SUSTAINABLE MODEL OF AGRICULTURAL ENTERPRISES IN THE ENVIRONMENT OF DIGITAL TRANSFORMATION

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A thesis submitted in partial fulfillment of the requirements
for The Doctor of Business Administration Program (International Program)
Academic Year 2025

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ABSTRACT

Against the backdrop of the global digital wave profoundly reshaping the economic landscape, agriculture, as the foundation of the national economy, has seen digital transformation emerge as a critical pathway to breaking through traditional development bottlenecks and achieving sustainable growth. Chinese agricultural enterprises are at a pivotal stage of transitioning from traditional production models to intelligent, data-driven paradigms, yet the implementation effects of digital transformation and its mechanism on enterprise performance require in-depth exploration. This study focuses on the sustainable development model of agricultural enterprises in the context of digital transformation, aiming to explore the impact mechanisms of digital transformation, corporate environment, and dynamic capabilities on the performance of agricultural enterprises.

This paper centers on the sustainable development model of agricultural enterprises amid digital transformation. Based on dynamic capability theory and corporate environment adaptation theory, it constructs a theoretical model of "digital transformation-dynamic capabilities-enterprise performance" by integrating quantitative analysis of 360 valid samples and in-depth interviews with 20 experts. The study finds that: at the direct effect level, digital transformation (mean 3.721, with marketing digitization scoring 3.781 as the highest) and corporate environment (mean 3.745, with the credit policy dimension performing optimally at 3.820) have significant direct impacts on the performance of agricultural enterprises (mean 3.657, with financial performance of 3.785 significantly leading social and ecological performance), with standardized path coefficients of 0.199 ($p<0.001$) and 0.23 ($p<0.001$), respectively, revealing that digital technology application and environmental adaptability are core drivers of performance improvement. At the mediating mechanism level, dynamic capabilities (mean 3.548, with the absorptive capacity dimension at 3.591 as the key pivot) play a partial mediating role in the above relationships, with indirect effects of 0.178 from digital transformation through dynamic capabilities and 0.2 from the corporate environment, and total effects reaching 0.377 and 0.43, respectively, verifying the industry-specific transmission path of "digital transformation/corporate environment⟶dynamic capabilities⟶enterprise performance". At the model validation level, the structural equation model shows CMIN/DF=1.079 (<3), CFI=0.997 (>0.9), and RMSEA=0.015 (<0.05), indicating excellent model fit, and the reliability and validity indicators of each dimension (CR>0.812, AVE>0.581) meet academic standards, confirming the theoretical rationality of dynamic capabilities as mediating variables.

This paper first reveals the performance generation mechanism of digital transformation in agricultural enterprises through a "two-wheel drive-mediating transmission" framework, identifying knowledge absorption and resource integration capabilities in dynamic capabilities as the key hub to address the "digital paradox". The study not only enriches the strategic management theory of agricultural enterprises in the digital economy but also provides empirical support for governments to formulate differentiated policies (such as special subsidies for weak links in R&D digitization). Meanwhile, it proposes a three-stage implementation path of "technology embedding-capability cultivation-environmental collaboration" for enterprises, holding significant practical guiding value for promoting the digital upgrading of the agricultural industry and the implementation of the rural revitalization strategy.

Keywords: Digital transformation; Agricultural enterprises; Dynamic capabilities; Enterprise performance; Sustainable development mode

Acknowledgement

I am grateful for the growth and progress I have made during this study period, and I am thankful and reluctant to part with everything.

I sincerely thank my supervisor Dr.Chaiyawit Muangmee, Each link is cohesive with the supervisor's sweat and blood, condensed with the supervisor's wisdom crystallization. My mentor's academic attainments, rigorous way of governance, diligent style of governance, and calm, optimistic, open-minded, and personal style of conduct have set a lifelong model for me to learn from, and have taught, encouraged, and inspired me to pursue innovation in the path of science and education. With deep respect to my mentor!

Thank you to the teachers who taught the professional courses. Their profound knowledge, rigorous learning style, and the demeanor of everyone have enabled me to appreciate the wisdom of the wise and the richness of the teachers, which has benefited me greatly and made me memorable for the rest of my life. I would like to express my heartfelt gratitude to these teachers and supervisors! Also, thank you for the help provided by the teachers in the graduate office!

Thank you to my fellow students. Thank you for inspiring me in academics and helping me in life. You made me adapt to the new environment of overseas study and life very quickly. The library, the dining room table, the sports field, the dormitory, the countless happy moments together will be treasured in the dreams after farewell, may we grow together in the future with grateful hearts.

Finally, I would like to express my heartfelt gratitude to my family and loved ones who have given me peace and warmth. I thank them for their encouragement and unfailing care and support throughout my studies, and it is this strong bond that has enabled me to complete my studies with confidence.

