Research Article

Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation

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Abstract | This study delves into the influence of digital transformation and the corporate environment on the performance of agricultural enterprises, with a primary focus on the mediating function of dynamic learning capabilities. Rooted in dynamic learning theory, a research framework that amalgamates enterprise performance theory and sustainable development theory is established. The data of 360 listed agricultural enterprises in China are analyzed using AMOS 26.0 software. Findings demonstrate that both digital transformation and the corporate environment exert significantly positive impacts on the performance of agricultural enterprises. Digital transformation streamlines business processes, optimizes resource allocation, and enhances competitiveness. In contrast, the corporate environment shapes enterprise performance via factors such as market competition, credit policies, internal control, and information disclosure. Furthermore, dynamic learning capabilities play a pivotal mediating role. They empower enterprises to acquire and integrate knowledge, foster innovation, and adapt to market fluctuations, thereby influencing enterprise performance. This research not only enriches the theoretical understanding of agricultural enterprise development but also offers practical insights for promoting digital transformation, optimizing the corporate environment, and strengthening dynamic capabilities.

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Introduction

Globally, the digital economy has achieved remarkable growth. In 2020, the total digital economy of 47 countries reached a staggering $32.6 trillion, accounting for 43.7% of the combined GDP of these countries (Zhang *et al*., 2022). Developed economies have played a leading role in this growth process. In China, the digital economy has become a new engine for economic growth (Jiang *et al*., 2023). It is characterized by the deep integration of digital infrastructure construction and industrial digital ecosystems, as well as seamless connection with the real economy, especially in the manufacturing sector.

Digital transformation is also an indispensable catalyst for the sustainable development of the agricultural sector (Robertsone and Lapiņa, 2023).

Globally, countries such as Argentina, Spain, and Israel are leveraging digital technologies to enhance agricultural productivity, optimize resource utilization, and strengthen market competitiveness. Technologies such as remote sensing, Geographic Information Systems (GIS), Global Positioning System (GPS), the Internet of Things (IoT), and artificial intelligence are being widely applied in the agricultural field (Jiang *et al*., 2023). This enables real-time monitoring, data-driven decision-making, and the optimization of supply chains. In the research field of agricultural digital transformation, some progress has been made. Scientists have developed precision agriculture models that combine multiple digital technologies and can accurately manage soil conditions, irrigation, and fertilization, thus increasing crop yields (Getahun *et al*., 2024). There are also some studies focusing on the application of blockchain in the agricultural supply chain to ensure the traceability and safety of food (Rana *et al*., 2021). However, compared with other industries, the overall research and application of digital transformation in the agricultural field are still in a relatively early stage.

Agricultural enterprises are at the forefront of the wave of digital transformation in the agricultural industry. Digital transformation has a multi-faceted impact on these enterprises (Rana *et al*., 2021). It streamlines production processes, promotes the implementation of intelligent management systems, optimizes resource allocation, and ultimately affects the overall performance of enterprises (Jiang *et al*., 2023). However, agricultural enterprises in China are facing numerous challenges, including limited digital capabilities, high costs, a shortage of digital talent, and unclear digital strategies (Qin *et al*., 2022). As of 2020, the proportion of the agricultural digital economy in China's industrial added value was only 8.9%, far behind that of the service industry and general industries (Qian *et al*., 2022).

Based on the dynamic learning theory proposed by Eisenhardt and Martin (2000), which emphasizes an organization's ability to adapt to market changes through astute resource management, this study aims to explore the direct impact of digital transformation on the performance of agricultural enterprises and the mediating role of dynamic capabilities. Research on digital technology applications for productivity enhancements and resource optimization primarily exists alongside sparse data concerning digital transformation's effects on different agricultural enterprise sizes. Research about digital transformation in agriculture primarily examines individual countries regarding their national settings while failing to employ cross-comparisons across various economic systems and technological levels. The evaluation of digital transformation along with dynamic capabilities faces limitations due to the absence of accepted measurement criteria. Financial difficulties along with digital human capital shortages are acknowledged barriers but researchers commonly neglect traditional barriers which include difficulties with cultural change and behavioral change and necessary infrastructure. Researchers need to examine how digital transformation will affect agriculture sustainability over an extended period through studies about its influence on soil health water utilization and environmental stability. Strengthening our knowledge about these areas enables more effective utilization of digital transformation for agricultural enterprise improvement and sustainability enhancement. Through this research, it provides a new perspective for understanding the complex relationship between digital transformation and the performance of agricultural enterprises. In addition, this study also offers innovative solutions for relevant stakeholders, including government agricultural regulatory agencies, agricultural enterprises, and agricultural social entities, to promote the digital transformation of agricultural enterprises.

Theoretical Analysis and Research Hypotheses

Digital transformation and agricultural enterprise performance

Digital transformation in scientific research, production, operation, and marketing all have significant positive impacts on the comprehensive performance of agricultural enterprises. Regarding production digital transformation, Browne (2021) believed that the Internet of Things technology enables real-time monitoring and precise control of the production process, and Soussi *et al*. (2024) mentioned that intelligent sensors can achieve precision agriculture, improving resource utilization, reducing costs, and enhancing product quality and yield, and the application of automated equipment also has many positive effects. In the field of operational digital transformation, Li and Wu (2021) research showed that relying on systems such as ERP and SCM can achieve information sharing and collaboration, and Miller (2024) pointed out that digital operations optimize processes, improve efficiency, reduce costs, and enhance enterprises' adaptability to market changes. As for digital marketing transformation, Appel *et al.* (2020) believe it provides broad promotion channels and precise marketing means, and Sohaib *et al.* (2022) proposed that through e-commerce platforms and social media, enterprises can expand their market and improve customer satisfaction and loyalty.

