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Research on High-quality development of enterprises based on an intelligent background

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Abstract. In the global economy, intelligent technology has attracted much attention as a crucial factor in propelling enterprises towards achieving high-quality development growth. Taking the financial reports of A-share listed companies in Shanghai and Shenzhen Stock exchanges published from 2007 to 2022 as samples, this study explores the influence and mechanism of intelligent technology on the high-quality development of enterprises. The study finds that intelligent technology has a substantial positive impact on enhancing the high-quality growth of businesses, especially by improving innovation efficiency and management efficiency. In addition, digital inclusive finance and the digital economy have a positive moderating effect on the relationship between intelligent technology and the high-quality development of enterprises. These results offer practical backing for the advancement of corporate intelligence and establish a vital theoretical and empirical foundation for companies to uphold their competitive edge in an intensely competitive market landscape.

Keywords: High-quality development of enterprises, digital economy, digital inclusive finance.

1. Introduction

The quality of enterprise development represents the efficiency and level of the enterprise's ability to realize economic and social value in the process of operation and development, as well as the ability to create value on a sustainable basis. In the global economy, the high-quality development of enterprises is particularly important. Those enterprises that fail to achieve high-quality development will encounter several challenges, including low productivity, insufficient innovation capacity, and difficulties in guaranteeing product quality. These challenges not only diminish market competitiveness but also exacerbate resource wastage and elevate environmental pressures, thereby impeding economic sustainability. Consequently, high-quality development has become a pivotal path and development paradigm for the realization of sustainable economic development.

In the context of digitalization, intelligent technologies such as big data analysis, machine learning, natural language processing, and automation technology are becoming key driving forces to promote enterprise transformation and upgrading. These technologies support organizations in deriving valuable insights from extensive data, enhancing production and supply chain management, and elevating both production efficiency and product quality. Simultaneously, Intelligent technology encompasses a financial intelligence system capable of automating financial processes, forecasting future trends, and conducting real-time financial analysis. This enhances the financial management capabilities and decision-making efficiency of enterprises. Digital inclusive finance and digital economy are important support and driving forces in the digitalization process. Through enhanced resource allocation and industrial advancement, the digital economy revitalizes enterprise innovation and management. It drives the transformation of traditional industries towards digitalization and accelerates the adoption of emerging technologies. By improving the accessibility and convenience of financial services, digital inclusive finance supports enterprises' innovation activities and management efficiency. It enhances the financing environment and capital operation efficiency, thereby bolstering enterprises' competitiveness and sustainable development capabilities in the global market.

The existing literature has made significant progress in exploring the impact of intelligent technology on enterprise development. However, there are some shortcomings in important fields that require further research. Firstly, current research predominantly examines the effects of intelligence on specific dimensions such as production efficiency, competitiveness, and market adaptability [1], yet lacks a comprehensive investigation into how intelligence fosters holistic high-quality enterprise development. This paper investigates management efficiency and innovation efficiency as mediating variables, alongside digital inclusive finance and the digital economy as moderating variables. Through this framework, it comprehensively reveals the multi-dimensional pathways by which intelligent technology fosters the high-quality development of enterprises. This comprehensive study makes up for the lack of a holistic perspective in existing studies. Secondly, some studies have explored how intelligent technology can improve the high-quality development of enterprises, which primarily emphasizes the direct influence of intelligent technology on the efficiency, competitiveness, and market performance of enterprises. However, this study goes further by examining how intelligent technology indirectly fosters high-quality development in enterprises by enhancing innovation efficiency and management efficiency. Through detailed empirical analysis, the study demonstrates the impacts and challenges of intelligent technology in real-world applications. This research offers a fresh perspective and theoretical foundation for the practical implementation and promotion of intelligent technology within enterprises. Thirdly, most existing research concentrates on short-term benefits derived from intelligent enterprises with relatively few studies investigating their long-term impacts and sustainable development prospects. By introducing digital inclusive finance and the digital economy as moderating variables, this paper further elucidates the role of intelligent technology in the long-term development of enterprises. This approach provides new insights into understanding the sustained effect of intelligent technology on high-quality enterprise development. Fourthly, this study ensures the robustness of its findings by employing multiple methods to address endogeneity issues. The use of Instrumental Variable construction, the Heckman two-stage method, and the Propensity Score Matching method collectively help mitigate potential biases and validate the reliability of the results.

