationship between AI and productivity. Secondly, research investigating how AI influences the convergence of productivity at the firm level is similarly weak, lacking systematic mechanism analyses. Theoretically, AI could narrow productivity gaps between firms by enhancing technical efficiency, optimizing resource allocation, and promoting innovation, yet detailed empirical analyses and studies on the heterogeneity of different types of firms supporting this hypothesis are still lacking. Therefore, this paper aims to fill this research gap and provide new insights for scholars and policymakers.

To achieve this, the paper will delve into several key points: First, through systematic empirical research, we will validate the positive impact of AI development on productivity at the firm level. This research will not only provide reliable empirical evidence to address the "Solow Paradox" but also offer a new perspective for future inquiries. Second, the paper will focus on exploring how AI development affects the convergence of total factor productivity among China's publicly listed companies, revealing its role in promoting equilibrium and high-quality development. Through comparative analysis of firms with varying scales, industries, and technological levels, we aim to deepen our understanding of AI's critical role in driving structural economic transformations and enhancing overall production efficiency. This research seeks to provide actionable recommendations for enterprise management practices and government policy-making, thereby better addressing the opportunities and challenges posed by AI.

3. AI and the Productivity Gap Among Enterprises

This study employs a β-convergence model to measure the productivity convergence of listed companies in China. Furthermore, it investigates the impact of artificial intelligence variables on productivity convergence from the perspective of regional technological spillovers. First, we construct the following equation for testing the absolute β-convergence of enterprise productivity.

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \varepsilon_{i,t} \qquad (1)$$

In this equation, $\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T$ represents the annual average growth rate of total factor productivity (TFP) for listed company i from the period $t-T$ to t, with T set to 1. $TFP_{i,t-T}$ denotes the total factor productivity of listed company i at the beginning of the period $t-T$; $\varepsilon_{i,t}$ is the error term. Next, we conduct a test for conditional β-convergence by constructing the following regression equation that includes control variables based on equation (1):

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \Lambda X_{i,t} + \varepsilon_{i,t} \qquad (2)$$

The above equation differs from the β absolute convergence test equation by incorporating a series of control variables that may influence the growth of enterprise total factor productivity (TFP). Specifically, these control variables include research and development (R&D) investment (measured by the annual R&D expense ratio), capital indicators (measured by capital intensity), trade dependency (the ratio of overseas business income to total operating income), and scale growth (measured by total asset growth rate).The convergence coefficient β and convergence speed are related by the following relationship $\beta = -\left(1 - e^{-\lambda t}\right)$. Conversely, based on the estimated convergence coefficient β, the convergence speed of TFP can be calculated as $\lambda = -\ln(\beta + 1)/t$.

Additionally, the time required for productivity convergence (half-life) can be calculated as $\tau = \ln(2)/\lambda$, this half-life value indicates the time it would take for low productivity firms to catch up with high productivity firms and reach a steady state (absolute convergence), or the time it takes for both to achieve a steady state within the overall environment (conditional convergence).

To examine the impact of artificial intelligence on the productivity convergence of listed companies in China during the period from 2002 to 2021, this study draws on the methods of Yu [21] and Wang, et al. [31] by directly incorporating the development indicator of artificial intelligence in the β convergence test equation. This approach allows for a more intuitive observation of the changes in the convergence coefficient and the calculation of convergence speed. The specific regression equation is as follows:

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \gamma AI_{i,t-T} + \varepsilon_{i,t} \qquad (3)$$

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \gamma AI_{i,t-T} + \Lambda X_{i,t} + \varepsilon_{i,t} \qquad (4)$$

In this context, $AI_{i,t-T}$ represents the artificial intelligence development indicator for listed company i during the period $t-T$ (the beginning of the period). The coefficient γ directly reflects the impact of artificial intelligence on the growth of corporate productivity. By observing the changes in β, we can assess the influence of artificial intelligence on the convergence direction and speed of corporate productivity.Regarding the measurement of artificial intelligence indicators, this paper categorizes the field of artificial intelligence into ten major categories: machine learning, natural language processing, knowledge engineering, information retrieval and recommendation, computer vision, speech recognition, robotics, data mining, human-computer interaction, and visualization. Under each category, relevant literature and professional bibliographies were collected and organized, resulting in a total of 188 specific keywords [49-51]. Based on the word segmentation of corporate annual reports, we can determine the total vocabulary for each annual report and statistically analyze the keyword frequency to use this as a variable for the level of artificial intelligence application within companies.