Hypothesis 1: Digital transformation has a direct and significant impact on the performance of agricultural enterprises.

Corporate environment and agricultural enterprise performance

The highly competitive agricultural market, credit availability, internal control, and information disclosure all significantly influence the dynamic capabilities of agricultural enterprises. Under competitive pressure, enterprises closely monitor their rivals' innovative achievements and management models. Regarding credit availability, enterprises that can easily access credit funds can introduce external resources. Low-interest or subsidized loans relieve financial pressure, enabling enterprises to invest in innovation and development. High-cost credit, however, hinders enterprises from upgrading and transforming. A loose credit environment encourages enterprises to attempt innovative projects and enhance their adaptability (Han and Cai, 2024). In terms of internal control, a sound risk management system allows enterprises to summarize experiences and optimize strategies when dealing with disasters, etc. Standardized processes help enterprises identify weaknesses, learn from peers to optimize processes, cultivate a culture of change, and strengthen their ability to respond to changes (Tetteh *et al.*, 2022). Information disclosure provides opportunities for enterprises to enhance their dynamic capabilities. Transparent information disclosure attracts investors, enabling enterprises to access cutting-edge thinking and broaden their horizons. Disclosing environmental protection and social responsibility fulfillment can obtain external feedback, prompting enterprises to reflect, correct, and update their development models, thus maintaining their adaptability (Caputo *et al.*, 2021).

Hypothesis 2: The corporate environment has a direct and substantial effect on the performance of agricultural enterprises.

Digital transformation and dynamic capabilities

Digital transformation in scientific research, production, operation, and marketing has a profound impact on the dynamic learning capabilities of agricultural enterprises. In scientific research, digital transformation breaks information barriers, allowing enterprises to access global databases and academic platforms to quickly obtain the latest findings and strengthen industry-academia-research cooperation, thus promoting dynamic learning (Guo and Xu, 2021). In production, sensors and IoT devices collect real-time data for process optimization, and the iteration of intelligent equipment forces enterprises to keep learning, deepening their understanding of production management and enhancing their ability to master complex technologies (Zhou *et al.*, 2022). In operation, digital systems like ERP and CRM help enterprises identify and improve inefficient processes, and digital supply chain platforms enable information sharing and cooperation among partners, accelerating organizational learning and enhancing cross-organizational learning capabilities (Li and Wu, 2021). In marketing, social media monitoring and e-commerce big data analysis help enterprises understand market preferences and adapt products and campaigns, and new marketing formats drive enterprises to learn new skills and update knowledge systems (Panyasupat *et al.*, 2024).

Hypothesis 3: Digital transformation has a direct and positive effect on the dynamic capabilities of agricultural enterprises.

Corporate environment and dynamic capabilities

The highly competitive agricultural market, credit availability, internal control, and information disclosure all significantly influence the dynamic capabilities of agricultural enterprises. Under competitive pressure, enterprises closely monitor their rivals' innovative achievements and management models. The emergence of new entrants and substitutes forces enterprises to step out of their comfort zones, learn new technologies and concepts to maintain market share and enhance their dynamic capabilities (Ghosh *et al.*, 2022). Regarding credit availability, enterprises that can easily access credit funds can introduce external resources. Low-interest or subsidized loans relieve financial pressure, enabling enterprises to invest in innovation and development. High-cost credit, however, hinders enterprises from upgrading and transforming. A loose credit environment encourages enterprises to attempt innovative projects and enhance their adaptability (Han and Cai, 2024). In terms of internal control, a sound risk management system allows enterprises to summarize experiences and optimize strategies when dealing with disasters, etc. Standardized processes help enterprises identify weaknesses, learn from peers to optimize processes, cultivate a culture of change, and strengthen their ability to respond to changes (Li and Wu, 2021). Information disclosure provides opportunities for enterprises to enhance their dynamic capabilities. Transparent information disclosure attracts investors, enabling enterprises to access cutting-edge thinking and broaden their horizons. Disclosing environmental protection and social responsibility fulfillment can obtain external feedback, prompting enterprises to reflect, correct, and update their development models, thus maintaining their adaptability (Caputo *et al*., 2021).

Hypothesis 4: The corporate environment has a direct and notable effect on the dynamic capabilities of agricultural enterprises.

Dynamic capabilities and agricultural enterprise performance

In the highly competitive and dynamic agricultural market environment, the dynamic capabilities of agricultural enterprises (including acquisition, integration, and innovation capabilities) are crucial for performance improvement. The acquisition capability serves as the foundation. Research by Wang *et al*. (2022) indicates that enterprises proficient in collecting information from multiple channels and tracking scientific research and market trends can introduce cutting-edge achievements through industry-university-research cooperation, transform them into productivity, improve product quality and quantity, and increase revenue. Panyasupat *et al*. (2024) also points out that they can accurately position innovation and seize advantages in niche markets. Meanwhile, as Alkhalaf and Al-Tabbaa (2024) stated, the atmosphere and prospects created by good acquisition capabilities can attract talents and promote knowledge sharing, laying a solid human-resource foundation for performance improvement. The integration capability is the key driving force. Yu *et al*. (2021) believe that enterprises can optimize operations, reduce costs, increase efficiency, and boost profits by coordinating departments and integrating key elements within the enterprise. Liu and Huang (2024) confirm that product innovation that meets market demands can bring new profit growth points. Broccardo *et al*. (2017) points out that business model innovation, such as contract farming and agritourism, can tap the potential of traditional agriculture and transform enterprise performance.

Hypothesis 5: Dynamic capabilities have a direct and decisive effect on the performance of agricultural enterprises.

Hypothesis 6: The dynamic capabilities of agricultural enterprises play a mediating role between digital transformation and performance.