2. Literature review

There are some factors influencing high-quality development. The advancement of fintech [2] and digital finance provides new opportunities for them, and government policies promote innovation and total factor productivity through subsidies and support policies [3]. Organizational and technological innovation, environmental regulation and green credit policy, equity structure reform, and ESG performance have also become important factors in promoting the high-quality development of enterprises. However, there is limited research on the intelligence and high-quality development of enterprises, especially how intelligence affects the high-quality development of enterprises.

In recent years, the impact of intelligence on enterprise development has become a research hotspot. Intelligent manufacturing technology effectively reduces production costs and improves enterprise productivity and total factor productivity through human-machine collaboration and deep integration of design, production, and management. Such technological progress not only optimizes the allocation of resources but also enhances the overall production efficiency and market competitiveness of enterprises. In addition, intelligently builds an open innovation network to support the formation of multiple innovation paradigms such as integrated innovation and user innovation to improve the innovation ability of enterprises. Intelligence also promotes internal collaboration, industrial chain collaboration, and supply chain collaboration of enterprises, accelerates the reconstruction of traditional industrial chains, and improves the market response speed and adaptability of enterprises. However, existing studies primarily concentrate on the effects of intelligence on enterprise performance, innovation capacity, and productivity, which is still insufficient. High-quality development includes not only the improvement of economic benefits but also the fulfillment of social responsibilities and the realization of sustainable development.

Consequently, it is essential to deeply investigate the pathways and mechanisms through which enterprises achieve high-quality development in the context of intelligence.

Previous literature mainly focuses on the direct impact of intelligent technology on enterprise efficiency, competitiveness, and market performance, while this study further discusses how intelligent technology indirectly promotes enterprises to achieve high-quality development by improving innovation efficiency and management efficiency. The main theories include the Cobb-Douglas production function, Schumpeter's innovation theory and disruptive innovation theory, principle-agent theory, and information asymmetry theory. First, as a classic model in economics, the Cobb-Douglas production function captures the impact of technological progress and efficiency improvement on output through total factor productivity (*TFP_LP*). In this study, *TFP_LP* is a dependent variable about the high-quality development of enterprises. Second, Schumpeter's innovation theory and disruptive innovation theory emphasize the central role of innovation in economic growth. As an important way of innovation, intelligent technology promotes enterprises to maintain their advantages in competition. It will redefine market rules and industry standards by improving their innovation efficiency, to promote enterprises to achieve high-quality development. Third, principal-agent theory and asymmetric information theory provide support for understanding the mediating role of managerial efficiency. Intelligent technology enhances the competitiveness of enterprises by enhancing information openness and transparency, reducing information asymmetry, and optimizing the internal decision-making and resource allocation process, to boost enterprise competitiveness.

3. Mechanism and Hypothesis

High-quality development of enterprises is a complex, multi-dimensional goal. As a new technical means, intelligence profoundly influences enterprise development in numerous ways. The logical pathways through which intelligence impacts high-quality enterprise development are primarily seen in aspects as follows.

Firstly, efficiency optimization and cost control. Through automated production processes, enterprises can significantly improve production efficiency. Refined supply chain management and intelligent equipment maintenance also contribute to reducing operating costs. Additionally, optimized human resource management helps enterprises take important steps toward sustainable development. The adoption of intelligent technology boosts enterprise competitiveness and facilitates efficient resource utilization. This provides solid support and continuous power for high-quality development. In addition, intelligent technology fosters more open and transparent information, reducing the possibility of information asymmetry in the principal-agent relationship. It also improves the decision-making and resource allocation process within the enterprise by enhancing management efficiency. The principal-agent theory points out that with the increase in information disclosure and transparency, the behavior of agents (such as enterprise managers) is more in line with the interests of principals (such as shareholders), thereby improving management efficiency. The theory of information asymmetry underscores how information asymmetry affects economic agents' behavior and market efficiency.