Table 1.
β convergence test for TFP and the impact of artificial intelligence.

	(1)	**(3)**	**(2)**	**(4)**	**(5)**	**(6)**
	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$
$l.\ln TFP$	-0.16059***	-0.15645***	-0.16260***	-0.15804***	-0.16106***	-0.15674***
	(0.00536)	(0.00622)	(0.00547)	(0.00626)	(0.00555)	(0.00635)
AI			0.00006**	0.00008**	0.00138**	0.00118**
			(0.00003)	(0.00004)	(0.00063)	(0.00059)
$l.\ln TFP \times AI$					-0.00057**	-0.00047*
					(0.00027)	(0.00025)
Controls	NO	YES	NO	YES	NO	YES
N	33949	33949	33949	33949	33949	33949
R^2	0.089	0.143	0.090	0.144	0.090	0.144
adj. R^2	0.089	0.143	0.090	0.144	0.090	0.144
F	898.53065	212.96333	448.89909	178.81209	301.17481	153.65299

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$。

Table 1 reports the regression results of β absolute convergence and conditional convergence, as well as the results after incorporating the artificial intelligence variable. From columns (1) and (2), we can see that the β coefficients are negative, indicating that during the period from 2001 to 2021, the productivity of publicly listed companies in China exhibited a trend of β convergence, meeting the characteristics of both absolute convergence and conditional convergence, with the absolute value of the conditional convergence result being slightly lower.

In terms of convergence speed, the speed of productivity convergence during the β absolute convergence regression was 0.00875, with a half-life of 79.19147. For the β conditional convergence regression, the speed of productivity convergence was 0.00851, with a half-life of 81.48149. In contrast, the results in columns (3) and (4) after incorporating artificial intelligence show that both the absolute convergence and conditional convergence coefficients remain negative and their absolute values have increased. After considering the impact of artificial intelligence, the calculated absolute convergence speed and conditional convergence speed for productivity were 0.00887 and 0.00860, respectively, representing increases of 1.37% and 1.06% compared to the results without including the artificial intelligence variable. The half-lives required for productivity convergence were also reduced to 78.12159 and 80.58784, respectively. It can be seen that the inclusion of artificial intelligence further accelerated the convergence speed of productivity among publicly listed companies, effectively shortening the convergence half-life of productivity.

In order to substantiate the role of artificial intelligence indicators in facilitating the convergence of productivity for listed companies, we included the interaction terms between the artificial intelligence indicators and the initial productivity variables in regression equations (3) and (4). As shown in columns (5) and (6), the coefficients of the interaction terms between the artificial intelligence indicators and the initial productivity variables are significantly negative, indicating that the inclusion of the artificial intelligence variables indeed enhances the absolute value of the convergence coefficient (negative), thereby promoting an increase in the convergence speed. Furthermore, an examination of the regression coefficients of the artificial intelligence indicator variables across the columns demonstrates that the development of artificial intelligence from 2001 to 2021 has overall contributed to the growth of total factor productivity in enterprises, with results being significant. If the entire sample is grouped by annual productivity medians, and regressions are conducted separately for high-productivity and low-productivity listed companies, it can further corroborate the related conclusions.

This paper employs the following methods to address the issue of endogeneity. Since the core explanatory variables in the regression equations are all lagged terms, we can exclude the direct influence of the explained variable (productivity growth) on the core explanatory variable (initial productivity). We use the first-order lagged term of total factor productivity as an instrumental variable to mitigate potential endogeneity issues affecting the results. According to Table 2, the direction of the convergence coefficient after employing the instrumental variable is consistent with the baseline regression, and the absolute value increases with the inclusion of artificial intelligence variables, indicating a faster convergence speed, which aligns with previous conclusions.

For robustness checks, this paper primarily adjusts the time span, utilizes past averages of total factor productivity variables, replaces the measurement methods for artificial intelligence indicator variables, and modifies the research time period. The specific details are as follows:

Table 2.
Regression results using instrumental variables.