Cui Haitao

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Rationale

The globalization trend of digital transformation

Digital transformation has significantly altered the global economic system and reshaped the pattern of global economic development. The integration of digital technology is now pervasive across various sectors, influencing the entirety of human economy, politics, culture, society, and ecological civilization construction through new concepts, business formats, and models. This transformation has had a far-reaching impact on human production and daily life. From an enterprise perspective, digital transformation can not only reduce information asymmetry, transaction and logistics costs, and labor costs, but also help enterprises improve quality and efficiency. It can also alter internal management methods, leading to a more flat and networked organizational structure and a flexible, modular, user-centered production model. From an industrial standpoint, digital transformation entails digital industrialization, industrial digitization, and the reshaping of industrial chains and layout through digital technology. The emergence of technologies like big data, artificial intelligence, and blockchain has given rise to new industries and a platform economy ecosystem. The adoption of digital technology has altered the combination of factors in traditional industries, impacting employment positions and requirements across various sectors, as well as the quality and availability of intermediate goods. This, in turn, has led to adjustments in industrial chains and layout. In terms of value creation, digital transformation deeply integrates production and service links, allowing consumers to participate in the entire process and expanding the value proposition beyond just final products.

According to the China Academy of Information and Communications Technology, the digital economy in 47 countries worldwide amounted to $32.6 trillion in 2020, representing 43.7% of their GDP, with a nominal growth rate of 3%.

Notably, developed countries contributed significantly to this total, with their digital economy valued at $24.4 trillion, making up 74.7% of the global figure. The United States led the pack with a digital economy worth around $13.6 trillion, making up approximately 41.7% of the global digital economy. Following closely, China held the second position with a digital economy valued at $5.4 trillion, accounting for roughly 16.6% of the global total. In order to further advance digital transformation, governments globally have implemented policies aimed at boosting support for digitalization, enhancing investment in digital initiatives, and offering robust backing for the process of digital transformation.

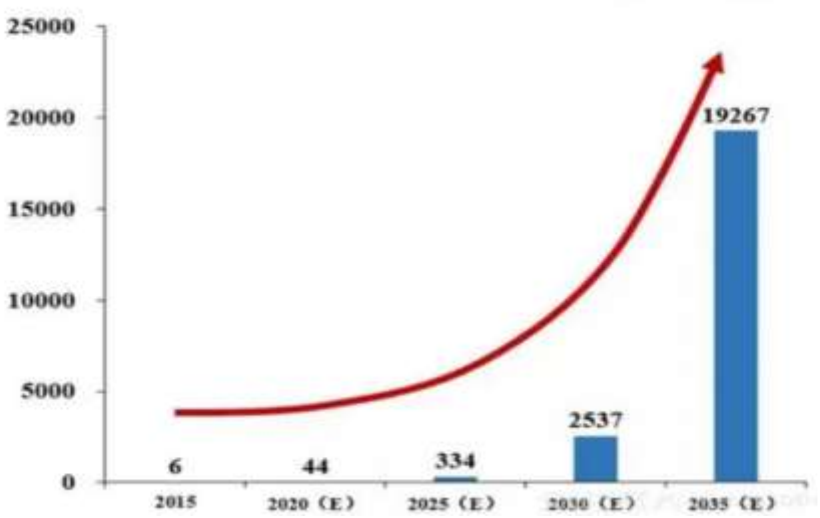

Figure 1.1 Global digital economy development trend

Trends in China's Digital Economy Development

In recent years, China's digital economy has continued to thrive, emerging as a new engine driving economic growth. According to the "Outlook on the Development of China's Digital Economy in 2024" (Outlook Series on China's Industrial and Informational Development, 2024), along with in-depth research conducted by institutions such as the Internet Industry Research Institute of Tsinghua University, China's digital economy is exhibiting two major development trends:

1. Deep integration of digital infrastructure construction and industrial digital ecosystems. With the leapfrog advancements in technologies like cloud computing, blockchain, and artificial intelligence, China is accelerating the development of its information infrastructure. By the end of June 2024, the total number of 5G base stations surpassed 3.917 million, demonstrating robust development momentum. Additionally, the scale of computing power has continued to expand, reaching 230EFLOPS by the end of 2023, securing China's second position globally. Notably, the intelligent computing power has led the trend with a growth rate exceeding 70%, laying a solid foundation for the development of the digital economy. Meanwhile, the vitality of technological innovation is booming, as evidenced by the surge in the number of invention patents granted to core industries of the digital economy, highlighting China's accelerated progress in technological innovation. These technologies will comprehensively support the data factor market and enterprise digitalization scenarios, promote industrial collaboration, and facilitate the establishment of digital credit systems in some cities through blockchain technology. Furthermore, driven by AIGC, AI applications continue to expand into new scenarios, injecting robust momentum into the digital economy.

2. Deep integration of the digital economy with the real economy, particularly prominent in the manufacturing sector. Industrial Internet platforms, as the key to transformation, are leading emerging industries such as new energy vehicles and photovoltaics towards intelligence and high-end development. It is estimated that the industrial Internet industry will exceed 1.5 trillion yuan in scale in 2024, with a stable growth rate of around 13%, indicating that the integration of the digital economy with the real economy will bring unprecedented development opportunities to the manufacturing sector. Furthermore, China is actively promoting high-level openness in the digital economy, with cross-border data trade emerging as a new highlight in service trade. It is exploring interconnected and mutually beneficial trade rules for data to promote the coordinated development of the global digital economy. At the regional level, the "East Data, West Compute" project continuously optimizes the allocation of computing resources, fostering complementarity between

the eastern and western regions. This not only alleviates the tension of computing resources in the east but also activates the economic growth potential in the west, injecting strong momentum into the balanced development of the regional digital economy.