Secondly, market expansion and product innovation. Intelligent technology promotes the education and training of enterprise employees, enabling them to master advanced technology and improve their skill level [2]. At the same time, intelligent transformation expands the scope of talent recruitment for enterprises. It promotes cultural exchange and regional collaboration, laying a solid foundation for long-term development. This transformation also improves the competitiveness and innovation ability of enterprises. According to Schumpeter's innovation theory, innovation is the core driving force of economic development, covering new product development, new production method adoption, new market development, and new organizational form establishment. By introducing advanced automation, digitalization, and information technology, intelligent technology comprehensively improves the innovation efficiency of enterprises and gives them an advantage in the competition. The disruptive innovation theory emphasizes that introducing disruptive technologies and business models can redefine market rules and industry standards. Intelligent technologies improve the innovation efficiency of enterprises, enabling them to quickly adapt to market changes and user needs. This promotes high-quality development. Therefore, as a mediating variable, innovation efficiency bridges intelligent technology and high-quality enterprise development. This underscores the necessity and importance of studying innovation efficiency in the context of intelligent technology.

Building on the analysis above, this paper posits the hypotheses as follows:

H1: Intelligent technology significantly promotes the high-quality development of enterprises.

H2a: Intelligent technology significantly promotes the high-quality development of enterprises by improving management efficiency.

H2b: Intelligent technology significantly promotes the high-quality development of enterprises by improving innovation efficiency.

As an important part of digital development, intelligent technology is profoundly affecting the operation and developmental approach of enterprises. In this context, digital inclusive finance and digital economy have gradually become crucial for promoting the high-quality development of enterprises. Digital financial inclusion encompasses all formal financial service actions that advance financial inclusion via digital financial services. The digital economy refers to the interconnected global economy and society facilitated by information and communication technologies like the Internet, mobile devices, and sensor networks. By improving the availability and ease of financial services, digital inclusive finance greatly supports the implementation of intelligent technology. This accelerates the enhancement of enterprise management efficiency and boosts innovation ability. At the same time, by optimizing data utilization and promoting digital technologies, the digital economy creates a favorable environment for intelligent technologies. This further promotes enterprises towards high-quality development. Therefore, to reveal how digital inclusive finance and the digital economy influence the connection between intelligent technology and high-quality enterprise development, this paper posits the hypotheses as follows:

H3a: Digital inclusive finance has a positive moderating effect between enterprise intelligent technology and the high-quality development of enterprises.

H3b: The digital economy has a positive moderating effect between enterprise intelligent technology and the high-quality development of enterprises.

4. Research Design

4.1. Sample Selection

This paper selects A-share listed companies in Shanghai and Shenzhen stock exchanges that have published financial reports from 2007 to 2022 as empirical research samples to study the impact of enterprise intelligence on their high-quality development. The reasons for choosing 2007 as the starting point of the study are as follows: first, the implementation of the new Accounting Standards for Business Enterprises in 2007 led to many changes in the information disclosure requirements of listed companies. Second, since 2007, the advantages of artificial intelligence technology have become increasingly obvious, and patents in the AI field have entered the development stage, making data collection feasible [4]. The patent text of this paper comes from the IRPDB intellectual property database, and the annual reports and other data of enterprises come from the CSMAR database.

This paper processes the data according to the following principles: (1) due to bankruptcy accounting standards for *ST* and **ST* enterprises, the financial industry's particularities, and the quasi-financial attributes of real estate enterprises, we exclude suspended, delisted, financial, and real estate enterprises from the study. (2) to ensure the precision and dependability of the analysis and avoid the bias and distortion of results caused by missing data, the samples of enterprises with missing important variables are eliminated. (3) To avoid the impact of outliers on the sample estimation, all continuous variables are winsorized at the 1% and 99% quantiles.

4.2. Variable Definition

High-quality development of enterprises refers to the process of enterprises achieving high production efficiency through technological innovation and value chain climbing. Total factor productivity (*TFP*) refers to the maximum output level that an enterprise can achieve with certain inputs of production factors. It comprehensively reflects the influence of elements such as technological progress, management efficiency improvement, and resource allocation optimization on production efficiency. In short, *TFP* captures productivity improvement and is a crucial indicator to capture the high-quality development of enterprises. There are four main methods for measuring *TFP*: *OLS, Levinsohn-Petrin, Olley-Pakes,* and *GMM* methods. Drawing on the ideas of Zhang Jichang et al. [5], this paper uses the Levinsohn-Petrin method to estimate TFP.