	(1)	(2)	(3)	(4)
	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$
$l.\ln TFP$	-0.27978***	-0.27999***	-0.26915***	-0.26973***
	(0.01058)	(0.01061)	(0.01071)	(0.01073)
AI		0.00001		0.00004**
		(0.00001)		(0.00002)
Asset			0.01174***	0.01174***
			(0.00113)	(0.00113)
RDpro			-0.11306***	-0.11601***
			(0.01288)	(0.01297)
KI			-0.00036*	-0.00036*
			(0.00021)	(0.00021)
AbroadRev			0.01244***	0.01233***
			(0.00280)	(0.00280)
KP rk LM p	0.0000	0.0000	0.0000	0.0000
KP F	6670.144	6632.167	6358.546	6331.129
S-Y (10%)	16.38	16.38	16.38	16.38
N	29740	29740	29740	29740
2rd step R2	0.163	0.163	0.213	0.213
2rd step adj. R2	0.063	0.063	0.118	0.118
2rd step F	99.04915	94.50680	101.62810	97.59668

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$。

3.1. Adjusting the Time Span

In the baseline regression, the time span T is set to one year. Here, we adjust the value of T to five years to observe the convergence of total factor productivity (TFP) of Chinese listed companies over a longer time frame and to test the robustness of the results. According to the regression results in Table 3, when the time span T is adjusted to five years, the absolute value of the convergence coefficient significantly decreases. The calculated absolute convergence and conditional convergence rates of corporate productivity are 0.00689 and 0.00706, respectively. The half-lives required for convergence are 100.54921 and 98.17498, respectively. Both the convergence rates are lower than those observed when T is one year, and the half-lives are longer than those under the one-year time span. Similarly, when the artificial intelligence index variable is included, the results show that the absolute convergence and conditional convergence coefficients (negative values) still increase in absolute value. After considering the influence of the artificial intelligence variable, the calculated absolute convergence rate and conditional convergence rate of productivity rise to 0.00692 and 0.00707, respectively, which represent increases of 0.44% and 0.14% compared to previous values. The half-lives reduce to 100.09906 and 97.99911, respectively. Unlike the baseline regression results, when T is adjusted to five years, the conditional convergence rate of total factor productivity for Chinese listed companies exceeds the absolute convergence rate, indicating that the time for listed companies to reach their respective steady-state levels is shorter than the time required to achieve a consistent steady state.

Table 3.
Regression Results When T=5.

	(1)	(2)	(3)	(4)
	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$
$l.\ln TFP$	-0.12879***	-0.12933***	-0.13169***	-0.13191***
	(0.00270)	(0.00271)	(0.00275)	(0.00276)
AI		0.00006***		0.00004***
		(0.00002)		(0.00001)
Asset			0.00097***	0.00097***
			(0.00035)	(0.00035)
RDpro			0.02871***	0.02721***
			(0.00600)	(0.00604)
KI			-0.00010*	-0.00010*
			(0.00006)	(0.00006)
AbroadRev			0.00787***	0.00780***
			(0.00194)	(0.00194)
_cons	0.30262***	0.30374***	0.30860***	0.30904***
	(0.00614)	(0.00616)	(0.00624)	(0.00624)
N	20706	20706	20706	20706
R2	0.410	0.411	0.427	0.427
adj. R2	0.410	0.411	0.427	0.427
F	2278.91923	1143.12254	491.34616	409.85005

Note: Standard errors in parentheses, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$。

3.2. Adjusting the Measurement of Artificial Intelligence Variables

In terms of measuring the artificial intelligence (AI) indicator variable, we replace the original total word frequency with a dummy variable indicating the presence of AI keywords and the proportion of AI keywords in the total vocabulary. This adjustment aims to test the robustness of the results. According to the findings presented in Table 4, regardless of whether the AI indicator uses the dummy variable or the proportion of keywords, the effect on the convergence coefficient of listed companies' productivity β aligns with the direction observed in the baseline equation. Specifically, the use of these measures contributes to an increase in the absolute value of the convergence coefficient, enhances the convergence speed, and reduces the duration of the convergence half-life. When the dummy variable is used as the development indicator for AI in listed companies, its impact on the β convergence coefficient is the most significant, with the absolute convergence speed and conditional convergence speed increasing to 0.00959 and 0.00930, respectively. The corresponding half-lives are reduced to 72.24073 and 74.53505. Conversely, when using the proportion of keywords in the total vocabulary to represent the development of AI in listed companies, the results are comparable to those obtained in the baseline regression, which used the total word frequency of keywords. This finding further validates the robustness of the baseline regression results.

