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Article

Does Artificial Intelligence Promote the Business Performance of Agricultural Enterprises

Yutao Liang [1,*]

[1] School of Economics and Management, Guangxi Normal University, Guilin, Guangxi, China
* Correspondence: Yutao Liang, School of Economics and Management, Guangxi Normal University, Guilin, Guangxi, China

Abstract: Artificial intelligence (AI) plays a pivotal role in advancing the development of agricultural enterprises and is essential for enhancing their business performance. This study empirically investigates the influence of AI on the operational performance of agricultural firms in China, drawing on data from A-share listed agricultural companies on the Shanghai and Shenzhen stock exchanges from 2003 to 2023. A fixed-effects model is employed to examine both the effects of AI and the underlying mechanisms. The empirical results show that AI significantly boosts the business performance of agricultural enterprises, with particularly pronounced effects among non-high-tech firms, non-heavy-pollution enterprises, and asset-intensive industries. AI also exerts a stronger positive impact on firms in their growth stage, whereas its effect on mature enterprises is not statistically significant. Mechanism analysis reveals that AI enhances performance by easing financing constraints, strengthening organizational resilience, and promoting collaborative R&D. Moreover, policy measures-such as government innovation subsidies-substantially amplify the positive impact of AI on firm performance. Based on these findings, the study recommends strengthening AI-driven technological innovation and application, designing differentiated policy measures tailored to the needs of various types of agricultural enterprises, enhancing complementary capabilities for smart transformation, and optimizing organizational structures to further unlock AI's potential in improving business performance.

Keywords: artificial intelligence; agriculture; business performance; innovation

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1. Introduction

This study provides an in-depth examination of the impact of artificial intelligence (AI) on the business performance of agricultural enterprises. Agricultural enterprises currently face challenges such as low production efficiency and significant resource waste, with improving business performance being a core issue in their digital transformation. As AI technologies continue to advance, their potential applications in agriculture have garnered significant attention from both academia and industry [1]. AI is seen as a key tool for enhancing business performance in agriculture, through intelligent production management, precision agriculture, and smart supply chain systems, all of which can improve efficiency, reduce costs, and optimize resource use, promoting the sustainable development of agricultural enterprises in a complex market environment [2]. However, practical challenges such as technological and financial limitations still hinder AI adoption [3].

From a policy perspective, national support for AI integration in agriculture has been growing, encouraging enterprises to explore and implement intelligent technologies. With government-backed initiatives like the "Intelligent Agriculture Development Plan," agricultural enterprises have received both technical support and financial relief, helping to alleviate the financial pressures of transformation. Despite these efforts, AI adoption faces significant barriers, including high implementation costs, the need for specialized skills, and substantial initial investments, which slow its widespread application. Additionally, disparities in the willingness and capacity for technology adoption among different types of agricultural enterprises lead to varying outcomes [4].

The innovation of this study lies in its focus on the mechanisms through which AI enhances business performance in agricultural enterprises, thereby enriching the existing literature. Combining theoretical insights with empirical analysis, this study explores how AI improves business performance by enhancing production efficiency and resource allocation. Furthermore, it examines how policy improvements can foster continuous AI innovation. In conclusion, by analyzing AI's role and mechanisms in boosting business performance, this study offers valuable theoretical insights and practical guidance for business decision-making and policy development, contributing to the high-quality development of agricultural enterprises.

2. Literature Review

In recent years, artificial intelligence (AI) technologies have rapidly developed and expanded across industries, particularly in enhancing the business performance (ROA) of agricultural enterprises. Business performance, a key indicator of profitability, is influenced by factors such as production efficiency, resource allocation, market responsiveness, and sustainability. Existing literature generally agrees that AI can significantly improve business performance in agriculture by optimizing production processes, enhancing resource utilization, and increasing market competitiveness [5]. Key pathways through which AI enhances agricultural enterprises' ROA include precision agriculture, smart marketing, supply chain optimization, and green technology innovation.

Artificial intelligence (AI) is significantly enhancing the business performance (ROA) of agricultural enterprises by optimizing key operations such as precision agriculture, marketing, supply chain management, and environmental sustainability. Through technologies like sensors, drones, and AI algorithms, precision agriculture enables real-time monitoring of soil, climate, and crop growth, improving production efficiency and reducing resource waste. AI also helps agricultural businesses develop personalized marketing strategies, optimize pricing, and improve customer relationships, thereby boosting competitiveness and profitability. In supply chain management, AI enhances inventory control, reduces costs, and optimizes logistics, improving operational efficiency and cash flow. Furthermore, AI promotes green technology innovations by optimizing resource use and minimizing environmental impact, contributing to sustainability and improving the corporate image of agricultural enterprises. Despite these benefits, challenges such as technology operability, capital investment, and environmental adaptability remain, requiring further research into cost-effective AI applications for sustainable agricultural development.