Artificial intelligence indicators (*AI*) can comprehensively reflect the progress of enterprises in technology application, innovation ability, and digital transformation. By capturing the performance of enterprises in R&D investment, number of patents, application level, and talent reserve, the level of digital intelligence can be accurately evaluated. Referring to the practice of Previous literature, the machine learning method is used to generate an artificial intelligence term dictionary, and enterprise-level artificial intelligence indicators are constructed through text analysis of China's publicly traded firms and their patents from 2007 to 2022. In the baseline model, we capture the frequency of artificial intelligence keywords in the annual filings of listed companies. For alternative indicators, this paper utilizes the frequency of these keywords in the MD&A section of annual reports and the count of AI patents filed by listed companies in the current year.

Referring to the practice of Xiao Tusheng et al. [6], the selected control variables in this study are as follows: enterprise Size (*Size*), asset-liability ratio (*Lev*), enterprise profitability (*ROA*), ownership concentration (*TOP10*), proportion of Intangible assets (Intangible), and Tobin’s q value（*Tobin-Q*）. Table 1 shows the precise definitions of the variables employed in this study as follows.

Table 1. Definitions of variables.

Variable type	Variable name	Symbol	Definition
Explanatory variables	Total factor productivity	*TFP_LP*	Olley-Pakes Method
Dependent Variable	Intelligence	*AI*	Shown Above
Control variable	Enterprise Size	*Size*	Natural logarithm of annual total assets
	Asset-liability ratio	*Lev*	Total liabilities/total assets at year-end
	Enterprise profitability	*ROA*	Net profit/average balance of total assets
	Ownership concentration	*TOP10*	Number of shares held by top ten shareholders/total number of shares
	Proportion of Intangible assets	*Intangible*	Net intangible assets/total assets
	Tobin-Q	*Tobin-Q*	(market value of tradable shares + number of non-tradable shares × net assets per share + book value of liabilities)/total assets

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3. Baseline Model

To explore the impact of intelligence on the high-quality development of enterprises, this paper constructs model (1):

$$TFP\_LP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \gamma_n Control_{i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

In model (1), the dependent variable is $TFP\_LP_{i,t}$, the high-quality development index of firm *i* in year *t*. The independent variable is $AI_{i,t}$, the artificial intelligence index of firm *i* in year t. β_0 is the constant term, β_1 is the regression coefficient term and γ_n is the coefficient term of the Control variable. $Control_{i,t}$ is the aforementioned control variable. λ_t is the time-fixed effect, μ_i is the individual fixed effect, and $\varepsilon_{i,t}$ is the random disturbance term. If β_1 is significantly greater than 0, H1 is validated.

5. Empirical analysis

5.1. Descriptive statistical analysis

Based on the descriptive statistics in Table 2, we can see the distribution of different variables in the samples. This study includes 20,685 observations from diverse enterprises, reflecting wide distributions of variables such as productivity, intelligence, and profitability. The volume and scope of the data are comparable to those found in existing literature, ensuring the representativeness and reliability of the analysis results.

The mean of total factor productivity (*TFP_LP*) is 8.477, with a standard deviation of 0.957, suggesting that the productivity level of the sampled enterprises is broadly high, but there is some variability. Some firms have significantly higher productivity than the average, probably due to their advantages in technological innovation and management efficiency. The minimum value of intelligence (*AI*) is 0, suggesting that the enterprise has not carried out intelligent transformation; the mean is 0.732, the standard deviation is 1.095, and the maximum value is 4.644. The level of intelligence varies greatly among enterprises. Some enterprises are highly intelligent, while some enterprises may still be in the early stage of intelligence. This difference may reflect different strategies and progress of firms in technology adoption and application.