Table 4.
Regression results using other measurement of AI.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\ln TFP$	$\Delta\ln TFP$	$\Delta\ln TFP$	$\Delta\ln TFP$	$\Delta\ln TFP$	$\Delta\ln TFP$
$l.\ln TFP$	-0.16059***	-0.17461***	-0.16264***	-0.15645***	-0.16972***	-0.15791***
	(0.00536)	(0.00583)	(0.00544)	(0.00622)	(0.00661)	(0.00624)
AI		0.00710***	0.00973***		0.00775***	0.01107***
		(0.00062)	(0.00339)		(0.00062)	(0.00401)
Asset				0.01401***	0.01401***	0.01400***
				(0.00129)	(0.00129)	(0.00129)
RDpro				-0.02563**	-0.04401***	-0.03385***
				(0.01283)	(0.01236)	(0.01305)
KI				-0.00034	-0.00035	-0.00034
				(0.00023)	(0.00023)	(0.00023)
AbroadRev				0.02053***	0.01863***	0.01994***
				(0.00282)	(0.00281)	(0.00284)
_cons	0.37629***	0.40529***	0.38055***	0.36503***	0.39239***	0.36802***
	(0.01225)	(0.01321)	(0.01242)	(0.01438)	(0.01518)	(0.01442)
N	33949	33949	33949	33949	33949	33949
R2	0.089	0.095	0.090	0.143	0.149	0.144
adj. R2	0.089	0.095	0.090	0.143	0.149	0.144
F	898.53065	455.24604	449.45079	212.96333	184.91264	179.08619

Note: Standard errors in parentheses, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$。

3.3. Using Past Average TFP

Considering the potential impact of short-term fluctuations in corporate productivity on empirical results, we replace the productivity measure with the average of the past three years [11]. Corresponding derived variables are also calculated using these averages, which are then incorporated into the regression equation to observe the robustness of the results. Table 5 reports the findings from this examination. During the period from 2001 to 2021, the convergence coefficient of total factor productivity for Chinese listed companies, calculated using the average of the previous three years, remains significantly negative. This maintains the characteristics of both absolute convergence β and conditional convergence; however, the absolute values are lower than those in the baseline regression results. At this point, the absolute convergence speed and conditional convergence speed of total factor productivity are reduced to 0.00361 and 0.00348, respectively, with the convergence half-lives extending to 192.10818 and 199.34341. Furthermore, when the artificial intelligence (AI) indicator variable is introduced, the results indicate that both the absolute values of the absolute convergence and conditional convergence coefficients increase. The convergence speeds accelerate to 0.00364 and 0.00351, which represent increases of 0.83% and 0.86% compared to the results without including the AI variable. The convergence half-lives shrink to 190.37789 and 197.6368023, respectively. This indicates that the influence of the AI variable on the convergence of listed companies' productivity is consistent with the direction observed in the baseline regression results.

Table 5.
Regression results using past average TFP.

	(1)	(2)	(3)	(4)
	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$
$l.\ln TFP$	-0.06962***	-0.07023***	-0.06718***	-0.06774***
	(0.00352)	(0.00355)	(0.00366)	(0.00367)
AI		0.00017**		0.00024**
		(0.00008)		(0.00011)
Asset			0.04135***	0.04133***
			(0.00579)	(0.00579)
RDpro			-0.15825**	-0.18304**
			(0.07527)	(0.07641)
KI			-0.00186*	-0.00186*
			(0.00105)	(0.00105)
AbroadRev			0.08491***	0.08360***
			(0.02332)	(0.02337)
_cons	0.78591***	0.79116***	0.75929***	0.76404***
	(0.03498)	(0.03526)	(0.03653)	(0.03656)
N	26929	26929	26929	26929
R2	0.057	0.058	0.089	0.089
adj. R2	0.057	0.057	0.089	0.089
F	391.77538	195.98426	97.86940	82.13633

Note: Standard errors in parentheses, $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$。

