The Influence of AI on Enterprises' High-Quality Economic Growth

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Abstract. As a new generation of information technology, artificial intelligence (AI) has emerged as a novel driver for enhancing high-quality economic development in enterprises. Utilizing panel data from listed companies, this study empirically examines the impact of AI on enterprise economic quality. Key findings include:(1) AI development significantly improves total factor productivity (TFP).(2) Mechanism analysis reveals that AI enhances economic quality by alleviating financing constraints.The conclusions provide insights into external drivers of enterprise development strategies and underscore the importance of industrial upgrading and economic growth. Policy recommendations include: strengthening government subsidies and legal frameworks for AI, encouraging intelligent investments, optimizing resource allocation, and prioritizing talent development with a "human-centric" approach.

Keywords: Artificial Intelligence; Total Factor Productivity; Financing Constraints

1 Introduction

Under resource and environmental constraints, shifting China's economic growth paradigm from high-speed to high-quality development has become a central theme of economic transformation. Enhancing total factor productivity (TFP) is pivotal to achieving this goal and reflects the core of China's economic progress in the new era. In recent years, the rapid expansion of artificial intelligence (AI) has positioned it as a novel engine for economic growth. As TFP serves as both the micro-foundation and driving force of national economic quality improvement, a critical question arises: can AI-driven technological innovation promote enterprise TFP? Addressing this question not only deepens the understanding of AI’s role in corporate high-quality development but also offers practical insights for integrating AI innovation with real economic activities.

Currently, a growing number of scholars adopt the research framework proposed by Chen Shiyi (2018)[1], which employs Total Factor Productivity (TFP) to measure the level of high-quality economic development in enterprises. With the gradual expansion of Artificial Intelligence (AI) applications in corporate production and management activities (Cheng, 2021)[2], AI not only exhibits a strong substitution effect on highly repetitive tasks, effectively reducing human involvement in production and managerial

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processes (Chen, 2019)[3], but also significantly enhances resource allocation efficiency (Kopalle et al., 2022)[4]. These improvements enable enterprises to achieve cost reduction and efficiency gains in both production and management practices, thereby elevating enterprise TFP and promoting high-quality economic development in firms.

Nevertheless, current literature lacks thorough exploration of the mechanisms through which AI enhances TFP. Most empirical studies rely on panel or cross-sectional data without robust theoretical underpinnings. To bridge these gaps, this study:Develops a theoretical framework to elucidate the causal relationship between AI and ownership structures;Identifies transmission channels, such as alleviating financing constraints, to establish actionable pathways for advancing corporate high-quality development.

2 Theoretical Analysis and Research Hypotheses

2.1 Direct Effects of AI on Enterprise High-Quality Economic Development

The deep integration of AI with the real economy reshapes the behaviors of microeconomic entities. First, AI optimizes the structure of production factors. Its intelligent, precise, and efficient features enhance resource utilization and production efficiency, reduce costs, and facilitate the transition from traditional production methods to intelligent automation. This creates a new production factor that may circumvent the law of diminishing returns to scale, fundamentally boosting total factor productivity (TFP). Second, AI improves resource allocation mechanisms. Machine learning, decision-making, and predictive capabilities enable complementary technological innovations, enhancing production efficiency. Concurrently, the digital economy breaks down inter-enterprise barriers, enabling cross-temporal and cross-domain knowledge acquisition, learning, and integration. This fosters open innovation platforms and interactive knowledge exchange, driving a spiral of innovation that elevates TFP. Finally, AI enhances organizational management efficiency. By leveraging AI for decision support, enterprises gain access to accurate, systematic, and comprehensive information, enabling predictive modeling, optimization, and tailored solutions for decentralized and flat organizational structures.

Based on this analysis, we propose Hypothesis H1:AI development promotes enterprise high-quality economic development.

2.2 Indirect Effects of AI on Enterprise High-Quality Economic Development

Chinese enterprises commonly face significant financing constraints—restrictions on accessing loans, issuing bonds, or equity financing due to market imperfections. These constraints arise from high financing costs and information asymmetry between financial institutions and firms, exacerbated by outdated risk-assessment technologies . In the digital economy, AI mitigates these challenges by improving information utilization and dissemination, thereby reducing information asymmetry in financial markets. This lowers investment risks for capital providers, decreases financing costs, diversifies funding sources, and alleviates traditional limitations like insufficient financial supply and reliance on singular financing channels. By optimizing financing structures, AI indirectly enhances TFP.

Based on this analysis, we propose Hypothesis H2:AI fosters enterprise high-quality economic development by alleviating financing constraints.