Hypothesis 7: The dynamic capabilities of agricultural enterprises play a mediating role between the enterprise environment and performance.

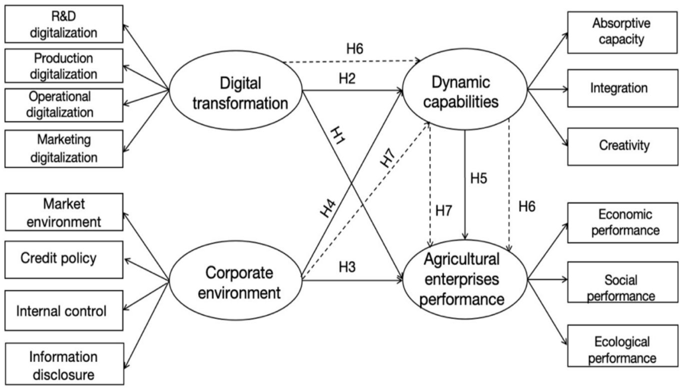

Figure 1: *Theoretical model.*

Research design

Variable selection

Digital transformation is the primary independent variable, which is further divided into four dimensions: R & D digitalization, production digitalization, marketing digitalization, and operational digitalization. To measure R & D digitalization, the prevalence of digital tools in research workflows and the sophistication of digital research platforms are considered, as suggested by Marion and Fixson (2021). Production digitalization is measured by factors such as the extent of digital control over production processes and the efficiency gains in resource allocation through digital means, as described by Buer *et al*. (2021). Marketing digitalization is assessed via the utilization rate of digital channels for promotion and the responsiveness of marketing strategies to digital analytics following Browne (2021). Operational digitalization is evaluated based on the integration of big data in decision-making and the automation level of business operations reported by Barkokebas *et al*. (2023). Dynamic capabilities serve as the mediating variable, encompassing absorptive capacity, integration ability, and innovation ability. Absorptive capacity is appraised by indicators like the company's reputation in the talent market and the allure of its remuneration packages, which are in line with Reid (2019). Integration ability is analyzed through aspects such as the fluidity of cross-departmental information sharing and the success rate of integrating external resources, as proposed by Xiufan and Yunqiao (2024). Innovation ability is quantified by metrics such as the proportion of R & D expenditure in revenue and the number of patented innovations, according to Wang *et al*. (2022).

Agricultural enterprise performance constitutes the dependent variable, which is decomposed into three main aspects: economic performance (including revenue growth rate, cost reduction efficiency, cash flow stability, and financial risk resilience), social performance (including employee satisfaction, community engagement initiatives, and workplace diversity promotion), and ecological performance (such as compliance with environmental regulations, energy consumption reduction achievements, effectiveness of green supply chain implementation, resource recycling rates, and environmental impact mitigation). Each aspect is precisely measured using specific and relevant indices similar to the methodology used by Johansson *et al*. (2019).

Questionnaire design

Based on the theories of (Porter, 1985) and Johansson *et al*. (2019), the questionnaire mainly consists of four parts. First, based on the theoretical framework of Johansson *et al*. (2019), digital transformation enterprises are screened and investigated, focusing on the application of digital tools in production, operation, marketing, and scientific research, so as to explore the actual effectiveness of digital transformation in the core businesses of enterprises. Second, drawing on the ideas of Rodríguez *et al*. (2020), the dynamic capabilities are measured, evaluating the enterprise's ability to absorb knowledge, integrate resources, and innovate in the digital environment, covering aspects

Table 1: *Variable design and sources.*

Variable	Dimension	Explanation	Sources
Digital transformation	R & D digital transformation	The extent to which agricultural enterprises integrate digital technologies in research and development to innovate and improve production processes.	Smith and Merritt (2020), Johansson *et al*. (2019)
	Production digital transformation	The use of digital tools in production activities, such as precision agriculture and automated farming systems, to enhance efficiency.	
	Operational digital transformation	The adoption of digital solutions in managing agricultural operations, including supply chain optimization and logistics.	
	Marketing digital transformation	The application of digital technologies for marketing, such as e-commerce platforms, digital branding, and online customer engagement.	
Corporate environment	Market environment	The external factors affecting agricultural enterprises, such as competition, consumer demand, and regulatory influences.	Xie *et al*. (2022)
	Credit policy	The financial policies and availability of credit that impact agricultural enterprises' ability to invest in digital transformation.	
	Internal control	The mechanisms and strategies within enterprises to monitor and regulate digital transformation processes.	
	Information disclosure	The level of transparency in digital reporting and sharing of relevant agricultural and financial information.	
Dynamic capabilities	Integration	The ability of enterprises to integrate digital solutions into their existing agricultural practices.	Rodríguez *et al*. (2020), Miguel *et al*. (2022)
	Absorptive	The capacity of agricultural enterprises to absorb and implement new digital knowledge and technologies.	
	Creativity	The role of digital tools in fostering innovation and creative problem-solving within agricultural enterprises.	
Agricultural enterprises performance	Economic performance	The financial impact of digital transformation, including profitability, cost reduction, and revenue growth.	Anderson *et al*. (2018)
	Social performance	The effect of digital transformation on labor conditions, community engagement, and overall social responsibility.	
	Ecological performance	The influence of digital solutions on sustainable agricultural practices, resource conservation, and environmental impact reduction.	

such as the cooperation models for acquiring new capabilities (Nonaka and Takeuchi, 1995). Third, basic information about agricultural enterprises, including scale, geographical location, and years of operation, is statistically analyzed to provide support for research and data analysis (Chandler Jr, 1969). Fourth, the performance evaluation is carried out from three aspects: economic, social, and ecological. Economic performance is measured by indicators such as revenue growth rate to assess profitability, social performance focuses on employee satisfaction, etc., to reflect social contribution, and ecological performance focuses on energy consumption, etc., to examine sustainable development performance.