4. Mediating Mechanisms of Regional Technological Spillovers

This study uses the frequency of keywords from corporate annual reports as an indicator of the development of artificial intelligence (AI) among publicly listed companies in China, reflecting the degree to which these companies focus on AI technology in their management practices and strategic planning. Whether companies are deeply engaged in key areas of AI or collaborate in various ways across the AI industry value chain, this indicator demonstrates their technological interest and investment preferences regarding AI.Investing more in AI—both financially and technically—can yield not only research and development outputs and returns on investment for the companies themselves but can also generate regional spillover effects through technical collaboration, application development, and the promotion of general AI technologies, thereby enhancing regional R&D levels. Moreover, increases in regional R&D capacity can improve corporate efficiency and significantly influence the productivity distribution among firms [13-15]. Given these considerations, if the advancement of AI can promote an overall increase in regional R&D levels, and if this improvement can differentially affect the total factor productivity of enterprises Sun and Hou [52] then we can study the mediating role of regional R&D outputs in the way AI influences the convergence of enterprises' total factor productivity. Specifically, this study selects the annual number of invention patent applications within a region as a quantitative measure of the R&D output level in that area Hu, et al. [45] and empirically examines its mediating effect on the relationship between AI and productivity convergence.

This study first verifies the impact of artificial intelligence on research and development (R&D) outputs. In Table 7, columns (1) and (2), presents the relevant results, where the core explanatory variable is the AI development indicator for listed companies. The provincial R&D output indicator variable $RRD_{i,t-T}$ is derived from the total number of patent applications filed by all listed companies in each province, weighted by the proportion of the companies' asset sizes. The control variables are consistent with those in the baseline regression. According to the regression coefficients, the AI indicator variable positively influences R&D outputs at the enterprise level. This finding extends to provincial R&D outputs as well, indicating a similarly positive impact that is statistically significant at the 5% level. This suggests that the development of AI among publicly listed companies from 2001 to 2021 has effectively contributed to enhancing the R&D output levels at the provincial level.

Table 7.
Regression results of mechanism tests.

	(1)	(2)	(3)	(4)	(5)
	RD	**RDP**	$\Delta \ln TFP$	$\Delta \ln TFP$	$\Delta \ln TFP$
$l.\ln TFP$			-0.16459***	-0.27723***	-0.34907***
			(0.00670)	(0.01106)	(0.01813)
AI	0.00657***	0.02372**			
	(0.00247)	(0.01205)			
RDP			0.00026***	0.00038***	0.01007***
			(0.00006)	(0.00007)	(0.00369)
Asset	-0.03015***	-0.18332**	0.01393***	0.01141***	0.01217***
	(0.01084)	(0.07643)	(0.00128)	(0.00140)	(0.00190)
RDpro	7.25488***	10.34076***	-0.02500*	0.09278***	-0.00724
	(0.56568)	(1.70015)	(0.01284)	(0.01597)	(0.01554)
KI	0.00020	-0.00334	-0.00034	-0.00655***	-0.00024
	(0.00026)	(0.00232)	(0.00023)	(0.00089)	(0.00020)
AbroadRev	1.05317***	3.57041***	0.02012***	0.01075***	0.02317***
	(0.09776)	(0.53668)	(0.00285)	(0.00277)	(0.00347)
_cons	2.13440***	2.29323***	0.38314***	0.67563***	0.76822***
	(0.01304)	(0.06156)	(0.01543)	(0.02605)	(0.03911)
N	33799	33799	33799	17660	16139
R2	0.090	0.011	0.146	0.345	0.225
adj. R2	0.090	0.011	0.146	0.345	0.225
F	90.79615	29.30141	180.76803	154.56837	150.78211

Note: Standard errors in parentheses，* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$。