Table 2. Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
TFP_LP	20685	8.477	0.957	5.957	12.062
AI	20685	0.732	1.095	0.000	4.644
Size	20685	22.045	1.148	19.695	25.890
Lev	20685	0.386	0.182	0.032	0.819
ROA	20685	0.050	0.060	-0.271	0.286
Intangible	20685	0.043	0.031	0.000	0.227
TOP10	20685	58.463	14.484	20.707	90.298
Tobin-Q	20685	2.065	1.260	0.000	10.127

5.2. Baseline Regression Results

Table 3 shows the regression results of enterprise intelligence and high-quality development (*TFP_LP*). Column (1) only controls for time-fixed effects, column (2) only controls for firm-fixed effects, while Table (3) controls for both time and firm-fixed effects. In these models, the coefficients for Intelligence (*AI*) are all significantly positive and significant at the 1% significance level, which are 0.027^{***},0.038^{***}, and 0.025^{***}, respectively. This indicates that for each unit increase in the application of intelligent technology, the average total factor productivity of enterprises increases by approximately 0.025 percentage points. Therefore, the improvement of intelligence significantly promotes the improvement of total factor productivity of enterprises, which validates hypothesis H1 that the application of intelligent technology can effectively improve the production efficiency and overall productivity of enterprises.

In addition to the significant positive impact of the level of intelligence, the control variables also significantly affect TFP to varying degrees. The high R^2 value of the model (0.706) suggests that the selected control variables effectively account for variations in total factor productivity. This enhances the explanatory capacity and confidence in attributing impacts to intelligent technology. These findings not only help to deeply understand how intelligent technology enhances enterprise production efficiency but also provide substantial empirical support and guidance for its future application in research and practice.

Table 3. Baseline regression results.

	(1) **TFP_LP**	**(2)** **TFP_LP**	**(3)** **TFP_LP**
AI	0.027^{***}	0.038^{***}	0.025^{***}
	(0.003)	(0.003)	(0.003)
Control	Yes	Yes	Yes
Firm	No	Yes	Yes
Year	Yes	No	Yes
Cons	-6.007^{***}	-4.616^{***}	-3.682^{***}
	(0.077)	(0.088)	(0.114)
N	20685.000	20685.000	20685.000
R2	0.762	0.688	0.706

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3. Robustness Checks

To ensure the reliability and consistency of the regression results, this study conducts robustness tests on the baseline regression results through various methods. These include including altering the capture methods of dependent variables and independent variables, adding control variables, and adjusting the sample size.

Table 4 shows the robustness test of replacing the independent variable with the dependent variable. The results indicate that irrespective of the capture method for the dependent variable—*LP* method (Column 1), *OP* method (Column 2), *OLS* method (Column 3), or fixed effect method (*FE*, Column 4)—the positive impact of artificial intelligence (*AI*) on corporate total factor productivity (*TFP_LP*) remains consistently significant at the 1% significance level. Furthermore, the results maintain stability when altering the capture method of independent variables to an extended lexicon incorporating AI (Column 5). These findings underscore the reliability and consistency of the baseline regression, further substantiating the significant role of intelligence in fostering high-quality enterprise development.

Table 4. Robustness-I.

	(1) TFP_LP	(2) TFP_OP	(3) TFP_OLS	(4) TFP_FE	(5) TFP_LP
AI	0.025^{***}	0.012^{***}	0.018^{***}	0.019^{***}	
	(0.003)	(0.003)	(0.003)	(0.003)	
AI_complex					0.023^{***}
					(0.003)
Control	Yes	Yes	Yes	Yes	Yes
Method_TFP	LP	OP	OLS	FE	LP
Method_AI	Independent	Independent	Independent	Independent	Extend
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Cons	-3.682***	-1.960***	-5.144***	-5.623***	-3.685***
	(0.114)	(0.116)	(0.109)	(0.111)	(0.114)
N	20685.000	20685.000	20685.000	20685.000	20685.000
R2	0.706	0.624	0.801	0.813	0.706

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In addition, this study conducts other types of robustness tests, as shown in Table 5. In Column (2), referring to the practice of Xiao et al. [6], to eliminate potential omitted variable bias, this paper adds more control variables: cash flow ratio, fixed assets ratio, company establishment years, shareholding ratio of institutional investors, and shareholding ratio of management. In Column (3), considering the significant impact of the 2008 financial crisis on enterprise development and the rapid advancement of artificial intelligence after 2012, restricting the sample to data from 2011 onwards mitigates abnormal fluctuations. This approach more accurately reflects the influence of intelligence on the high-quality development of enterprises. Column (4) tests the sensitivity of the model to the time lag effect by introducing the independent variable lagged by one order. Table 5 demonstrates that across various robustness tests, the coefficient of AI remains statistically significant, affirming the consistently positive impact of intelligence on high-quality enterprise development. These findings bolster the credibility of the research conclusions.