Data collection and sample selection

Before officially launching the data collection work, this study fully considered the geographical division of China into the three major regions of the East, Central, and West. It closely integrated with the spatial layout characteristics of agricultural enterprises, extensively referred to the research findings of many scholars such as (Li and Wu, 2021) and deeply analyzed the differences in economic development levels and agricultural resource conditions among various regions, aiming to identify areas with a high degree of representativeness. Through rigorous analysis and screening, Beijing, Shanghai, Hubei, Guangxi, and Yunnan were finally selected as the formal survey regions.

Beijing and Shanghai, as typical representatives of the highly developed eastern region (Zhou *et al.*, 2022), not only have advanced industrial systems and complete infrastructure but also possess significant advantages in fields such as technological innovation and financial services, providing a favorable external environment for the development of agricultural enterprises. Hubei is located in the central region. In recent years, it has experienced rapid economic growth and has a prominent development level (Wang *et al.*, 2022). Relying on its superior geographical location and abundant natural resources, it has achieved remarkable results in the process of agricultural modernization, and the development of agricultural enterprises has also been thriving. Guangxi and Yunnan are located in the western region. Although the overall economic growth rate is relatively slow, these two regions have unique and abundant agricultural resources. Their agricultural gross domestic products rank first and second, respectively, in the western region (Zou *et al.*, 2024), and their characteristic agricultural industries are developing well, occupying an important position in the national agricultural landscape. The careful selection of these regions fully ensures the diversity and representativeness of the research samples in terms of geographical distribution and economic development, enabling a comprehensive and accurate reflection of the overall situation of agricultural enterprises in China.

This study targeted agricultural enterprises within the selected regions as the core data collection objects. During the distribution process, the questionnaire was widely distributed to agricultural enterprises within the selected regions through various channels, and active communication and coordination were carried out with the enterprises to obtain their full cooperation and effective feedback, maximizing the response rate of the questionnaire and the quality of the data. After completing the questionnaire collection, meticulous and strict preliminary screening and cleaning of the data were immediately carried out. Each questionnaire was carefully examined one by one, and invalid questionnaires with issues such as incomplete information filling, logical errors, or obvious random responses were strictly excluded. Through this strict screening and cleaning process, 360 valid questionnaires were finally obtained.

Reliability testing and questionnaire validation

From Table 2, we can see that all the indicators present relatively satisfactory results. The Cronbach's alpha value of the Digital Transformation dimension is 0.88, indicating that the measurement variables under this dimension, including R & D Digital Transformation, Production Digital Transformation, Operational Digital Transformation, and Marketing Digital Transformation, have a high level of internal consistency, and the data is highly reliable. The Cronbach's alpha value of the Business Environment dimension is 0.82, which shows that there is good consistency among the measurement variables, such as Market Environment, Credit Policy, Internal Control, and Information Disclosure, and the data has a relatively high level of stability. Likewise, for all the variables, the values were ≥0.81. In terms of validity, Composite Reliability (CR) and Average Variance Extracted (AVE) are key indicators for evaluating validity. The CR values of all dimensions are ≥ 0.8 and AVE ≥ 0.81. This further proves that these dimensions have good convergent validity, indicating that there is a high degree of correlation among the measurement variables under each dimension, and they can effectively explain most of the variance of the latent variables. In conclusion, these data perform well in terms of both reliability and validity and can provide a reliable basis for subsequent research.

Results

Statistical description

As can be seen from Table 3, in terms of digital transformation, the means of R & D digital transformation, production digital transformation, operational digital transformation, and marketing digital transformation are 3.658, 3.743, 3.700, and 3.781, respectively. The overall mean is 3.721, the minimum value is 0.791, and the maximum value is 5.000, indicating that the values of each measurement variable are distributed within a certain range. The Skewness (SK) values range from -1.057 to 1.500, and the Kurtosis (KU) values range from -1.004 to 1.290. Both are judged to be at a high level, suggesting that the data distribution has certain characteristics deviating from the normal distribution.

Table 2: *Reliability and validity tests.*

Latent variable	Measure variable	Normalized factor loading	Cronbach's α	CR	AVE
Digital transformation	R & D Digital Transformation (RDDT)	0.85	0.88	0.89	0.83
	Production Digital Transformation (PDT)	0.82			
	Operational Digital Transformation (ODT)	0.88			
	Marketing Digital Transformation (MDT)	0.80			
Business environment	Market Environment (ME)	0. 87	0.82	0.84	0.88
	Credit Policy (CP)	0.82			
	Internal Control (IC)	0.88			
	Information Disclosure (ID)	0.82			
Organizational learning capacity	Innovation Capability (IN)	0.86	0.85	0.87	0.81
	Absorptive Capacity (AC)	0.81			
	Integration Capability (INTC)	0.86			
Corporate performance	Economic Performance (EP)	0.90	0.91	0.85	0.87
	Social Performance (SP)	0.84			
	Ecological Performance (EP)	0.89			