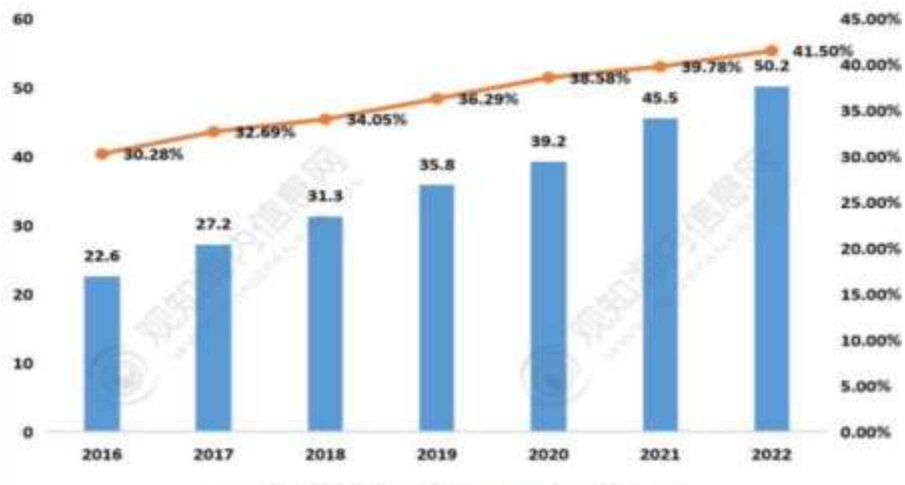

Figure 1.2 Regions of China's Digital Economy Development and Their Contributions to GDP.

Digital Transformation and Agricultural Sustainable Development

Digital transformation is a crucial driving force for enhancing the sustainable development of agricultural modernization. In Argentina, a leading agricultural country in Latin America, the adoption of agricultural digital platforms is rapidly increasing, leading to improved digital capabilities among farmers. In Spain, known as the European 'vegetable basket', the implementation of Internet of Things technology has enhanced productivity and efficiency in vegetable and fruit cultivation. Meanwhile, in Israel, a country with limited arable land, digital innovation in agriculture has established a robust scientific research and promotion system. The global focus is now on leveraging digital technology to empower rural development and drive the transformation of traditional agriculture. This digitalization of agriculture involves the comprehensive utilization of remote sensing technology (RS), geographical information systems (GIS), global satellite positioning systems (GPS), and other technologies to gather soil information, monitor yields, analyze crop data, and produce high-quality agricultural products with minimal investment and high efficiency. By promoting the digital transformation of agriculture through the integration of big data, artificial intelligence, and agricultural practices, countries can enhance resource utilization, reduce transaction costs, boost agricultural market competitiveness, and ultimately improve the overall benefits of agriculture. The integration of IOT technology in agriculture enables real-time monitoring of temperature, humidity, soil pH, and other key parameters, with data being uploaded to the cloud for analysis. Constant advancements in sensor technology empower farmers to gain a deeper understanding of their land conditions and make timely adjustments to their agricultural practices. The vast amount of data generated in agriculture, including meteorological data, crop growth data, and market conditions, can unveil valuable patterns and trends through data analysis, aiding farmers in making informed decisions. By leveraging algorithms, pests and diseases can be identified, crop diseases can be predicted, and farmers can receive timely warnings and recommendations. Artificial intelligence plays a crucial role in optimizing agricultural supply chains, improving logistics and distribution efficiency, and facilitating swift delivery of agricultural products to consumers. Furthermore, cloud computing technology allows agricultural data to be securely stored in the cloud, enabling real-time data sharing and remote access. Blockchain technology ensures the traceability and transparency of agricultural products, eliminating information asymmetry and bolstering consumer trust in agricultural goods. These technological advancements are pivotal in combating counterfeit agricultural products, enhancing market competitiveness, and improving overall consumer confidence in agricultural products. The prospects of digital agriculture are extensive. Firstly, it aids in addressing the food requirements of an expanding global population by enhancing crop yields and quality, thereby meeting the increasing food demand and alleviating food security challenges. Secondly, digital agriculture plays a role in the economic advancement of rural regions, creating job opportunities and enticing young individuals to engage in agriculture. Lastly, digital agriculture promotes sustainable agriculture practices and facilitates the sustainable development of agriculture by minimizing resource wastage and environmental pollution.