3. Theoretical Analysis

3.1. Direct Impact of Artificial Intelligence on Agricultural Development

The application of Artificial Intelligence (AI) in agricultural enterprises has a significant direct impact on business performance (ROA). First, AI optimizes production processes through precision agriculture technologies, improving production efficiency and resource utilization while reducing waste. For example, AI can automatically adjust irrigation systems based on real-time data, ensuring optimal conditions for crop growth, thus increasing yields and reducing production costs. Secondly, in marketing, AI optimizes pricing and customer relationship management through data analysis, helping agricultural enterprises achieve precise marketing strategies that enhance customer satisfaction and conversion rates, thereby improving profitability. Furthermore, AI-optimized supply chain management improves inventory efficiency, reduces logistics costs, and enhances asset utilization. Through these direct effects, AI significantly enhances the overall business performance and ROA of agricultural enterprises.

Hypothesis 1: Artificial intelligence can enhance the business performance of agricultural enterprises.

3.2. Research on Impact Mechanisms

AI alleviates financing constraints and significantly promotes the business performance (ROA) of agricultural enterprises. First, AI technologies, by improving production efficiency and optimizing resource allocation, lower production costs, thus increasing profitability and cash flow, improving financial conditions [6]. This strengthens the creditworthiness and reduces risks for agricultural enterprises when seeking financing, increasing the likelihood of obtaining external capital. Secondly, AI applications in supply chain management, through real-time inventory monitoring and logistics optimization, reduce the capital tied up in inventory, improving cash flow efficiency and further decreasing reliance on external short-term financing. Additionally, AI, through big data analysis and predictive modeling, helps agricultural enterprises better manage risks, lowering uncertainties arising from market fluctuations and natural disasters, which in turn enhances their financing ability. Through these methods, AI alleviates financing constraints, improving capital utilization efficiency and overall business performance.

Hypothesis 2: Artificial intelligence can improve business performance by alleviating financing constraints for agricultural enterprises.

3.3. Effect of Organizational Resilience

AI enhances the organizational resilience of agricultural enterprises, thereby indirectly improving their business performance, as measured by ROA. Organizational resilience refers to a company's capacity to rapidly adapt and maintain operational efficiency in the face of sudden events, market fluctuations, and external pressures. In the agricultural sector, where uncertainties such as natural disasters, climate variability, and fluctuating market demand are prevalent, AI supports data-driven decision-making, strengthening enterprises' responsiveness and overall performance.

Firstly, AI technologies facilitate precise forecasting and intelligent analysis, enabling agricultural enterprises to identify potential risks and implement timely adjustments. For instance, AI can predict crop growth patterns and potential climate variations by integrating meteorological data, soil conditions, and market trends. This allows enterprises to develop more effective production and supply strategies, mitigating the adverse effects of natural disasters [7]. Secondly, AI-driven supply chain management systems provide real-time monitoring of inventory and logistics, optimizing production processes, enhancing resource allocation efficiency, and reinforcing the enterprise's capacity to handle market volatility [8]. Furthermore, AI-powered production and precision agriculture applications promote efficient resource utilization under uncertain conditions, reducing production costs and improving financial stability. By bolstering organizational resilience, AI enables agricultural enterprises to enhance risk management, optimize asset use, and ultimately increase ROA.

Hypothesis 3: Artificial intelligence can enhance organizational resilience in agricultural enterprises, thereby improving production efficiency.