Table 5. Robustness-II.

	(1) TFP_LP	(2) TFP_LP	(3) TFP_LP	(4) TFP_LP
AI	0.025^{***}		0.036^{***}	
	(0.003)		(0.003)	
AI_complex		0.019^{***}		
		(0.003)		
L.ai				0.024^{***}
				(0.003)
Control	Yes	Yes	Yes	Yes
Excontrol	No	No	No	Yes
Sample	No	No	Yes	No
Lag	No	No	No	Yes
Cons	-3.682^{***}	-3.310^{***}	-4.427^{***}	-3.608^{***}
	(0.114)	(0.125)	(0.105)	(0.124)
N	20685.000	20685.000	18517.000	17908.000
R2	0.706	0.726	0.650	0.692

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4. Endogeneity Test

This study addresses endogeneity by employing instrumental variable construction, the Heckman two-stage method, and propensity score matching (*PSM*), as shown in Table 6.

Columns (1) and (2) correspond to the instrumental variable approach. Following Xiao Tusheng 's method for constructing instrumental variables [6], we select the industry-wide average of artificial intelligence excluding sample enterprises as instrumental variables for *AI* transformation (*Iv_ai*). The rationale is twofold: (1) After excluding the sample enterprises, the average of artificial intelligence in the whole industry can indicate the industry's overall intelligence level, avoid the data interference of individual enterprises, and have strong exogeneity, to effectively alleviate the endogeneity problem. (2) The industry-wide AI average is highly correlated with the intelligent transformation of individual enterprises, which can not only capture the general intelligent trend of the industry but also maintain independence, making it an ideal instrumental variable to improve the robustness and reliability of regression results. The regression results of the first stage are shown in Column (1) of Table 6, the intelligent technology lagged by one phase, and the intelligent technology in the industry except the sample enterprises had a significantly positive impact on intelligent technology. In addition, the instrumental variable passed the unidentifiable test (*LM=1506.07*), the weak instrumental variable test (*F=1643.84*), and the over-identification test (*P= 0.000*). The second-stage regression results are shown in Column (2) of Table 6, and the benchmark regression results are still robust.

Column (3) presents the Heckman two-stage method results. Following Zhang Jichang's approach [5], the dependent variable is set as a dummy variable *AI_Dum*, coded as 1 if AI exceeds the median, indicating higher intelligent transformation, and 0 otherwise. The first-stage model includes instrumental variables, control variables, industry, province, and year dummy variables, with the Probit function used to compute the inverse Mills ratio *(IMR*). *IMR* is then included in the second-stage regression. The results in Column (3) confirm the robustness of the baseline regression results.

Column (4) displays the *PSM* results. The dependent variable *AI_Dum* is coded as 1 for the high-intelligence technology group (experimental group) if *AI* is greater than the median, and 0 for the low-intelligence technology group (control group). The propensity score is calculated using the Logit function, and samples are matched using the radius matching method. The results in Column (4) confirm the robustness of the baseline regression.

Table 6. Results of endogeneity problem processing.

	(1) AI	(2) TFP_LP	(3) TFP_LP	(4) TFP_LP
AI		0.089^{***}	0.029^{***}	0.015^{**}
		(0.011)	(0.008)	(0.006)
Iv_ai	0.726^{***}			
	(0.018)			
IMR			-0.366^{***}	
			(0.123)	
Control	Yes	Yes	Yes	Yes
Firm	Yes	Yes	No	No
Province	No	No	Yes	Yes
Industry	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes
Cons			-4.677^{***}	-3.363^{***}
			(0.580)	(0.346)
N	20111.000	20111.000	20462.000	20407.000
R2		0.696		0.698

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.5. Mediating Mechanism Results

In this study, we explore not only the direct impact of intelligence on high-quality enterprise development but also introduce management efficiency and innovation efficiency as mediating variables. This approach aims to provide a comprehensive analysis of the specific pathways through which intelligence supports high-quality enterprise development. As a reflection of the internal management level of an enterprise, management efficiency can effectively support the application of technologies brought by intelligence by optimizing resource allocation and improving operational efficiency. Innovation efficiency represents the ability of enterprises in R&D and technological innovation. The integration of intelligent technology provides new tools and methods for enterprise innovation activities, thereby enhancing innovation outcomes and competitive advantages. Thus, this paper separately examines management efficiency and innovation efficiency as mediating variables, aiming to elucidate how intelligence promotes enterprises to achieve high-quality development through enhanced management and innovation capabilities.