3 Research Design

3.1 Model Specification

3.1.1 Panel Fixed-Effects Model.

To empirically examine the impact of artificial intelligence (AI) adoption on total factor productivity (TFP), this study employs a two-way fixed-effects panel model, specified as follows:

$$\mathrm{TEP}_{it} = \beta_0 + \beta_1 \mathrm{AI}_{it} + \sum \beta_n \,\mathrm{Controls}_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

In the model, subscripts i and t denote province and year, respectively.TEP_{it} represents the total factor productivity index of enterprise i in year t.AI_{it} indicates the artifical intelligence adoption level of enterprise i in year t.$\mathrm{Controls}_{it}$ denotes the set of control variables.μ_i captures enterprise fixed effects.γ_t represent year fixed effects.

3.1.2 Mechanism Effect Model.

This study posits that artificial intelligence (AI) impacts enterprise total factor productivity (TFP) by alleviating financing constraints. Drawing on Jiang Ting's mediation approach, we empirically examine the underlying mechanisms of this effect.

$$\mathrm{Mediator}_{it} = \beta_0 + \beta_1 \mathrm{AI}_{it} + \sum \beta_n \,\mathrm{Controls}_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$\mathrm{Mediator}_{it}$ represents the mediating variable, operationalized as financing constraints. The definitions and specifications of all other variables remain consistent with those outlined in Equation (1).

3.2 Variable Selection

Explained Variable: Total Factor Productivity (TFP). TFP reflects the overall efficiency with which enterprises convert inputs into outputs. Four primary methodologies are employed to estimate TFP: the Levinsohn-Petrin (LP) method, the Olley-Pakes (OP) method, Ordinary Least Squares (OLS), and the fixed-effects approach. For baseline regressions, this study adopts the OP method, while alternative measurement approaches are utilized in robustness checks.

Explanatory Variable: Artificial Intelligence (AI) Adoption. Following Wu et al. (2021)[5], AI adoption intensity at the enterprise level is quantified by the frequency of AI-related keywords extracted from listed companies annual reports.

Mediating Variable: Financing Constraints. the SA index is employed to measure financing constraints. A higher SA index value indicates greater financing constraints faced by firms.

Control Variables: Based on prior research from domestic and international scholars, the control variables in this study are selected as follows: (1)Cflow: Net cash flow from operating activities scaled by total assets. (2)Size: Firm size, measured by total operating revenue.(3)Tobin's q: Ratio of a firm's market value to its asset replacement cost. (4)Leverage: Total liabilities divided by total assets, expressed as a percentage.(5)Revenue Growth: Year-on-year growth rate of operating revenue.(6)Listing Age: Calculated as the sample year minus the firm's initial public offering year.

4 Empirical Analysis

4.1 Baseline Regression

This study employs Equation (1) to investigate the impact of artificial intelligence (AI) adoption on enterprise total factor productivity (TFP). The regression results are presented in Table 1. Column (1) reports estimates without incorporating control variables, Column (2) introduces control variables, and Column (3) further incorporates both entity and year fixed effects alongside the control variables. As shown in Table 1, the estimated coefficients of AI adoption on TFP are consistently positive and statistically significant at the 1% level across all specifications, indicating that AI adoption significantly enhances enterprise TFP.

Table 1. Baseline Regression Results

	(1)	(2)	(3)
VARIABLES	TFP_OP2	TFP_OP2	TFP_OP2
ai	0.0523***	0.0108***	0.0232***
	(0.0034)	(0.0024)	(0.0015)
cflow		53.3997***	80.8942***
		(5.0874)	(3.4803)
size		45.6066***	44.3557***
		(0.3565)	(0.5533)
tl		47.5698***	4.7729**
		(2.1616)	(2.1929)
rg		0.0391	0.0928***
		(0.0282)	(0.0170)
tobin		0.5817***	1.5481***
		(0.2026)	(0.1753)
age		0.6570	-2.0088*
		(0.5351)	(1.0422)
Constant	665.3179***	-371.4637***	-322.9731***
	(0.5341)	(7.4540)	(12.0917)
Observations	28,940	28940	28940
R-squared	0.008	0.512	0.875

4.2 Robustness Analysis

To further validate the reliability of our findings,this study conducted a series of robustness checks.First, a winsorization test was performed by trimming the top and bottom 1% of all research variable to mitigate the potential influence of extreme value.Second, the dependent variable was substituted using alternative methodologies for total factor productivity (TFP) estimation. this study specifically employed LP and OLS methods as robustness proxies to verify the consistency of results.Third,industry subsamples closely associated with intelligent transformation,particularly the"Computer Communication,and other Electronic Equipment Manufacturing" sector, were excluded from the analysis to address potential confounding effects. As demonstrated in Table 2, all robustness tests confirmed the stability and reliability of the baseline results.