Digital Transformation and Agricultural Enterprise Performance

Agricultural enterprises play a crucial role in the ongoing digital transformation of the agriculture sector, a prevalent trend in the industry. This transformation significantly impacts the performance of these companies by enhancing production processes, implementing intelligent management systems, optimizing resource utilization, improving production efficiency, reducing operational costs, and boosting innovation capabilities. These changes ultimately have a substantial influence on the overall performance of agricultural businesses. Currently, developed regions within the country are actively exploring digital transformation in agriculture through initiatives like establishing 'industrial brain + future factory', creating a digital Corporate Environment, innovating digital finance, and setting industry technical standards. However, Chinese agricultural enterprises are encountering challenges such as limited digital transformation capabilities, high costs, scarcity of digital talent, and unclear digital strategies. As of the end of 2020, the agricultural digital economy in China only accounted for 8.9% of the industry's added value, significantly lower compared to the service industry and general industry (40.7% and 21.0% respectively). The pace of agricultural digitalization remains relatively slow. Eisenhardt and Martin (2000) define dynamic capabilities as organizational processes and strategic routines that help companies adapt to market changes by acquiring, utilizing, integrating, updating, and reorganizing resources. In the context of agricultural enterprises, digital transformation can significantly reduce operating costs, improve digital marketing capabilities in the agricultural sector, and impact overall enterprise performance. This study, based on dynamic capabilities theory, explores the direct influence of digital transformation on agricultural enterprise performance, as well as the mediating role of dynamic capabilities. It offers a fresh perspective for agribusinesses to comprehend the effects of digital transformation on performance and suggests innovative solutions for government agricultural management departments, agricultural enterprises, and agricultural social entities to support the digital transformation of agricultural enterprises.

Research Question

1. What is digital transformation and agricultural enterprise performance?
2. How to analyze the impact of digital transformation, corporate environment, and Dynamic capabilities on agribusiness performance?
3. What strategies can agribusinesses adopt to improve overall performance and achieve greater success during digital transformation?

Objectives

1. To study digital transformation and agricultural enterprise performance.
2. To analyze the underlying mechanisms through which digital transformation, corporate environment, and organizational learning capabilities influence the performance of agricultural enterprises.
3. To find a model for enhancing agricultural enterprise performance, focusing on digital transformation, corporate environment, and organizational learning capabilities.

Research Hypothesis

Digital transformation plays a key role in lowering operating costs for enterprises. The integration and connectivity of digital technology facilitate the sharing of industry information, helping to mitigate information asymmetry and decrease costs associated with information retrieval, negotiation, transaction monitoring, and post-processing. Furthermore, the seamless integration of digital technology with business processes can help reduce resource matching and channel operation expenses, enabling companies to address the diverse needs of customers more cost-effectively.

Digital transformation plays a crucial role in enhancing the operational efficiency of enterprises. By implementing intelligent management systems and decision support systems that have undergone digital upgrades, organizations can significantly enhance their operational management and decision-making capabilities, leading to more streamlined decision-making processes and business operations. Furthermore, digital transformation provides real-time market information, enabling enterprises to optimize resource allocation based on their specific needs, harmonize production plans, and accelerate inventory turnover. Research conducted by Li Lianshui et al. (2020) revealed that digital transformation resulted in an 8.2% increase in total factor productivity for enterprises during the research and development phase.

Digital transformation has the potential to foster innovation within enterprises by enabling distributed, virtualized, and large-scale knowledge exchange and collaboration with external partners. This facilitates innovative interactive methods and strategic cooperation among enterprises. Furthermore, the resource complementarity that arises from collaboration with external parties can enhance the efficiency of corporate innovation activities. According to Xiao Xu and Qi Yudong (2019), digital transformation can enhance industrial efficiency, reshape competition models within industrial organizations, facilitate cross-border integration of industries, and empower industrial upgrading, thereby revitalizing industrial development.

Hypothesis 1: Digital transformation has a direct effect on agricultural enterprise performance.

The corporate environment has a direct impact on a company's production and operational activities. Optimizing the corporate environment can lead to the establishment of a new government-enterprise relationship, boost corporate development vitality, and enhance performance levels. A high-quality corporate environment enables companies to mitigate risks, improve performance, and drive development (Xu Zhiduan and Ruan Zhouyilong, 2019). By optimizing the corporate environment, not only are institutional transaction costs reduced, but government public resources are also allocated more efficiently, thus curbing corporate rent-seeking behavior and ultimately enhancing performance (Xu Helian et al., 2018). In a conducive corporate environment, companies are better positioned to engage in fair market competition, secure necessary production resources, drive profitability, and increase overall profits (Claessens et al., 2014).

Hypothesis 2: Corporate environment has a direct effect on agricultural enterprise performance.

Digital transformation is crucial for modern enterprises, enabling them to adapt to new technologies, enhance efficiency, cut costs, and boost customer satisfaction. However, achieving digital transformation necessitates the rapid adoption of new technologies, processes, and business models. Businesses must also be agile to maintain a competitive edge in a fierce market. Dynamic capabilities play a vital role in digital transformation, enabling enterprises to respond to external changes and enhance internal processes. Success in digital transformation hinges on possessing adequate dynamic capabilities. Enterprises must swiftly adapt to market competition and external changes, while also fostering innovation and flexibility to embrace new technologies and business models. Continuous learning and adaptation are essential for enterprises to meet evolving customer needs and market demands during the digital transformation journey.