3.4. Effect of Collaborative Innovation Incentives

Figure 1 illustrates the structural relationship between artificial intelligence and the operational performance of agricultural enterprises.AI stimulates innovation and promotes cooperation between industry, academia, and research, further enhancing the business performance (ROA) of agricultural enterprises. Innovation is a core driver of improving the competitiveness and long-term development of agricultural enterprises, and AI introduces new pathways and opportunities for technological innovation in agriculture. First, AI technologies accelerate the research and development (R&D) of agricultural products and innovations in production processes. For instance, AI-driven precision agriculture technologies enable agricultural enterprises to use resources more efficiently, increase crop yield and quality, and thus improve production efficiency and market competitiveness [9]. Secondly, AI application in agricultural technological innovation promotes breakthroughs in smart devices, agricultural robots, drones, and sensor technologies, which effectively enhance production efficiency, reduce labor costs, and ultimately drive business performance improvement [10]. Additionally, AI applications facilitate cooperation between agricultural enterprises and academic or research institutions, thereby deepening industry-academia-research collaboration. AI not only provides agricultural enterprises with more precise data support and analytical tools but also empowers researchers with enhanced computational power and data processing capabilities, enabling more efficient cooperative research between enterprises and academic institutions to drive new technological developments. For example, collaboration between agricultural enterprises and universities to develop AI-driven climate forecasting models and crop growth analysis systems allows enterprises to make more informed decisions in production, reducing risks and improving efficiency. Through strengthening collaboration with academic and research institutions, agricultural enterprises can enhance their technological capabilities and access more innovative outcomes, thereby significantly improving ROA.

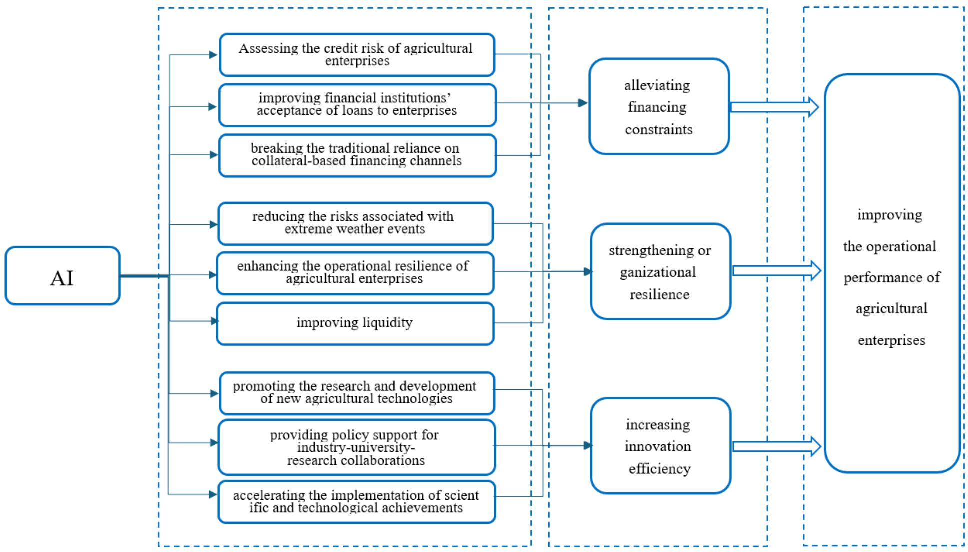

Figure 1. Mechanism Analysis Diagram.

Hypothesis 4: Artificial intelligence can improve innovation efficiency through enhanced industry-academia-research cooperation, thus promoting increased production efficiency in agricultural enterprises.

4. Model, Variables, and Data Sources

4.1. Data Sources

Agricultural enterprises refer to companies involved in agricultural production, processing, sales, services, etc., including those directly engaged in agricultural production (e.g., agriculture, forestry, planting, animal husbandry, fisheries) as well as those providing related products and services to agriculture. In this study, agricultural enterprises are matched based on the latest industry classification released by Shenwan Securities Research Institute.

To ensure data quality, the following sample processing steps were applied: (1) Companies in the financial industry were excluded; (2) Companies in the information transmission, software, IT services, and scientific research and technical services industries were excluded, as these industries inherently use cloud computing, big data, and AI technologies and disclose related information, which might make it difficult to clearly assess the impact of AI applications on their production efficiency; (3) Samples that were in ST or *ST status during the year were excluded; (4) Samples with missing data were excluded. As a result, 1,718 observations were retained.

The AI-related indicators in this study were sourced from the annual reports of listed companies, while the operating performance was calculated based on the financial data of these companies. Basic company information and financial data were obtained from the China Securities Market & Accounting Research Database (CSMAR), with data from 2007 to 2023 compiled for the study.

4.2. Variable Setting

Dependent Variable: Operating Performance (ROA)

In academic research, Return on Assets (ROA) is widely adopted as a measure of firm performance due to its comprehensiveness, comparability, and strong theoretical foundation. ROA captures a firm's overall ability to generate profits from its assets, making it well-suited for comparative analyses across companies and industries. Moreover, it is closely linked to fundamental financial concepts such as profitability and asset management efficiency, which underpins its extensive use in studies evaluating firm performance.