Table 2. Robustness Test Results

VARIABLES	TFP_OP2_w	TFP_LP2	TFP_OLS2	TFP_OP2
ai_w	0.1249***			
	(0.0111)			
ai		0.0033**	0.0068***	0.0210***
		(0.0015)	(0.0014)	(0.0016)
Control	YES	YES	YES	YES
Constant	-240.9559***	-507.8616***	-653.8504***	-271.6420***
	(11.7552)	(11.9161)	(11.1868)	(13.8268)
Observations	28940	28940	28940	20,806
R-squared	0.886	0.913	0.945	0.873

4.3 Addressing Endogeneity

To mitigate potential endogeneity concerns arising from omitted variables, this study augments the baseline regression with more rigorous fixed effects specifications. As reported in Columns (1)–(3) of Table 3, the baseline results remain robust after progressively controlling for individual, year, industry, and region fixed effects.

Table 3. Endogeneity Check Results

	(1)	(2)	(3)
VARIABLES	TFP_OP2	TFP_OP2	TFP_OP2
ai	0.0228***	0.0232***	0.0230***
	(0.0015)	(0.0015)	(0.0015)
Control	YES	YES	YES
Constant	-311.3803***	-326.3610***	-312.5396***
	(12.2767)	(12.1260)	(12.3256)
Observations	28940	28940	28940
R-squared	0.885	0.876	0.886

4.4 Mechanism Analysis

To delve into the mechanisms through which artificial intelligence (AI) affects firms' total factor productivity (TFP), this study selects financing constraints as the mediating variable based on the preceding theoretical framework.We employ a regression model to test the mediating effects. The regression results presented in Table 4 reveal that AI significantly enhances corporate TFP by alleviating financing constraints. As shown in column (1), the estimated coefficient of AI is statistically significant at the 1% level with a negative sign, indicating that reduced financing constraints serve as a crucial transmission channel for AI to improve production efficiency.

Table 4. Mechanism Analysis

VARIABLES	SA
ai	-0.0000***
	(0.0000)
Control	YES
Constant	-3.8914***
	(0.0191)
Observations	28940
R-squared	0.970

5 Conclusions and Policy Recommendations

5.1 Research Conclusions

The baseline regression results confirm that artificial intelligence (AI) significantly The baseline regression results demonstrate that artificial intelligence (AI) exerts a statistically significant enhancement effect on firms' total factor productivity (TFP), with this conclusion remaining robust across multiple sensitivity tests including winsorization, alternative TFP measurement methodologies, and subsample exclusion analyses. Further mechanism analysis reveals that financing constraints serve as a critical mediating channel through which AI drives TFP improvement. Empirical evidence indicates that AI alleviates financial barriers by reducing information asymmetry and optimizing financing structures, thereby facilitating TFP enhancement. These findings underscore AI's pivotal role in elevating resource allocation efficiency and mitigating traditional developmental constraints faced by enterprises. The results corroborate the theoretical proposition that AI promotes high-quality economic development through restructuring production factor combinations and organizational management paradigms

5.2 Policy Recommendations

5.2.1 Encourage Firms to Expand Intelligent Investment.

Policymakers should incentivize firms to scale up AI-driven intelligent investment. Insufficient investment in AI by listed enterprises may hinder sector-wide growth. Targeted subsidies and policy support should prioritize competitive "unicorn" firms and those engaged in core technology R&D, enabling them to expand intelligent production capabilities through diversified financing channels. Concurrently, fostering industrial chain integration and a healthy ecosystem for innovation and production is essential.

5.2.2 Optimize Development Strategies and Resource Allocation.

AI enterprises must adopt context-specific strategies, avoid ingindiscriminate expansion and redundant capital or labor inputs. Overinvestment in non-critical areas or excessive hiring for low-impact roles should be curtailed. Instead, firms should focus on refining cost management, workforce optimization, and strategic realignment of resources.

5.2.3 Strengthen Talent Development with a Human-Centric Approach.

Human capital is the cornerstone of AI advancement. Enterprises must prioritize cultivating high-caliber R&D talent and enhancing the overall competency of AI professionals. Given the technology-intensive, interdisciplinary, and innovation-driven nature of AI, sustained breakthroughs in emerging fields rely on robust talent pipelines and incentive mechanisms.

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