Hypothesis 3: Digital transformation has a direct effect on dynamic capabilities.

The quality of the Corporate Environment significantly impacts the success of market entities, as well as the movement of production factors and overall development momentum. Regions with a favorable Corporate Environment offer a stable market environment, comprehensive legal and regulatory frameworks, transparent market information, and more. This facilitates the smooth flow of capital, technology, products, industries, and personnel, making it easier for enterprises to access financing, talent, and technical support. This, in turn, promotes innovation in technology, products, and management, enhancing the market competitiveness and dynamic capabilities of enterprises.

Hypothesis 4: The corporate environment has a direct effect on dynamic capabilities.

Enterprises must continuously enhance their learning capabilities and effectively allocate and integrate resources to improve their supply chain system, ensuring alignment with the environment for sustained high-level performance. Numerous theoretical and empirical studies have highlighted that an enterprise's ability to swiftly and agilely reconfigure resources in response to environmental changes, known as dynamic capabilities, is key to gaining competitive advantages and achieving strong Agricultural enterprise performance. Leiponen's survey of 489 manufacturing companies, which involved extensive primary data collection and analysis, revealed a positive correlation between dynamic capabilities and Agricultural enterprise performance. Dynamic capabilities are defined as the core capabilities and competitive advantages that continuously restructure organizational resources to align with the changing market environment. This ability is crucial for achieving sustained Agricultural enterprise performance and ensuring competitiveness. Rapidly perceiving environmental changes and learning quickly enable companies to adapt and potentially create an advantageous environment for themselves. Strong environmental scanning and learning capabilities can help companies differentiate themselves from competitors by being the first to explore new markets or develop innovative products and services. Additionally, when existing resources and capabilities are unable to meet new environmental demands, dynamic capabilities facilitate rapid adjustments, resource reallocation, and innovation based on knowledge acquisition. By creatively dismantling outdated competitive advantages and reconstructing core competencies, businesses can maintain and enhance their performance levels over time.

Hypothesis 5: Dynamic capabilities has a direct effect on agricultural enterprise performance.

Digital transformation thrusts enterprises into a complex and uncertain environment, disrupting traditional organizational practices. As a result, enterprises must cultivate dynamic capabilities to effectively manage this transition (Liu Yang et al., 2020; Gregory, 2019). This transformation necessitates enterprises to leverage their innovative capabilities to overcome organizational inertia, drive the development of new products, and explore new markets. Furthermore, it requires them to utilize absorptive capabilities to identify, assimilate, and apply valuable external information, facilitating the integration of digital transformation-driven insights. The abundance of information and knowledge resources demands adaptability from enterprises to swiftly identify opportunities and adapt to evolving external conditions by reconfiguring and integrating resources. Dynamic capabilities also prompt companies to strategize ways to gain competitive advantages in a highly competitive landscape, shift focus from goals to behaviors, and optimize resource allocation in turbulent environments, ultimately enhancing Agricultural enterprise performance. Scholars such as Zhang Jichang and Long Jing (2022), Chi Maomao et al. (2020), as well as Warner and Wäger (2019) have explored the mediating role of dynamic capabilities in the context of digital transformation and Agricultural enterprise performance.

Enterprise innovation behaviors triggered by digital transformation must be supported by specific resources and capabilities. The existing literature highlights the significance of dynamic capabilities in the digital transformation process. Dynamic capabilities have always been recognized as strengths of Chinese enterprises and play a crucial role in corporate innovation endeavors. According to Wang et al., dynamic capabilities encompass three dimensions: innovation capability, absorptive capability, and adaptive capability. This categorization has been validated by local researchers and is considered highly representative and typical. Innovation capability refers to an organization's capacity to develop new products and explore new markets. Absorptive capability pertains to an organization's ability to identify, absorb, transform, and apply valuable external knowledge, encompassing internal learning and external knowledge assimilation. Adaptability denotes an organization's proficiency in reallocating corporate resources to promptly identify and seize opportunities.

Digital transformation enhances corporate innovation performance by improving innovation capabilities through the use of digital technology. This technology provides powerful information capture and intelligent analysis capabilities, allowing enterprises to adjust their innovation strategies and goals dynamically. Moreover, solely focusing on developing products or technologies within familiar technical fields may increase innovation efficiency but hinder the evolution of innovation capabilities, leading to dependency on existing paths and potential stagnation. The shift in management models during digital transformation encourages companies to adapt to external influences and disrupt organizational routines, ultimately enabling a focus on enhancing innovation capabilities and exploring new knowledge and technology areas.

Digital transformation enhances corporate innovation performance by boosting absorptive capacity. In an increasingly interconnected digital ecosystem, boundaries between enterprises and with the external environment are gradually dissolving. Through digital transformation, enterprises acquire knowledge from stakeholders such as partners, consumers, and competitors, enabling them to swiftly access internal and external information sources, broaden information scope, and facilitate interactive learning between internal cognition and external environment. The updating of internal knowledge and exchange of external knowledge can effectively facilitate resource optimization and value extraction, ultimately enhancing absorptive capacity. By absorbing and integrating vast information and knowledge resources through digital transformation, enterprises can elevate operational capabilities supporting digital transformation into advanced dynamic capabilities that are hard to replicate or substitute, thereby propelling enterprise innovation.

