The Impact of Artificial Intelligence on Total Factor Productivity of China's Specialized, Refined, Distinctive, and Innovative Enterprises: An Heterogeneity Perspective

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Abstract： Against the backdrop of deep integration between the digital economy and the real economy, and the national strategy to vigorously develop new quality productive forces, this study examines the impact of artificial intelligence on firm-level total factor productivity (TFP) and its heterogeneity. Using a sample of China's A-share specialized, refined, distinctive, and innovative enterprises (SRDI) from 2005 to 2023, we establish a two-way fixed effects model. Results indicate that AI significantly boosts corporate TFP, a conclusion that remains robust after controlling for proxy variables, tail trimming, and excluding exceptional years. Heterogeneity analysis further reveals structural variations in AI's enabling effects: its impact is stronger in state-owned enterprises than non-state-owned enterprises, greater in inland regions than coastal regions, and dynamically changes across different life cycle stages. The enhancement effect is most pronounced for mature-stage enterprises, while no significant impact is observed for declining-stage enterprises. This study systematically uncovers the context-dependent nature and complex mechanisms through which AI influences corporate productivity across three dimensions: ownership structure, geographic location, and development stage. It provides empirical evidence for deepening our understanding of the relationship between digital technologies and high-quality corporate development, while also offering decision-making references for promoting the intelligent transformation of enterprises through targeted approaches.

Keywords: artificial intelligence; TFP; SRDI enterprises; Heterogeneity

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Introduction

Against the backdrop of the digital economy deeply integrating into the global economic system, artificial intelligence (AI) has emerged as the core engine driving technological innovation and leapfrog improvements in productivity. Total Factor Productivity (TFP), as a key indicator measuring the quality of economic growth and resource allocation efficiency, has consistently been a central topic in macroeconomic and industrial research. In China, “Specialized, Refined, Distinctive, and Innovative” (SRDI) enterprises—high-quality market entities focused on niche markets with robust innovation capabilities and growth potential—serve as the backbone for advancing manufacturing transformation and upgrading while underpinning the high-quality development of the real economy. Their productivity performance not only shapes their own competitive advantages but also demonstrates and drives efficiency upgrades across entire industries. Therefore, exploring the relationship between artificial intelligence technology and the total factor productivity of SRDI enterprises represents both a frontier direction for digital technology to empower the real economy and aligns with China's practical needs for high-quality industrial development. Although the impact of AI on TFP has garnered significant academic attention, existing research has largely focused on the macro-industry level or general enterprises, with targeted analyses of SRDI enterprises remaining relatively scarce. Compared to ordinary enterprises, specialized, refined, distinctive, and innovative enterprises typically focus deeply on niche sectors, maintain higher innovation investment intensity, and receive greater guidance from policy support. These characteristics determine that the impact of artificial intelligence on their total factor productivity may not follow a homogeneous pattern but instead exhibit significant heterogeneous differences.

Based on this, this paper presents the following innovations: (1) It analyzes the impact of AI on TFP for China's specialized, refined, distinctive, and innovative enterprises. (2) To address the existing shortcomings in heterogeneity, this study examines the varying impacts of artificial intelligence on total factor productivity across different geographical regions in China and at different stages of the corporate life cycle.

1 Literature review and research hypotheses

Artificial intelligence serves as a key driver for enhancing total factor productivity. Digital infrastructure development significantly boosts regional total factor productivity by promoting pure technological progress (Zixun & Yahong, 2021), while enterprises' accumulated patent portfolios in Fourth Industrial Revolution technologies also enhance their performance, confirming the contribution of technological knowledge accumulation to productivity (Benassi et al., 2022). In the manufacturing sector, intelligent technologies not only elevate green total factor productivity but also support sustainable industrial upgrading (Zhang & Wu, 2021). In specific sectors like agriculture, AI-based automation and IoT solutions reduce labor burdens and boost production efficiency by optimizing decision-making (Micle et al., 2021). The application of generative AI in retail directly drives sales growth, translating into observable productivity gains (Fang et al., 2025). Theoretically, artificial general intelligence (AGI) as an advanced form can influence TFP by substituting or complementing labor and capital, with its specific impact determined by integration methods within production processes (Stiefenhofer, 2025). Concurrently, AI's effects on global resource flows and productivity underscore the importance of policy frameworks for guiding its effective deployment (Piasecki et al., 2021). Based on this multidimensional evidence, this paper hypothesizes:

H1: Artificial intelligence can enhance the total factor productivity of specialized, refined, distinctive, and innovative enterprises。

Additionally, existing research indicates that the role of artificial intelligence in boosting total factor productivity may be particularly pronounced during the growth stage of enterprises. This phase is often characterized by active technological innovation, and technological progress driven by digital economic development has been proven to be a key mechanism for enhancing total factor productivity. Although technological innovation may cause short-term fluctuations, its long-term net effect is significantly positive, which is especially important for growth-stage enterprises undergoing investment and adjustment phases (Li, 2021). A stable policy environment can mitigate the negative impact of economic uncertainty on productivity, thereby creating conditions for enterprises to sustainably apply AI and realize benefits (Li et al., 2021). Effective governance and strategic alignment are crucial safeguards for unlocking AI's potential (Piasecki et al., 2021). Simultaneously, AI facilitates green technological progress and enhances renewable energy efficiency (Liu et al., 2021; Zhang et al., 2021), aligning with growth enterprises' demand for sustainable competitiveness. From regional and sectoral perspectives, productivity gains in growth enterprises are also influenced by regional innovation capacity and targeted policies (Nguyen, 2021; Hua et al., 2021). From a regional development perspective, digital economy development and its associated technological progress serve as core drivers for enhancing total factor productivity in inland regions (Qiu & Zhou, 2021). Market integration and openness, meanwhile, facilitate the diffusion of technologies including AI, thereby improving energy and environmental efficiency and enabling greener resource utilization (Su & Liang, 2021). Based on this, this paper proposes the following hypothesis:

H2: The positive effect of artificial intelligence on the total factor productivity of specialized, refined, distinctive, and innovative enterprises is more pronounced in inland regions and during the enterprise growth phase.

2 Data and methods

2.1 Data description

This study employs a sample of specialized, refined, distinctive, and innovative enterprises listed on China's A-share market from 2005 to 2023. The data underwent the following processing: (1) Companies designated as ST, *ST, and PT were excluded. (2) Missing values and outliers were removed. The final dataset comprises 4,218 observations. Data sources include the CNRDS and CSMAR databases.

2.1.1 Dependent variable

The dependent variable in this study is total factor productivity (TFP). Following the methodology of Lu Xiaodong & Lian Yujun (2012), we employ a fixed-effects regression approach to obtain a consistent and unbiased estimate of the production function. This result is used to measure total factor productivity (TFP_FE). Additionally, an estimate calculated using a simple linear estimation method serves as a replacement variable (TFP_OLS) for conducting robustness analysis.

2.1.2 Independent variable

The independent variable in this study is artificial intelligence (AI). Following the methodology of Yao Jiaquan et al., (2024), Python was employed to conduct text analysis on the frequency of AI-related terms in corporate annual reports. The resulting metrics were ultimately utilized to measure the prevalence of AI.。

2.2 Model specification

To investigate the impact of AI on the total factor productivity of specialized, refined, distinctive, and innovative enterprises, this study establishes the following two-way fixed effects model:

$$TFP_{F}E_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \lambda Controls_{i,t} + \tau_t + \varepsilon_i + \gamma_{i,t} \quad (1)$$

In this context, subscripts i and t denote firm and year, respectively; TFP_FEi,t represents the total factor productivity level of firm i in year t; AIi,t indicates the artificial intelligence level of firm i in year t; Controlsi,t denotes the control variable; τt is the time fixed effect; εi is the firm-specific fixed effect; and γi,t is the random error term.