Core Independent Variable: Artificial Intelligence (AI)

This study adopts the method for calculating AI-related variables as outlined in *Management World* and constructs a dictionary of AI-related terms, supplemented with additional keywords specific to agricultural AI. Python was employed to extract the frequency of these AI-related terms from the annual reports of listed companies. To mitigate potential endogeneity issues, the AI indicator was transformed using a logarithmic scale after adding one.

Mechanism Variables:

Financing Constraints: Financing constraints for agricultural enterprises are measured using the SA index. A higher SA index indicates higher financing constraints for the enterprise.

Organizational Resilience: Organizational resilience is measured using two variables: long-term growth and financial volatility. Long-term growth is measured by the cumulative net sales growth over three years, and financial volatility is measured by stock return volatility.

Cooperative R&D Level: The level of cooperative R&D is measured based on whether a company has jointly applied for patents with other institutions. If the number of institutional applicants on a company's patents exceeds one, the variable is assigned a value of 1, indicating a higher level of cooperative R&D; otherwise, it is assigned a value of 0.

Control Variables:

In line with existing literature, the control variables selected for this study include:

Company Age (Age)

Leverage Ratio (Leverage)

Board Size (BoardSize)

Ownership Concentration (Top1)

Sales Expense Growth Rate (Growth)

4.3. Model Specification

To verify the causal relationship between AI and the high-quality development of agricultural enterprises, this study constructs the following model:

In order to examine the impact of AI on the operating performance of agricultural enterprises, this study sets up the following benchmark regression model:

$$TFP_{\mathrm{it}} = \alpha + \beta AI_{it} + \gamma Controls_{it} + year + ind + pro + \varepsilon_{it} \quad (1)$$

Where i and t denote the firm and year, respectively. ROA represents the firm's operating performance. AI refers to the artificial intelligence indicator, measured by the frequency of AI-related keywords in the annual reports of listed companies. ϵ\epsilonϵ is the random error term. year, ind, and pro represent year, industry, and province fixed effects, respectively. Controls denotes the set of control variables included in the model.

5. Empirical Analysis

5.1. Benchmark Regression Results

Table 1 examines the impact of artificial intelligence (AI) on productivity. Column (1) shows that the regression coefficient for AI is 0.0005 and is statistically significant at the 1% significance level. Column (2) displays the results after adding control variables, where the regression coefficient for AI remains significantly positive. Economically, holding other factors constant, for every one-unit increase in the AI level of a company, its operating performance (ROA) increases by 0.0004, a result that is also economically significant. These findings indicate that, ceteris paribus, artificial intelligence significantly enhances a company's operating performance, thus supporting the validity of Hypothesis 1. The regression results for the control variables align with previous literature.

Table 1. Regression Results of Artificial Intelligence on Agricultural Enterprise Performance.

Variables	**(1) Basic regress**	**(2) Basic regress**	**(3) PSM**
AI	0.0005**	0.0004**	0.0004*
	(0.000)	(0.000)	(0.000)
Age		0.0003	0.0006
		(0.000)	(0.000)
Leverage		-0.1645***	-0.1901***
		(0.010)	(0.014)
BoardSize		0.0006	0.0001
		(0.000)	(0.001)
Top1		0.0009***	0.0011***
		(0.000)	(0.000)
Growth		0.0010***	0.0110**
		(0.000)	(0.004)
Constant	0.0280***	0.0577***	0.0627***
	(0.002)	(0.008)	(0.011)
Ind	Yes	Yes	Yes
Year	Yes	Yes	Yes
Pro	Yes	Yes	Yes
R^2	0.137	0.308	0.271
Observations	1,718	1,718	1,148

Note: * * *, * *, * respectively indicate significance at the 1%, 5%, and 10% significance levels, with standard errors in parentheses. Unless otherwise specified, the following tables are marked with the same note.

5.2. Robustness Checks

5.2.1. Propensity Score Matching (PSM)

The adoption of AI technologies by firms is shaped by multiple factors, including internal attributes-such as human capital, managerial practices, and technological capabilities-as well as shifts in the external environment. These influences may introduce self-selection bias into empirical analyses. To address this concern, the present study employs the Propensity Score Matching (PSM) method to mitigate potential endogeneity. Specifically, firms are classified into a treatment group and a control group based on the presence of AI-related keywords in their annual reports, and the control variables in Model (3) are used as matching criteria. We implement 1:1 nearest-neighbor matching with replacement to ensure appropriate sample pairing.