Digital transformation enhances corporate innovation performance by fostering adaptability. Adaptability is the capacity of an organization to incorporate and restructure existing resources in response to evolving environmental changes. This transformation encompasses a comprehensive and multi-dimensional overhaul and advancement of enterprises. Through digital technology, enterprises can disrupt the business models, operational processes, innovation systems, etc. that they depend on for survival, and utilize more intelligent tools to design, produce, and support the entire enterprise along with its products and technological innovations in the value chain. This further strengthens enterprises' ability to adapt to the new environment. Without strong adaptability, even with continuous integration of digital technologies, an enterprise may struggle to effectively adjust its internal organizational processes, innovation methods, and resource base, ultimately hindering the enhancement of the enterprise's innovation performance.

Hypothesis 6: Digital transformation has an indirect effect on agricultural enterprise performance.

The corporate environment plays a crucial role in influencing the production and operational activities of enterprises. By optimizing the corporate environment, organizations can establish diverse communication and collaboration channels with the government, reduce the barriers for government-enterprise partnerships, foster a new form of relationship between them, and enhance both market and government resources. This optimization also paves the way for enterprises to enhance their dynamic capabilities. Companies can leverage government financing platforms, technology research institutions, and similar resources to bolster their dynamic capabilities. Those with stronger dynamic capabilities are better positioned to attract government resources, integrate them with market resources through innovation, curb rent-seeking behavior, and ultimately enhance Agricultural enterprise performance. A favorable corporate environment eliminates institutional barriers to the flow of market resources and enhances market efficiency. Enterprises with robust dynamic capabilities can forge closer partnerships with upstream and downstream entities, minimize resource flow costs, enhance inter-firm cooperation efficiency, and consequently boost overall performance.

Hypothesis 7: Corporate environment has an indirect effect on agricultural enterprise performance.

Scope of the Research

Scope of Content

This research is a study sustainable model of agricultural enterprises in the environment of digital transformation which contains the following variables:

1. Digital Transformation: In today's digital era, digital transformation has emerged as a crucial variable for enterprises to enhance their competitiveness, a fact widely acknowledged for its universality and significance (Zhang Qiang, 2023). Both traditional industries and emerging sectors are actively embracing digital transformation to optimize operations, reduce costs, bolster innovation capabilities, and enhance customer experiences (Li Na, 2022). Particularly in agriculture, digital transformation is spearheading innovative practices such as precision agriculture, agricultural product traceability, and agricultural financial services (Wang Lei, 2021), enabling precise planting, boosting yields and quality, and simultaneously establishing traceability systems for agricultural products to strengthen consumer trust (Liu Fang, 2023). Furthermore, digital transformation drives innovation in agricultural financial services, facilitating more accessible financial support for agricultural enterprises and accelerating their development (Chen Ming, 2021, explored the impact of digital transformation on agricultural finance).

2. Corporate Environment: When examining the performance of agricultural enterprises, selecting the corporate environment as a variable is equally crucial with a global perspective. This is grounded in studies by Van Tongeren (1998) and Bergstrom (2000), among others, who illuminated how external factors like fiscal and taxation policies, market environments, etc., affect agricultural enterprise performance in countries like the Netherlands and Sweden. Van Tongeren noted that while fiscal subsidies may enhance an agricultural enterprise's solvency, they may not significantly boost profitability, suggesting the complexity and multifaceted nature of external environments' impact on performance. Bergstrom's long-term research indicated that government subsidies could initially elevate agricultural enterprise earnings but that as subsidy scopes and amounts expanded, business performance was actually constrained, further emphasizing the profound influence of

dynamic changes in the enterprise environment on performance. Simultaneously, research emphasizes the internal environment's vital role in supporting agricultural enterprise performance, particularly internal control and information disclosure mechanisms. Doyle, Ge, & McVay (2007) and others demonstrated that effective internal control significantly reduces financial and operational risks, enhances operational efficiency, and safeguards rational resource utilization through standardized business processes and strengthened risk management. Additionally, Ashbaugh-Skaife, Collins, & Kinney (2008) pointed out that internal control quality directly impacts financial reporting reliability, thereby strengthening investor confidence in enterprise performance. Lang & Lundholm (1993) and Healy & Palepu (2001) underscored the importance of transparency in information disclosure for agricultural enterprises, arguing that timely, accurate, and comprehensive disclosure enhances trust and market value, ultimately boosting performance. Thus, agricultural enterprises should prioritize internal control systems and information disclosure regimes to tackle market challenges, ensure stable development, and achieve long-term value enhancement.