To observe the differential effects and convergence trends of regional R&D output levels on corporate productivity, this study categorizes the sample of all listed companies into high-productivity and low-productivity firms based on the median total factor productivity (TFP) for each year. Columns (3) to (5) report the regression results. The regression coefficients for the regional R&D output variable are significantly positive, indicating that improvements in regional R&D output levels can effectively drive increases in corporate productivity, thus corroborating findings from the existing literature [53]. From the convergence regression coefficient of corporate total factor productivity in column (3), the convergence speed is estimated at 0.00899, which shows an improvement compared to the scenario where regional R&D output levels were not considered. The half-life required for productivity convergence is 77.08802. Further comparison between columns (4) and (5) reveals that the regression coefficient for the regional R&D output variable in the low-productivity firms is significantly higher than that in high-productivity firms. This suggests that regional R&D output levels have a much greater positive impact on the total factor productivity growth of low-productivity firms compared to high-productivity firms, thereby validating the "catch-up effect." It also highlights the role of regional R&D output in facilitating the convergence of corporate productivity. Consequently, during the period from 2001 to 2021, the development of artificial intelligence among China's listed companies can enhance the overall regional R&D output level, thereby creating conditions for low-productivity firms to catch up with high-productivity firms in terms of total factor productivity, and accelerating the convergence trend of TFP among listed companies.

5. Conclusion and Recommendations

The main findings of this study are as follows: From 2001 to 2021, an examination of the total factor productivity (TFP) of Chinese listed companies through β-convergence tests revealed clear signs of both absolute and conditional convergence during this period. This indicates that low-efficiency firms are gradually aligning themselves with high-efficiency firms. Additionally, the research highlights that artificial intelligence (AI) technology plays a critical role in enhancing TFP. It not only strengthens the ability of low-efficiency enterprises to catch up but also accelerates the β-convergence rate of TFP, thereby contributing to balanced and comprehensive development for these firms. Furthermore, advancements in AI within companies not only improve their own production efficiency but also enhance the overall research and development output in their respective regions, creating conditions to reduce the productivity gap between enterprises.

Based on the above research findings, this paper presents the following key recommendations: First, during the rapid development of artificial intelligence (AI), it is essential to continuously optimize relevant policies and measures to ensure that this strategic engine effectively enhances industrial efficiency. The development of AI relies not only on market forces but also on the precise formulation and implementation of policies. As technological advancement accelerates, policymakers must be forward-thinking to prevent issues such as inefficient resource allocation or economic polarization due to lagging policies. Establishing a dynamic monitoring mechanism to timely assess policy effectiveness is crucial for providing data support for policy adjustments.

Second, there should be a proactive push for the research and application of general-purpose AI technology, particularly in traditionally inefficient manufacturing sectors, to facilitate its integration with industry-specific needs. The government can enhance funding and policy support for the R&D of general-purpose AI technologies by establishing a support system that combines public and market resources. This will ensure that research outcomes can be successfully transformed into productivity and help set standards for the integration of enterprises and technologies. Additionally, more precise policies should be developed based on regional contexts to encourage low-efficiency firms to leverage AI for innovation and transformation, helping them reach higher levels of development. Third, it is hoped that R&D-focused enterprises within regions can serve as the core to build internationally competitive AI industry clusters through effective planning and guidance. Such clusters would create an innovation ecosystem that fosters collaborative industrial development. By integrating local advantages and strengthening cooperation within domestic industrial chains, the overall economic quality can be enhanced. Moreover, promoting cross-regional collaboration and resource sharing is essential. Encouraging high-tech R&D firms in eastern regions to establish closer cooperative relationships with traditional manufacturing enterprises in central and western regions will facilitate complementary advantages, resource sharing, and joint development. Fourth, in the context of deepening the reform of state-owned enterprises and supporting the expansion of private enterprises, it is necessary to focus on the autonomy in basic research on AI and the degree of application in various fields. Strengthening technical exchanges and cooperation with foreign enterprises can expedite the technology transfer process and narrow the gap in AI application technologies among domestic companies. By creating a favorable policy environment, state-owned and private enterprises can be encouraged to leverage AI for high-quality development, promoting improvements in the overall economic quality and optimization of the industrial structure.

In summary, facing the rapid development of this emerging technology, Chinese listed companies must align with trends and actively engage in this transformation, centering on innovation-driven strategies to continually enhance their competitiveness and production efficiency. By integrating policy support, technological research, and proactive corporate initiatives, a solid foundation can be laid for building a more efficient and sustainable economic system. In the future, AI will play an increasingly important role in promoting regional economic integration, enhancing industry competitiveness, and driving innovative development.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3: 228-242, 2024
DOI: 10.55214/25768484.v9i3.5183