Management efficiency reflects the ability of enterprises in resource allocation, process optimization, and operation management, and is the direct benefit field of intelligent technology application. By improving management efficiency, intelligent technology can better realize its potential in improving productivity and reducing costs, thereby establishing a robust basis for the high-quality development of enterprises. Based on the research of Previous literature, this paper adopts the ratio of the sum of the enterprise's administrative expenses, sales expenses, and total revenue to capture management efficiency. The larger the management efficiency index value (*Ofee*), the lower the management efficiency of the enterprise. Taking the management cost rate as the intermediary variable, and drawing reference from the study of Jiang Jian [7], the intermediary effect model is built as follows:

$$Ofee_{i,t} = \beta_2 + \beta_3 AI_{i,t} + \gamma_n Control_{i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{2}$$

When considering the impact of intelligent technology on enterprise efficiency, the improvement of management efficiency is a key factor. However, simply improving management efficiency may not fully reveal the profound impact of intelligent technology on overall business performance. To understand its mechanism more comprehensively, it is necessary to introduce innovation efficiency as a mediating variable. Innovation efficiency focuses on not only optimizing resource allocation, process refinement, and operation management but also on how intelligent technology can enhance the ability of enterprises to innovate in products, services, or business models. Therefore, concerning the research method of Li Lei et al. [8], this paper regards the number of granted invention patents (*Patent_Award*) as an intermediary variable to capture innovation efficiency, and draws on the research of Jiang Jian [7] to build the intermediary effect model as follows:

$$Patent\_Award_{i,t} = \beta_4 + \beta_5 AI_{i,t} + \gamma_n Control_{i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{3}$$

The test results of the mechanism of action are shown in Table 7. The regression coefficient of intelligence in column (2) is significantly negative ($\beta_3 = -0.006$, $P < 0.01$), indicating that intelligence technology significantly enhances enterprise management efficiency. Previous studies have demonstrated that management efficiency is pivotal in fostering high-quality enterprise development. For example, Yang Yi et al. [9] pointed out that the digital economy indirectly promoted the high-quality development of the manufacturing industry in two ways of technological innovation effect and the management efficiency effect. Simultaneously, the research of Shen Jie et al. [10] shows that industrial intelligence can improve the management efficiency of enterprises and effectively support private small and medium-sized enterprises to achieve high-quality development. The study establishes the mechanism through which intelligent technology enhances management efficiency to promote high-quality enterprise development, thereby validating hypothesis H2a.

In column (3), the regression coefficient of intelligence is significantly negative ($\beta_5 = -0.106$, $P < 0.01$), indicating that intelligence technology plays a crucial role in improving the innovation efficiency of enterprises. Existing studies have deeply explored the important influence of innovation on the high-quality development of enterprises. For example, Huang Bo et al. [11] pointed out that digital technology innovation has significantly enabled the high-quality development of the real economy and provided key enlightenment for the formulation of China's digital technology policy and enterprise digital strategy. In addition, Chen Zhao et al. [12] hypothesized that innovation can effectively improve the quality of enterprise development, and emphasized the positive role of innovation in promoting enterprises to move towards higher quality development. It shows that the influence mechanism of intelligent technology to improve the high-quality development level of enterprises by improving innovation efficiency is established, and hypothesis H2b is verified.

Table 7. Mechanism test results.