3. Dynamic capabilities: In agricultural enterprise performance research, selecting dynamic capabilities as a variable plays a pivotal role in enhancing performance. According to Cohen and Levinthal (1990), dynamic capabilities is crucial for enterprises to maintain competitiveness in rapidly changing market environments. They argued that by continuously learning, absorbing, and applying new knowledge, enterprises can adapt more quickly to technological innovations and shifts in consumer demand, thereby securing advantageous market positions. Specifically, dynamic capabilities impacts agricultural enterprise performance in multiple ways. As Nonaka and Takeuchi (1995) noted, robust dynamic capabilities foster knowledge sharing and creation within enterprises, aiding in the adoption of new technologies to improve production efficiency and product quality, thereby enhancing market competitiveness. Argote and Ingram (2000) emphasized that organizational learning also strengthens enterprises' adaptability, enabling them to swiftly adjust strategies in response to market fluctuations and policy changes, maintaining stable

development. Furthermore, studies widely explore the positive correlation between dynamic capabilities and enterprise performance. Sinkula (1994) found that enterprises with strong learning orientations tend to identify market opportunities faster, formulate effective market strategies, and achieve higher performance levels. Bontis et al. (2002) further noted that dynamic capabilities is an essential component of intangible assets, intimately linked to key performance indicators such as innovation capabilities and market responsiveness.

4. Agricultural Enterprise Performance: Smith (2010) points out that performance is the core criterion for measuring the success of an enterprise, especially in the agricultural sector, where it is directly related to the survival and development of the enterprise. Performance not only reflects the production efficiency and market response speed of the enterprise but also embodies its resource utilization efficiency and strategic management capabilities. Jones (2015) notes that the study of agricultural enterprise performance is of great significance for understanding industry trends, guiding policy formulation, and promoting industry transformation. By deeply analyzing the performance of agricultural enterprises, we can evaluate their operational effectiveness and efficiency, thereby guiding corporate decision-making and planning, as stated by Brown (2012). Furthermore, performance research also helps enterprises respond to policies and market demands. Davis (2008) points out that the policy environment and market demand are important factors affecting the performance of agricultural enterprises, and through performance research, we can better understand the mechanism of these factors. Performance research is also an essential bridge between theory and practice, as Wilson (2018) states. Empirical research can verify theoretical hypotheses, providing empirical support for theoretical innovation, while successful cases in practice can also provide rich materials and inspirations for theoretical research.

Table 1.1 Variable Design Adoption

Author	Digital Transformation	Corporate Environment	Dynamic Capabilities	Agricultural enterprise performance
Hao Lu, Yiwei Fan, Liudan Jiao & Ya Wu. (2024)			√	√
Shuigen Hu, Xiaochi Wu & Yilin Cang. (2024)		√	√	
Mele Gioconda, Capaldo Guido, Secundo Giustina & Corvello Vincenzo. (2024).	√	√	√	
Mengdi Guo. (2024).		√		
ShiZheng Huang, HongHong Tian & Onanong Cheablam. (2023)	√	√		√
Liu Laihui, An Suxia & Liu Xiangyu. (2022)	√		√	
Shen Lei, Zhang Xi & Liu Hongda. (2021)	√			√
Qiuling Yu. (2021).	√		√	
Petrushevskaya A A & Aleshkin N A. (2021)	√		√	
Rohani Mina, Shahrasbi Nasser & Gregoire Yany. (2021)	√	√		√
Kim Jin Kwon & Ahn Tony Donghui. (2021)	√		√	
Count the frequency	**8**	**5**	**7**	**4**

Scope of Population

According to data released by the National Bureau of Statistics of China, as of the end of 2023, there were exceeds 25103 legal person enterprises in China engaged in wholesaling agricultural, forestry, animal husbandry, and fishery products. This study focuses on a total of 25103 regional agricultural enterprises in China.

The Sample Group

The number of pre-survey samples is 30, and the number of formal survey samples is 360.

Scope of area

The area selected for the pre-research sample is Guanggxi, China. The pre-survey area is Guangxi, China. Guangxi, China, is a major agricultural province with an agricultural GDP of 426.981 billion yuan in 2022, ranking first in China, accounting for approximately 1/8 of China's agricultural GDP.

Based on China's geographical division into eastern, central, and western regions, as well as the spatial layout characteristics of agricultural enterprises, the selection of the official survey regions was informed by the research findings of various scholars (Li Hua, 2020), aiming to identify the most representative regions. The official survey regions were determined to be Beijing, Shanghai, Hubei, Guangxi, and Yunnan. Among them, Beijing and Shanghai, as representatives of the eastern region, have long maintained their leading position in economic development, belonging to the more economically advanced areas (Zhang Wei, 2018). Hubei, located in the central region, has experienced rapid economic development in recent years, with a relatively developed economy (Wang Qiang, 2019). As for Guangxi and Yunnan, situated in the western region, despite the relatively slower overall economic growth, they boast abundant agricultural resources, and their agricultural GDP stands out in the western region, ranking first and second respectively (Zhao Min, 2021).

Scope of Time

From September 2023 to December 2024.

Advantages

1. The research focuses on the background of digital transformation in agricultural enterprises, providing valuable insights for government officials to understand the importance of digital transformation.

2. The study explores the concepts of digital transformation and performance in enterprises, which aids researchers, governments, businesses, and social institutions in understanding these concepts.