3 Empirical Findings and Analysis

3.1 Descriptive Statistics

Table 1 presents descriptive statistics that provide an initial overview of the overall distribution characteristics and data structure of the sample, laying a foundational basis for subsequent empirical testing. Regarding the core variables, the mean value for artificial intelligence is 0.903, with a standard deviation of 1.221, a minimum value of 0.000, and a maximum value of 6.277. The mean value of Total Factor Productivity is 10.382 with a standard deviation of 0.824, ranging from 8.005 to 15.038.

Table 1 Descriptive statistics of variables

Variable	count	mean	min	max	sd
AI	4218	0.903	0.000	6.277	1.221
TFP_FE	4218	10.382	8.005	15.038	0.824
SIZE	4218	21.439	19.084	26.409	0.800
AGE	4218	1.487	0.000	3.434	0.886
LEV	4218	0.321	0.008	1.221	0.178
ROA	4218	0.048	-0.635	0.664	0.070
CASH	4218	0.043	-0.647	0.351	0.068
BOARD	4218	2.079	1.386	2.773	0.187
BALANCE	4218	0.404	0.003	1.000	0.280

3.2 Baseline regression

Based on the aforementioned descriptive statistics, this study further constructs a two-way fixed effects model to examine the actual impact of artificial intelligence on firms' total factor productivity. The benchmark regression results are presented in Table 2. Model (1) includes only the core explanatory variable AI and dual fixed effects for firm and time. Results indicate that AI's regression coefficient is 0.070, significantly positive at the 1% level, preliminarily confirming the hypothesis that AI technology positively promotes firm TFP. After progressively incorporating firm-level control variables, the coefficients for AI in Models (2) and (3) remained significantly positive, though their values decreased to 0.028 and 0.026, respectively. This indicates that the productivity-enhancing effect of AI remains robust even after controlling for multidimensional characteristics such as firm size, age, and financial structure, thereby validating Hypothesis H1.

Table 2 Baseline regression results

Variable	TFP_FE	TFP_FE	TFP_FE
	(1)	(2)	(3)
AI	0.070***	0.028***	0.026***
	(0.011)	(0.007)	(0.006)
SIZE		0.742***	0.708***
		(0.013)	(0.012)
AGE		-0.021	0.038***
		(0.014)	(0.012)
LEV		0.508***	0.786***
		(0.048)	(0.043)
ROA			2.303***
			(0.087)
CASH			0.615***
			(0.076)
BOARD			0.119***
			(0.039)
BALANCE			-0.055**
			(0.028)
Constant	9.360***	-5.910***	-5.673***
	(0.075)	(0.265)	(0.248)
ID FE	YES	YES	YES
YEAR FE	YES	YES	YES
N	4218	4218	4218
Adj R-squared	0.323	0.691	0.758

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Same below.

3.3 Robustness tests

Building upon the baseline regression, this study further conducted robustness tests through three approaches. The corresponding results are presented in Table 3. First, model (1) replaces the TFP estimation method with ordinary least squares (TFP_OLS) to examine whether different productivity estimation approaches affect core findings. The results show that the estimated coefficient for artificial intelligence (AI) is 0.022, remaining significantly positive at the 1% level. Additionally, to eliminate potential interference from outliers, model (2) applied trimmed tailing to continuous variables at the upper and lower 1% thresholds. After adjustment, the AI coefficient remained at 0.026, fully consistent with the benchmark regression result, and its significance did not change. Finally, considering 2019 as a pivotal year marked by significant shifts in the macroeconomic and policy landscape—particularly external trade fluctuations and internal industrial policy adjustments that may have structurally impacted the production, operations, and technological investments of specialized, refined, distinctive, and innovative enterprises—Model (3) specifically excluded samples from this year for re-regression. Results show that AI's coefficient remains at 0.026, with both significance and value consistent with the baseline model, while the adjusted R^2 slightly increases to 0.767. This reinforces the temporal universality of the research findings.