Table 3: *Sample statistical characteristics.*

Latent variable	Measure variable	Mean	S.D.	MIN	MAX	SK	KU
Digital transformation	R & D Digital Transformation	3.658	1.010	5.000	1.500	-0.531	-0.770
	Production Digital Transformation	3.743	0.894	5.000	1.000	-1.004	1.290
	Operational Digital Transformation	3.700	1.001	5.000	1.000	-1.057	0.673
	Marketing Digital Transformation	3.781	0.958	5.000	1.000	-0.799	0.320
	Total	3.721	0.791	5.000	1.125	-0.921	0.906
Business environment	Market Environment	3.678	1.035	5.000	1.400	-0.611	-0.757
	Credit Policy	3.820	0.909	5.000	1.000	-1.158	1.372
	Internal Control	3.696	1.038	5.000	1.000	-1.161	0.873
	Information Disclosure	3.785	1.025	5.000	1.000	-0.883	0.371
	Total	3.745	0.822	5.000	1.100	-1.105	1.147
Organizational learning capacity	Innovation Capability	3.547	0.944	5.000	1.000	-0.483	-0.510
	Absorptive Capacity	3.591	1.000	4.833	1.000	-0.718	-0.374
	Integration Capability	3.506	1.033	5.000	1.200	-0.472	-0.494
	Total	3.548	0.824	4.944	1.133	-0.748	0.187
Corporate performance	Economic Performance	3.785	0.995	5.000	1.000	-1.210	1.364
	Social Performance	3.591	0.965	5.000	1.000	-0.450	-0.684
	Ecological Performance	3.596	1.010	5.000	1.000	-0.679	-0.486
	Total	3.657	0.819	5.000	1.000	-0.726	0.434

Confirmatory tests

Confirmatory tests of digital transformation factors: The measurement items under each dimension of the digital transformation factors of agricultural enterprises demonstrate good reliability and validity. For instance, the loading coefficient of RDDT ranges from 0.71 to 0.85, with an AVE of 0.606 (Table 4). The loading coefficient of PDT is between 0.67 and 0.88, and its AVE is 0.621. The loading coefficient of ODT varies from 0.73 to 0.89, having an AVE of 0.647. The loading coefficient of MDT is in the range of 0.74-0.82, with an AVE of 0.581. The overall model has a good fit. The Chi-Square value is 211.711, the degree of freedom (df) is 185, the P-value is 0.087, and the comparative fit index (CFI) is 0.994. This indicates that the constructed model has a high degree of fit with the data and can effectively explain the relationships among the various dimensions of digital transformation.

Table 4: *Digital transformation factors.*

Dimension	Options		Loading coefficient	R^2	CR	AVE
Digital transformation	RDDT	-	0.87	0.759	0.87	0.628
	PDT	-	0.72	0.521		
	ODT	-	0.75	0.561		
	MDT	-	0.82	0.669		
	R & D digital transformation	RDDT1	0.71	0.504	0.902	0.606
		RDDT2	0.75	0.560		
		RDDT3	0.79	0.616		
		RDDT4	0.85	0.723		
		RDDT5	0.78	0.615		
		RDDT6	0.79	0.619		
	Production digital transformation	PDT1	0.88	0.780	0.907	0.621
		PDT2	0.81	0.656		
		PDT3	0.77	0.593		
		PDT4	0.67	0.453		
		PDT5	0.79	0.624		
	Operational digital transformation	ODT1	0.89	0.789	0.901	0.647
		ODT2	0.82	0.664		
		ODT3	0.79	0.619		
		ODT4	0.79	0.630		
		ODT5	0.73	0.534		
	Marketing digital transformation	MDT1	0.75	0.557	0.874	0.581
		MDT2	0.75	0.570		
		MDT3	0.75	0.560		
		MDT4	0.74	0.548		
		MDT5	0.82	0.671		

Chi-Square= 211.711, df=185, P=0.087, CFI= 0.994, TLI=0.993, SRMR=0.033, RMSEA=0.02

Confirmatory tests of environmental factors: Results mentioned in Table 5 show that in the corporate environment dimension, the loading coefficients of each option (ME, CP, IC, ID) are 0.806, 0.748, 0.892, and 0.742, respectively, with the R^2 ranging from 0.551 to 0.796, the CR being 0.876, and the AVE being 0.639. Regarding the model fit, the Chi-square value is 134.375, the degree of freedom is 115, the P - value is 0.105, the CFI is 0.995, the TLI is 0.994, the SRMR is 0.032, and the RMSEA is 0.022, indicating that the model has a good fit. The measurements of each dimension are reliable and valid.

Table 5: *Environmental factors.*

Dimension	Options		loading coefficient	R2	CR	AVE
Corporate Environment	ME	-	0.806	0.650	0.876	0.639
	CP	-	0.748	0.560		
	IC	-	0.892	0.796		
	ID	-	0.742	0.551		
	Market environment	ME1	0.712	0.507	0.892	0.624
		ME2	0.809	0.654		
		ME3	0.862	0.743		
		ME4	0.789	0.623		
		ME5	0.770	0.593		
	Credit policy	CP1	0.811	0.658	0.878	0.643
		CP2	0.821	0.674		
		CP3	0.790	0.624		
		CP4	0.786	0.618		
	Internal control	IC1	0.877	0.769	0.88	0.647
		IC2	0.801	0.642		
		IC3	0.793	0.629		
		IC4	0.741	0.549		
	Information disclosure	ID1	0.710	0.504	0.861	0.609
		ID2	0.768	0.590		
		ID3	0.811	0.658		
		ID4	0.827	0.684		

Chi-Square=134.375, df= 115, P= 0.105, CFI=0.995, TLI=0.994, SRMR=0.032, MSEA=0.022

Confirmatory tests of dynamic capability factors: The dynamic capabilities dimension level, the loading coefficients of CR, AC, and IN are 0.76, 0.78, and 0.77, respectively, with the R^2 ranging from 0.573 to 0.605, the composite reliability (CR) being 0.812, and the average variance extracted (AVE) reaching 0.59 (Table 6). Regarding the model fit, the Chi-Square value is 114.832, the degree of freedom is 101, the ratio of Chi-Square to the degree of freedom is 1.137, the P-value is 0.164, the CFI is 0.996, the TLI is

0.995, the SRMR is 0.027, and the RMSEA is 0.02. All these data indicate that the model is a good fit, the measurements of each dimension are highly reliable and valid, and the research results are reliable and valid.