	(1) TFP_LP	(2) Ofee	(3) Patent_Award
AI	0.025^{***}	-0.006^{***}	0.106^{***}
	(0.003)	(0.001)	(0.009)
Control	Yes	Yes	Yes
Cons	-3.682^{***}	0.425^{***}	-10.083^{***}
	(0.114)	(0.021)	(0.332)
N	20685.000	20685.000	20685.000
R2	0.706	0.226	0.315

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.6. Moderating Mechanism Results

To reveal the difference in the influence of AI technology on the total factor productivity of enterprises of artificial intelligence technology on the total factor productivity of enterprises, this paper selects the digital inclusive financial index and digital economy index as moderating variables for analysis. Referring to the research methods of Guo et al. [13] and Zhao et al. [14], this paper selects the digital inclusive financial index (*Gov*) and digital economic index (*Eco*) to construct the mediating effect model as follows:

$$TFP_LP_{i,t} = \beta_6 + \beta_7 AI_{i,t} + \beta_8 Gov_{i,t} + \beta_9 int_{1,i,t} + \gamma_n Control_{i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{4}$$

$$\mathrm{TFP_LP_{i,t}} = \beta_{10} + \beta_{11}\mathrm{AI_{i,t}} + \beta_{12}\mathrm{Eco_{i,t}} + \beta_{13}\mathrm{int_{2,i,t}} + \gamma_n \mathrm{Control_{i,t}} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{5}$$

In the above two models, where $\mathrm{int}_{1,i,t}$ is the cross term of $AI_{i,t}$ and $Gov_{i,t}$ and $\mathrm{int}_{2,i,t}$ is the cross term of $AI_{i,t}$ and $Eco_{i,t}$. Table 8 presents the moderating effects test. Columns (1) and (2) display the regression results with *Gov* and *Eco* as the moderating variables, respectively. The results reveal significantly positive cross-terms, indicating that digital financial inclusion and the digital economy facilitate the relationship between intelligent technology and high-quality enterprise development. This validates hypotheses H3a and H3b.

Table 8. The moderating effects.

	(1) TFP_LP	(2) TFP_LP
AI	0.022***	0.023***
	(0.004)	(0.004)
Gov	-0.001**	
	(0.000)	
int1	0.000**	
	(0.000)	
Eco		-0.011
		(0.008)
int2		0.005**
		(0.002)
Control	Yes	Yes
Year	Yes	Yes
Firm	Yes	Yes
Cons	-2.857***	-2.961***
	(0.157)	(0.149)
N	14033.000	14033.000
R2	0.649	0.649

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusions and Suggestions

Through an empirical analysis of A-share listed companies in Shanghai and Shenzhen that have published financial reports from 2007 to 2022 in China, this paper examines how intelligent technology enhances the high-quality development of enterprises and derives the following conclusions. (1) Intelligent technology significantly promotes the high-quality development of enterprises by improving production and operational efficiency. It optimizes resource allocation, enhances production efficiency, and reduces costs. (2) Intelligent technology improves management efficiency and innovation ability. It enhances decision-making accuracy and timeliness, boosts production and operational efficiency, and augments enterprise innovation capabilities, facilitating the development of new products and services, and strengthening market competitiveness. (3) Digital inclusive finance and digital economy, as moderating variables, play a positive role in promoting the relationship between enterprise intelligent technology and high-quality development.

This paper reveals how intelligent technology enhances the high-quality development of enterprises on the micro level. Here we provide some suggestions. (1) Increase investment in intelligent technology. Enterprises should enhance investment in intelligent technologies such as automated production, refined supply chain management, intelligent equipment maintenance, and optimized human resource management to further boost production efficiency, reduce costs, and achieve high-quality development. (2) Optimize management efficiency. Introducing intelligent management tools and technologies like intelligent data analysis and automated decision-making systems can improve management efficiency and decision-making accuracy, optimize resource allocation, reduce costs, and enhance market responsiveness. (3) Strengthen innovation capacity. Enterprises should invest more in R&D, encourage cross-departmental collaboration and knowledge sharing, and foster an innovation culture. Continuous innovation will help optimize products and services to meet changing customer needs, enhancing market share and brand influence. (4) Utilize digital inclusive finance and digital economy: Embracing digital inclusive financial services and leveraging the internet and big data technologies can expand market reach, improve financing efficiency, and enhance financial management capabilities. Utilizing the platform and ecological characteristics of the digital economy can help explore new business models, growth opportunities, and profit avenues.

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