Table 3 Robustness test results

Variable	TFP_OLS	TFP_FE	TFP_FE
	(1) Replace the dependent variable	(2) Truncate the tail	(3) Exclude 2019
AI	0.022***	0.026***	0.026***
	(0.007)	(0.006)	(0.007)
ID FE	YES	YES	YES
YEAR FE	YES	YES	YES
N	4218	4218	3883
Adj R-squared	0.724	0.758	0.767

3.4 Heterogeneity Analysis

3.4.1 Regional Location Heterogeneity

To investigate whether regional differences exist in the impact of artificial intelligence on total factor productivity in enterprises, this study follows the methodology of Luo, Fangyong et al., (2023) by dividing the sample into coastal and inland cities for heterogeneity testing. The regression results are presented in Table 4. Results indicate that the coefficient for artificial intelligenceis significantly positive in both groups, yet the intensity of its impact exhibits pronounced regional divergence: in the inland city sample, the AI coefficient is 0.066 and highly significant at the 1% level; whereas in the coastal city sample, the coefficient is 0.018 and significant at the 5% level. This divergence indicates that AI's contribution to TFP growth is more pronounced in inland regions, thereby validating Hypothesis H2.

Table 4 Regional Location heterogeneity regression results

Variable	TFP_FE	TFP_FE
	Coastal cities	Inland cities
AI	0.018**	0.066***
	(0.007)	(0.014)
ID FE	YES	YES
YEAR FE	YES	YES
N	3287	931
Adj R-squared	0.749	0.816

3.4.2 Lifecycle Heterogeneity

To examine whether the impact of artificial intelligence on total factor productivity varies dynamically across different stages of corporate development, this study further divides the sample into three subgroups—growth, maturity, and decline—based on corporate life cycle theory and research by Liang Shangkun (2011) and Li Yunhe et al., (2019) to conduct heterogeneity tests. Table 5 reveals that the coefficient for artificial intelligence exhibits significant differences across life cycle stages, indicating that a firm's developmental phase serves as a crucial contextual factor moderating the impact of technological empowerment. Specifically, among mature-stage enterprises, the AI coefficient reaches 0.070 and is statistically significant at the 5% level, indicating that the enhancement effect of AI on TFP is most pronounced during this phase, thereby validating Hypothesis H2.

Table 5 Lifecycle heterogeneity regression results

Variable	TFP_FE	TFP_FE	TFP_FE
	Growth	Maturity	Decline
AI	0.024***	0.070**	0.029
	(0.008)	(0.031)	(0.024)
ID FE	YES	YES	YES
YEAR FE	YES	YES	YES
N	2913	522	783
Adj R-squared	0.799	0.472	0.246

4 Conclusions and Recommendations

This study systematically examines the impact of artificial intelligence on firm-level total factor productivity and its heterogeneous performance across different contexts, based on data from China's A-share specialized, refined, distinctive, and innovative enterprises from 2005 to 2023. Through empirical testing using a fixed-effects model, the following key findings emerge: (1) Artificial intelligence significantly enhances firm-level TFP. (2) The positive impact of AI on TFP is more pronounced in state-owned enterprises, firms located in inland regions, and companies in their growth phase.

Based on the aforementioned research findings, this paper offers the following recommendations: For enterprises, it is essential to fully recognize the strategic value of AI technology in enhancing production efficiency. Companies should develop differentiated technology integration pathways tailored to their proprietary rights attributes, regional locations, and developmental stages. State-owned enterprises can leverage their resource and institutional advantages to advance the systematic integration of AI into critical processes and strategic segments, thereby playing a leading role in demonstrating industry-wide digital transformation. Non-state-owned enterprises should focus on enhancing the precision and sustainability of technology application, strengthening market-driven agile innovation, and avoiding blind investment. Enterprises in coastal regions should prioritize deep AI application in high-value-added segments and business model innovation, while inland enterprises can leverage their technological latecomer advantage to concentrate on optimizing foundational processes and addressing efficiency gaps, achieving leapfrog improvements. Growing enterprises must synchronize AI adoption with organizational capability development. Mature enterprises can explore full-chain, integrated intelligent upgrades, while declining enterprises should combine technology application with strategic restructuring and organizational transformation to create structural conditions for efficiency gains.