Prior to running the PSM regression, we conducted a balance test. The results indicate that the standard errors of firm characteristics between the treatment and control groups were reduced by 68.7% to 96.2%. After matching, the standardized bias of all covariates falls below 5%, and the corresponding tests fail to reject the null hypothesis of no significant coefficient differences between the two groups. These findings demonstrate that the observable characteristic differences have been effectively mitigated and that the matching quality is satisfactory. As shown in Figure 2, the matched sample test further confirms that, after alleviating self-selection bias, the study's conclusions remain robust.

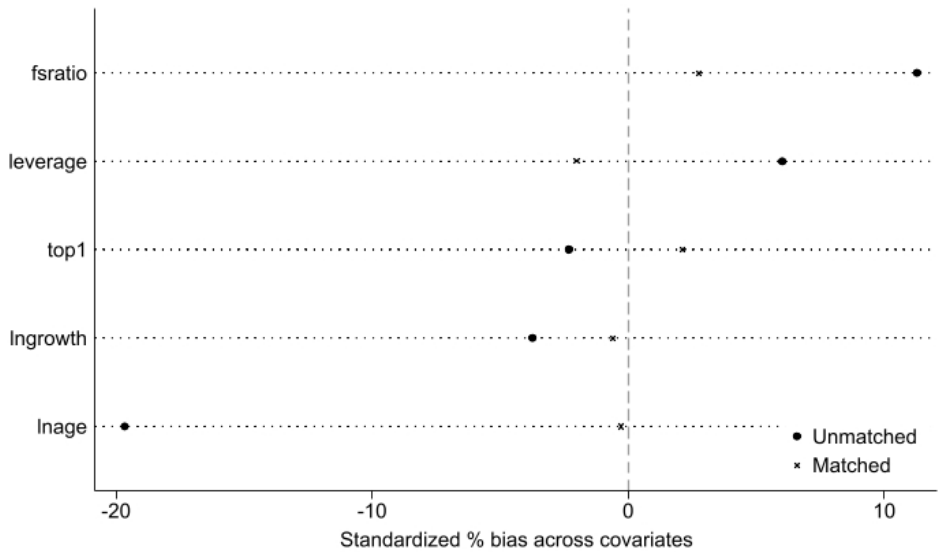

Figure 2. Standardized deviation plot of all covariates after matching.

5.2.2. Substitute Explanatory Variables

To ensure the robustness and reliability of the constructed core explanatory variable, this study further uses two alternative indicators to measure the level of artificial intelligence in companies. Specifically, the first substitute indicator uses the natural logarithm of the AI-related keywords (with 1 added) from the Management Discussion and Analysis (MD&A) section of the annual reports of agricultural listed companies. The second alternative is the natural logarithm of the number of AI patents applied for by the company during the year (with 1 added). These two substitute variables are used to replace the original core explanatory variable in regression analysis. Table 2 shows that whether using the logarithm of AI-related keywords from the MD&A section or the logarithm of AI patents applied for by the company, the conclusions remain robust, further supporting the positive impact of artificial intelligence on agricultural enterprise performance.

Table 2. Replacement of explanatory variable regression results.

Variable	(1)	(2)
	Roa	Roa
MDA	0.0097***	

	(0.003)	
Ln-Artificial Intelligence Patent		0.0189*** (0.004)
Constant	0.0570*** (0.008)	0.0599*** (0.008)
Controls	Yes	Yes
Ind	Yes	Yes
Year	Yes	Yes
Pro	Yes	Yes
R^2	0.265	0.271
Observations	1,718	1,718

5.2.3. Change in Sample Size

To further verify the robustness of the results, this study excludes food-related enterprises from the agricultural sector sample and applies a 5% winsorization to the data. Food-related companies generally face distinct market demands, production models, and levels of technological innovation compared to other agricultural enterprises. Consequently, their relationship with the application of artificial intelligence may differ significantly from that of other firms in the sector. Excluding these companies helps mitigate the potential confounding effects of industry heterogeneity on the regression results, thereby enhancing the generalizability of the findings. Following this adjustment, as shown in Table 3, the results remain consistent with the original analysis, confirming the robustness of the conclusion that artificial intelligence positively contributes to the operating performance of agricultural enterprises.

Table 3. Regression results with food enterprises excluded and tails reduced.