Table 6: *Dynamic capability factors.*

Dimension	Options		Loading coefficient	R2	CR	AVE
Dynamic capabilities	CR	-	0.76	0.573	0.812	0.59
	AC	-	0.78	0.605		
	IN	-	0.77	0.591		
	Integration	CR1	0.79	0.623	0.886	0.61
		CR2	0.78	0.605		
		CR3	0.81	0.656		
		CR4	0.80	0.632		
		CR5	0.73	0.533		
	Absorptive	AC1	0.78	0.604	0.911	0.629
		AC2	0.77	0.591		
		AC3	0.77	0.594		
		AC4	0.81	0.658		
		AC5	0.85	0.726		
		AC6	0.78	0.604		
	Creativity	IN1	0.77	0.599	0.904	0.653
		IN2	0.74	0.552		
		IN3	0.87	0.752		
		IN4	0.81	0.661		
		IN5	0.84	0.702		

Chi-Square=114.832, df= 101, P= 0.164, CFI=0.996, TLI=0.995, SRMR=0.027, RMSEA=0.02

Confirmatory tests of factors affecting agricultural enterprise performance: From Table 7, at the dimension level of agricultural enterprise performance, the loading coefficients of EP, SP, and ECP are 0.834, 0.739, and 0.745, respectively, with R^2 values ranging from 0.546 to 0.696, the composite reliability (CR) at 0.817. The average variance extracted (AVE) at 0.599 indicates good internal consistency and convergent validity of this dimension measurement. The Chi-square value is 67.315, the degrees of freedom is 62, the chi-square to degrees of freedom ratio is 1.086, the P - value is 0.3, the comparative fit index (CFI) is 0.998, the Tucker - Lewis index (TLI) is 0.997, the standardized root - mean - square residual (SRMR) is 0.027. The root mean square error of approximation (RMSEA) is 0.015, and all these indicators show that the model is a good fit and that the research results are reliable. It can provide strong data support for research related to agricultural enterprise performance.

Table 7: *Factors affecting agricultural enterprise performance.*

Dimension	Options		Loading coefficient	R2	CR	AVE
Agricultural enterprises performance	EP	-	0.834	0.696	0.817	0.599
	SP	-	0.739	0.546		
	ECP	-	0.745	0.555		
	Economic performance	EP1	0.852	0.725904	0.872	0.631
		EP2	0.792	0.627264		
		EP3	0.782	0.611524		
		EP4	0.747	0.558009		
	Social performance	SP1	0.746	0.556516	0.861	0.608
		SP2	0.828	0.685584		
		SP3	0.793	0.628849		
		SP4	0.749	0.561001		
	Ecological performance	ECP1	0.784	0.614656	0.893	0.626
		ECP2	0.799	0.638401		
		ECP3	0.784	0.614656		
		ECP4	0.797	0.635209		
		ECP5	0.793	0.628849		

Chi-Square=67.315, df=62, P= 0.3, CFI=0.998, TLI= 0.997, SRMR=0.027, RMSEA=0.015

The fit test

Table 8 shows that the chi-square value (CMIN) is 76.63, the degree of freedom (DF) is 71, and the ratio of chi-square to the degree of freedom (CMIN/DF) is 1.079. This ratio is far below the upper standard limit of 3, indicating that the complexity of the model is relatively well-matched with the degree of data fit. The P-value is 0.303, which means that, in a statistical sense, the fitting result of the model is reasonable. The goodness-of-fit index (GFI) reaches 0.97, and the incremental fit index (IFI), Tucker-Lewis's index (TLI), and comparative fit index (CFI) are 0.997, 0.996, and 0.997, respectively. All these values are significantly higher than the standard of 0.9, showing that the model fits the data well and can effectively explain the relationships among variables. The root mean square error of approximation (RMSEA) is 0.015, and the standardized root mean square residual (SRMR) is 0.029. Both are less than the standard threshold of 0.05, further confirming that the model has a high fitting accuracy and that the model fitting results are reliable.

Table 8: *Fit test.*

Goodness of fit	CMIN	DF	CMIN/DF	p	GFI	IFI	TLI	CFI	RMSEA	SRMR
Result	76.63	71	1.079	0.303	0.97	0.99	0.99	0.99	0.015	0.029
Standard			<3		>0.9	>0.9	>0.9	>0.9	<0.05	<0.05

Table 9: *Direct path test.*

Path	Path coefficient (Standardized)	Unstand-ardized	S.E	T	P
Agricultural Enterprises Performance←Digital transformation	0.199	0.194	0.065	2.98	0.003
Agricultural Enterprises Performance← Corporate environment	0.23	0.231	0.07	3.31	0.001
Dynamic capabilities←Digital transformation	0.374	0.292	0.052	5.56	0.002
Dynamic capabilities← Corporate environment	0.422	0.34	0.056	6.10	0.005
Agricultural enterprises Performance← Dynamic learning ability	0.475	0.592	0.108	5.46	0.001

Direct path identification

In terms of the performance of agricultural enterprises, the standardized path coefficient between digital transformation and enterprise performance is 0.199, the unstandardized coefficient is 0.194, the standard error is 0.065, the T-value is 2.985, and the P-value is 0.003 (Table 9). This indicates that digital transformation has a significant positive impact on the performance of agricultural enterprises. The standardized path coefficient between the corporate environment and the performance of agricultural enterprises is 0.23, the unstandardized coefficient is 0.231, the standard error is 0.07, the T-value is 3.318, and the P -value is 0.001, meaning that the corporate environment has a significant positive promoting effect on the performance of agricultural enterprises.