References

[1]Benassi, M., Grinza, E., Rentocchini, F., & Rondi, L. (2022). Patenting in 4IR technologies and firm performance. Industrial and Corporate Change, 31(1), 112-136.
[2]Fang, L., Yuan, Z., Zhang, K., Donati, D., & Sarvary, M. (2025). Generative AI and Firm Productivity: Field Experiments in Online Retail. arxiv preprint arxiv:2510.12049.
[3]Hua, X., Lv, H., & Jin, X. (2021). Research on high-quality development efficiency and total factor productivity of regional economies in China. Sustainability, 13(15), 8287.
[4]Li, K., Guo, Z., & Chen, Q. (2021). The effect of economic policy uncertainty on enterprise total factor productivity based on financial mismatch: Evidence from China. Pacific-Basin Finance Journal, 68, 101613.
[5]Li, P. (2021). An empirical analysis of the impact of technological innovation on China’s total employment. In E3S Web of Conferences (Vol. 235, p. 02042). EDP Sciences.
[6]Li, Y., Li, Z., & Tang, S. (2011). Firm life cycle, corporate governance, and capital allocation efficiency. Nankai Business Review, 14(3), 110–121.
[7]Liang, S., Zhang, Y., & Wang, Y. (2019). Internal pay gap and firm value: A new exploration based on life cycle theory. Journal of Financial Research, 466(4), 188–206.
[8]Liu, D., Zhu, X., & Wang, Y. (2021). China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. Journal of Cleaner Production, 278, 123692.
[9]Lu, X., & Lian, Y. (2012). Estimation of total factor productivity of industrial enterprises in China: 1999–2007. China Economic Quarterly, 11(2), 541–558.
[10]Luo, F., Yang, S., & Li, S. (2023). Research on the impact of digital economy on factor market integration. Review of Industrial Economics, 2023(3), 31–53.
[11]Micle, D. E., Deiac, F., Olar, A., Drența, R. F., Florean, C., Coman, I. G., & Arion, F. H. (2021). Research on innovative business plan. Smart cattle farming using artificial intelligent robotic process automation. Agriculture, 11(5), 430.
[12]Nguyen, H. Q. (2021). Total factor productivity growth of Vietnamese enterprises by sector and region: Evidence from panel data analysis. Economies, 9(3), 109.
[13]Piasecki, R., Wolnicki, M., & Betancourt, E. W. (2021). Artificial Intelligence in the Context of Global Resource Mobility. What Can Be Expected from It?. Comparative Economic Research. Central and Eastern Europe, 24(3), 93-107.
[14]Piasecki, R., Wolnicki, M., & Betancourt, E. W. (2021). Artificial Intelligence in the Context of Global Resource Mobility. What Can Be Expected from It?. Comparative Economic Research. Central and Eastern Europe, 24(3), 93-107.
[15]Stiefenhofer, P. (2025). The Future of Work and Capital: Analyzing AGI in a CES Production Model. arxiv preprint arxiv:2502.07044.
[16]Su, H., & Liang, B. (2021). The impact of regional market integration and economic opening up on environmental total factor energy productivity in Chinese provinces. Energy Policy, 148, 111943.
[17]Yao, J., Zhang, K., Guo, L., et al. (2024). How does artificial intelligence improve enterprise productivity? Based on the perspective of labor skill structure adjustment. Management World, 40(2), 101–116, 133, 117–122.
[18]Zhang, Y., & Wu, Z. (2021). Intelligence and green total factor productivity based on China’s province-level manufacturing data. Sustainability, 13(9), 4989.
[19]Zhang, Y., Jin, W., & Xu, M. (2021). Total factor efficiency and convergence analysis of renewable energy in Latin American countries. Renewable Energy, 170, 785-795.
[20]Zixun, Q., & Yahong, Z. (2021). Development of digital economy and regional total factor productivity: An analysis based on national big data comprehensive pilot zone. Journal of Finance and Economics, 47(07), 4-17.
[21]Zixun, Q., & Yahong, Z. (2021). Development of digital economy and regional total factor productivity: An analysis based on national big data comprehensive pilot zone. Journal of Finance and Economics, 47(07), 4-17.