Variable	**(1)**
	ROA
AI	0.0080*** (0.003)
Constant	5.5794*** (0.071)
Controls	Yes
Ind	Yes
Year	Yes
Pro	Yes
R^2	0.586
Observation	1583

5.3. Heterogeneity Analysis

This study analyzes how artificial intelligence affects the operating performance (ROA) of agricultural enterprises by distinguishing between high-tech versus non-high-tech firms and high-pollution versus non-high-pollution industries. As shown in Table 4, due to substantial differences in technological capability, non-high-tech agricultural enterprises exhibit greater marginal gains from AI adoption, as AI upgrades production efficiency and management in firms with relatively traditional systems, whereas high-tech enterprises-already equipped with strong technological foundations-experience smaller incremental benefits. Likewise, AI has a stronger positive effect on ROA in non-high-pollution agricultural enterprises. While prior research highlights AI's ability to reduce emissions in high-pollution firms, this study finds that in non-high-pollution enterprises

AI more directly enhances production efficiency and resource allocation, thereby improving performance. In contrast, high-pollution enterprises often rely on AI primarily for pollution control and resource conservation, limiting the extent to which AI directly boosts ROA. Overall, the heterogeneous impacts of AI across technological and environmental attributes underscore the varied mechanisms through which AI contributes to performance improvement in agricultural enterprises.

Table 4. Heterogeneity test for distinguishing between high-tech and heavy pollution.

Variables	(1)	(2)	(3)	(4)
	high-tech	**Non high tech**	**heavy pollution**	**Non heavy pollution**
AI	0.0004	0.0006**	0.0004	0.0006*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.1249**	0.0631***	0.0399***	0.0822***
	(0.062)	(0.008)	(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Pro	Yes	Yes	Yes	Yes
R^2	0.524	0.313	0.356	0.297
Observation	145	1,573	750	968

This study examines how artificial intelligence influences agricultural firms' performance (ROA) by considering differences in technological, asset, and labor intensity, as well as firms' lifecycle stages. Firms are classified as being in the growth stage (≤12 years) or maturity stage (>12 years) to test whether AI's impact varies with development level. As shown in Table 5, results show clear heterogeneity: AI significantly improves performance in asset-intensive and labor-intensive firms, but has a weaker effect in technology-intensive firms that already possess strong technological capabilities and thus gain lower marginal benefits from AI adoption. From a lifecycle perspective, AI markedly enhances ROA in growth-stage agricultural enterprises, which tend to be more flexible, innovative, and responsive to technological upgrades. Conversely, mature enterprises-with stable, traditional technological and managerial systems-show no significant performance gains from AI implementation. Overall, the performance effect of AI is heterogeneous and shaped by firms' resource structures and lifecycle stages, with the greatest benefits concentrated in growth-stage and labor-intensive agricultural enterprises.

Table 5. Heterogeneity test based on industry attributes.

Variable	(1)	(2)	(3)	(4)	(5)
	technology-intensive	**asset intensive**	**Labour-intensive**	**Growth period**	**maturation stage**
AI	0.0003	0.0028*	0.0006**	0.0003	0.0012***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.1748**	0.2398***	0.0638***	0.0743***	0.0433**
	(0.073)	(0.068)	(0.009)	(0.010)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Pro	Yes	Yes	Yes	Yes	Yes
R^2	0.514	0.511	0.272	0.276	0.421

Observation	132	147	1,439	1,164	551

Overall, artificial intelligence has promoted the operational performance of agricultural enterprises in various aspects, and this conclusion still holds true after undergoing a series of tests.

6. Conclusion and Policy Recommendations

This study empirically demonstrates that artificial intelligence (AI) serves as a key driver in improving the operating performance of agricultural enterprises in China, based on data from Shanghai and Shenzhen A-share listed agricultural firms from 2003 to 2023. Using fixed-effect models and extensive robustness tests, the findings show that AI significantly enhances operating performance, with particularly strong effects in non-high-tech, non-heavy-pollution, and asset-intensive enterprises, as well as in firms at the growth stage rather than the mature stage. AI improves performance by alleviating financing constraints, strengthening organizational resilience, and promoting collaborative R&D, while government innovation subsidies, procurement policies, and tax incentives further amplify these benefits. Accordingly, the study recommends promoting AI technological innovation and application by enhancing data quality, improving computing infrastructure, and cultivating high-level AI talent; refining targeted "AI+" policies tailored to enterprise characteristics and development stages; and strengthening complementary inputs and organizational restructuring to support intelligent transformation through public data platforms, industry-university-research collaboration, and enhanced vocational training.

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