In the dimension of dynamic capabilities, the standardized path coefficient of digital transformation to it is 0.374; the unstandardized coefficient is 0.292; the standard error is 0.052, the T-value is 5.562, and the P-value is 0.002, indicating that the digital transformation has a significant impact on the enhancement of dynamic capabilities. The standardized path coefficient between the corporate environment and dynamic capabilities is 0.422; the unstandardized coefficient is 0.34; the standard error is 0.056; the T - T-value is 6.106, and the P-value is 0.005, reflecting that the corporate environment has an obvious positive impetus on dynamic capabilities. In addition, the standardized path coefficient between dynamic learning capabilities and agricultural enterprise performance reaches 0.475; the unstandardized coefficient is 0.592, the standard error is 0.108, the T-value is 5.461, and the P-value is 0.001, indicating that the positive impact of dynamic learning capabilities on agricultural enterprise performance is extremely prominent.

Indirect path identification

From Table 10 and Figure 2, it can be seen that in the relationship among the performance of agricultural enterprises, dynamic capabilities, and digital transformation, the indirect effect of digital transformation on the performance of agricultural enterprises through dynamic capabilities is 0.178, with a standard error of 0.046. The bias-corrected 95% confidence interval is (0.103, 0.285), and the P-value is 0, indicating that this indirect effect is significant. The direct effect is 0.199, with a standard error of 0.071, a confidence interval of (0.052, 0.329), and a P - value of 0.011, so the direct effect is also significant. The total effect is 0.377, with a standard error of 0.065, a confidence interval of (0.245, 0.497), and a P-value of 0, highlighting that the overall impact of digital transformation on the performance of agricultural enterprises is very significant. In the relationship among the performance of agricultural enterprises, dynamic capabilities, and the corporate environment, the indirect effect of the corporate environment on the performance of agricultural enterprises through dynamic capabilities is 0.2, with a standard error of 0.051. The 95% confidence interval is (0.114, 0.32), and the P-value is 0, indicating a significant indirect effect. These data suggest that digital transformation and the corporate environment indirectly and directly affect the performance of agricultural enterprises through dynamic capabilities.

Table 10: *Indirect path test.*

Path	Effects	Effect	S.E.	Bias-corrected 95% CI		
				Lower	Upper	P
The agricultural enterprise performance ← Dynamic capabilities ← Digital transformation	Indirect effects	0.178	0.046	0.103	0.285	0.00
	Direct effect	0.199	0.071	0.052	0.329	0.011
	Total effect	0.377	0.065	0.245	0.497	0.00
The agricultural enterprise performance← Dynamic capabilities← The corporate environment	Indirect effects	0.2	0.051	0.114	0.32	0.00
	Direct effect	0.23	0.078	0.075	0.375	0.006
	Total effect	0.43	0.066	0.295	0.553	0.00

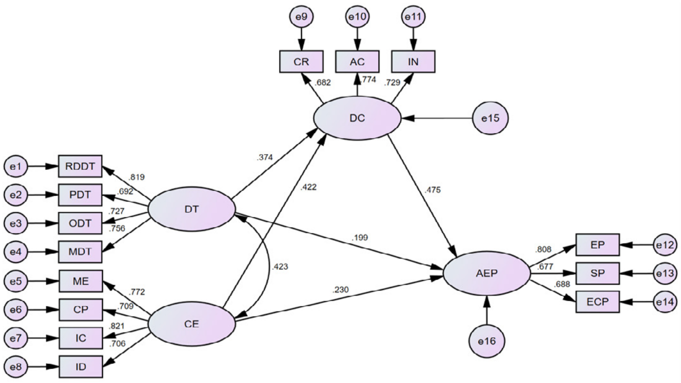

Figure 2: *Structural equation modelling.*

Discussion

Many existing studies tend to conduct fragmented analyses, exploring specific elements in isolation. For instance, Panichakarn *et al.* (2024) focused on electric vehicle enterprises, mainly revolving around factors such as digital transformation and agility, without integrating the characteristics of agricultural enterprises to build a universal framework. Wang *et al.* (2024) studied the impact of digital transformation on enterprise performance but were limited to the mediating role of dual innovation with a relatively narrow perspective. This study innovatively integrates the dynamic learning theory, the enterprise performance theory, and the enterprise sustainable development theory, creating a comprehensive and systematic research framework suitable for agricultural enterprises. It precisely delineates the complex correlations among elements, providing a complete reference for subsequent theoretical research related to agricultural enterprises and addressing deficiencies in previous partial studies (Muangmee *et al*., 2023).

Many previous studies described only superficial correlations between factors and performance, with vague causal transmission logic. For example, Zheng and Bu (2024) explored the relationships among enterprise ESG performance, digital transformation, and enterprise performance but did not analyze the intermediate transmission links in detail. Similarly, Juharsah *et al.* (2024) examined the moderating effect of digital transformation on the relationship between intellectual capital and enterprise performance but failed to explain the underlying causality. In contrast, this study, through empirical tests, accurately identifies the mediating effect of dynamic learning ability and systematically clarifies a complete causal chain. This enhances theoretical granularity and promotes a deeper expansion of the theory of agricultural enterprise performance, surpassing the limitations of similar studies in explaining transmission mechanisms Panyasupat (2024).

Traditional agricultural economic theories struggle to keep pace with the digital era, and innovation efforts in existing studies remain insufficient. For instance, Wang *et al.* (2024) have explored digital transformation and enterprise performance but have not revised the core assumptions of traditional agricultural theories sufficiently. This study reshapes the understanding of traditional theories based on empirical conclusions and recalibrates key assumptions, ensuring that agricultural enterprise theories align with the new dynamics of the digital economy. It significantly outpaces previous similar studies in terms of the speed and depth of theoretical renewal ((Muangmee *et al*., 2023).

Previous practical guidance on the digital transformation of agricultural enterprises often remained superficial. For instance, Chen *et al.* (2023) conducted a case study on listed companies' digital transformation but did not specifically address the unique characteristics of agricultural enterprises, such as long production cycles and susceptibility to natural factors. The strategies proposed were general and lacked specificity. This study, based on empirical analysis of listed Chinese agricultural companies, thoroughly explores real enterprise challenges. The proposed digitalization strategies directly tackle these issues and provide significantly more practical value than previous generalized suggestions (Muangmee, 2021; Muangmee *et al*., 2024).

Existing practical studies are often confined to individual enterprises, ignoring the synergy effect across the supply chain. Cheng *et al*. (2024), for example, investigated the impact of digital technology usage on enterprise performance but focused only on individual enterprises rather than the linkage between upstream and downstream sectors. The results of this study, based on a macroscopic view, provide guidance for the coordinated development of the agricultural industry chain, spurring systematic industrial upgrading. This addresses the fragmentation in previous studies and contributes to a more integrated industrial ecosystem (Muangmee *et al*., 2024).

Previous studies on digital transformation and enterprise performance often lacked strong data support for talent development and policy formulation. This study, through rigorous analysis of large-scale data, provides concrete pathways for talent cultivation in agricultural enterprises and presents an evidence-based foundation for policymaking. This comprehensively strengthens the sustainability of agricultural enterprises and fills the gaps in previous practical research on implementation support (Muangmee *et al*., 2024).

Conclusions and Recommendations

As the global economy shifts towards a low-carbon and green model, digitalization has become a new impetus for agricultural development. The integration of technologies like big data and the Internet of Things with agriculture has created new opportunities. Against this backdrop, promoting the sustainable development of agricultural enterprises through digitalization is of great significance for carbon reduction, efficiency improvement, and competitiveness enhancement. Therefore, studying the impact of digitalization on the performance of agricultural enterprises is particularly crucial.

Based on the dynamic capability theory, this paper integrates the enterprise performance theory and the sustainable development theory to construct a research framework covering digital transformation, the agricultural enterprise environment, dynamic learning capabilities, and agricultural enterprise performance. The results show that both digital transformation and the agricultural enterprise environment have a significantly positive impact on the performance of agricultural enterprises. Dynamic learning capabilities play a significant mediating role; that is, the two indirectly affect the performance of agricultural enterprises through dynamic learning capabilities. Research results show that digital transformation and the corporate environment significantly and positively impact the performance of agricultural enterprises, with dynamic learning capabilities playing a significant mediating role between them and corporate performance, meaning they indirectly affect the performance of agricultural enterprises through these capabilities. Based on this, four countermeasures and suggestions are put forward: Strengthen the construction of digital transformation by improving infrastructure, promoting technological innovation and application, and cultivating digital talents; optimize the agricultural enterprise environment through policy support, strengthening industry cooperation and exchanges, and improving the level of social services; enhance dynamic learning capabilities by building a learning organization, strengthening cooperation and learning with the outside world, and encouraging employees self-improvement; strengthen coordinated development by promoting the coordination between digital transformation and the enterprise environment and giving full play to the bridging role of dynamic learning capabilities while strengthening the management and evaluation of the dynamic learning process.

Limitations

This study only selected 360 listed agricultural companies in China as samples, so the sample coverage is relatively narrow. Listed companies generally outperform non-listed companies in terms of scale, financial strength, and management level. Thus, the applicability of the research findings to the vast number of small and medium-sized agricultural enterprises is questionable. It fails to accurately reflect the real situation of the entire agricultural enterprise group and is likely to overlook the differential performances of enterprises with different scales and natures during digital transformation. This empirical study is mostly based on cross-sectional data at a specific time and adopts a static analysis method. However, digital transformation is a dynamically evolving process, and the enterprise environment also changes rapidly over time. The static analysis makes it difficult to capture the long-term, dynamic interaction relationships among variables, limiting the insight into the deep development laws of digital transformation.

Future research prospects

Future research can include agricultural enterprises of different scales and ownership forms, taking both listed and non-listed companies into account and broadening the geographical selection to cover different agricultural production areas and regions with various levels of economic development. More micro and macro variables can be introduced. At the micro level, factors such as differences in employees' digital literacy and the flexibility of corporate culture can be considered; at the macro level, factors such as the consistency of regional policies and fluctuations in the macroeconomic cycle can be incorporated. By doing so, a more three-dimensional and complex theoretical model can be constructed to deeply explore the all-round factors affecting the performance of agricultural enterprises, making the research more in line with the complex real-world situations.

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Novelty Statement

This study is the first to use a dynamic learning theory, enterprise performance theory, and sustainable development theory to establish how digital transformation and corporate environment impact the success of agricultural enterprises.

Author's Contribution

Cui Haitao: Conceptualized the research framework, worked on the methods section, and performed the analysis. He also participated in writing the manuscript and result analysis.
Chaiyawit Muangmee: He was involved in the formulation of the research framework, part of the literature review section, and the analysis of the results. He also contributed to the revision of the manuscript.
Nusanee Meekaewkunchorn: Participated in data collection procedures, contributed to interpreting the results, and reviewed a draft of the manuscript. She contributed to the section on discussion.
Tatchapong Sattabut: Helped in the process of analyzing data, offered inputs for statistical techniques that were adopted, and actively participated in the preparation of this manuscript.

Consent to participate

Not applicable. No animal or human participants or data are involved in this study.

Data availability

The data, materials and code that support this study's findings are available upon reasonable request from the corresponding author.

Conflict of interest

The authors have declared no conflict of nterest.

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