3. The research delves into the mechanism of how digital transformation impacts agricultural enterprise performance, offering fresh perspectives for researchers, governments, enterprises, and social institutions to comprehend the role of digital transformation and its effects on performance.

4. The study investigates the mediating role of dynamic capabilities in the relationship between digital transformation and agricultural enterprise performance, providing new avenues for enterprises to improve their performance.

5. The research discusses countermeasures and suggestions for enhancing agricultural enterprise performance through digital transformation, offering new solutions and pathways for enterprises aiming to improve their performance.

Definition of Terms

Sustainable model

The "sustainable model" generally refers to the "sustainable development model", and the two share a high degree of consistency in core connotations (WCED, 1987; Barbier, 1989). The concept of sustainable development, as defined by the World Commission on Environment and Development (WCED) in 1987 in the "Brundtland Report", is "development that meets the needs of the present without compromising the ability of future generations to meet their own needs". This definition emphasizes the integration of economic, social, and environmental dimensions.

The concept of sustainable development capacity refers to the comprehensive ability of a system (such as an enterprise, region, or country) to coordinate social equity, environmental protection, and rational resource utilization while pursuing economic growth, so as to achieve long-term healthy development (World Commission on Environment and Development, 1987). It emphasizes the dynamic balance of the three dimensions of economy, society, and environment, requiring the system to have the ability to adapt to internal and external changes and maintain its own survival and development. Economically, it is reflected in the system's enhancement of resource utilization efficiency, reduction of production costs, and strengthening of economic competitiveness through technological innovation, industrial upgrading, etc. (United Nations, 2015); socially, it focuses on improving people's livelihood areas such as fair distribution, social security, education, and medical care to ensure the continuous improvement of residents' quality of life; environmentally, it requires the system to adopt green production and low-carbon development models to reduce ecological damage and environmental pollution and ensure the sustainable supply of natural resources. For example, an enterprise with such capacity means not only maintaining stable profit growth but also fulfilling social responsibilities through actions like energy conservation, emission reduction, and community construction to build a Healthy interactive relationship with stakeholders (Schaltegger & Wagner, 2017), while governments and social organizations also need to collaboratively enhance regional or global sustainable development capacity through policy guidance, resource integration, etc.

Digital transformation

The concept of digital transformation refers to the dynamic process in which organizations systematically reconstruct business models, organizational structures, operational processes, and value creation methods through the in-depth application of digital technologies (such as big data, artificial intelligence, cloud computing, etc.) to adapt to the changing needs of the digital era (Manyika et al., 2016). This concept emphasizes the collaboration between technological application and organizational change, involving not only IT system upgrades but also the requirement to break traditional thinking patterns. It achieves efficiency improvement, cost optimization, and the excavation of new value growth points through data-driven decision-making, business process reengineering, and business model innovation (Porter & Heppelmann, 2014). In essence, digital transformation is an organization's strategic response to changes in competition rules, customer needs, and value creation logic in a digital environment. Its core lies in using digital technologies to reshape the way organizations interact with customers, suppliers, and other stakeholders, promoting the transformation of organizations from traditional operation models to digital ecosystems (Kane et al., 2017). For example, enterprises can achieve visual supply chain management, personalized product service customization, and real-time response to user needs through digital transformation, while government departments can leverage digitization to enhance the efficiency and transparency of public services (Wu et al., 2020).

Corporate environment

The concept of the corporate environment refers to the sum of various internal and external factors affecting an enterprise's survival and development, including the macroeconomic, political-legal, socio-cultural, and technological innovation factors in the external environment, as well as the internal resources, organizational structure, and corporate culture within the enterprise (Daft, 2015). In the external environment, macroeconomic conditions such as the business cycle and inflation rate influence an enterprise's market demand and investment decisions; political-legal factors (e.g., industrial policies, environmental regulations) define the boundaries of corporate behavior; socio-cultural elements (e.g., consumption concepts, values) shape market preferences; and technological progress drives corporate innovation and industrial transformation (Porter, 2008). In terms of the internal environment, an enterprise's resource elements such as human resources, financial strength, and technical capabilities form the foundation of its core competitiveness, while the efficiency of organizational structure and the orientation of corporate culture (e.g., innovation culture, team culture) affect the enterprise's response speed and adaptability to external environmental changes (Robbins, 2017). The corporate environment is dynamic and complex, requiring enterprises to identify opportunities and threats through environmental scanning and analysis, and coordinate internal resources to achieve sustainable development (Dunning, 2013).

Agricultural enterprise performance

The concept of agricultural enterprise performance refers to the comprehensive output and efficiency level achieved by agricultural enterprises in economic, social, and ecological dimensions within a specific operation cycle through integrating agricultural production factors such as land, labor, and capital (Coelli et al., 2005). This concept includes not only economic indicators like profitability and asset turnover (e.g., net profit margin, input-output ratio), but also social benefits such as driving farmer employment and ensuring agricultural product supply (Diao et al., 2019), as well as ecological sustainability dimensions including resource utilization efficiency (e.g., water resource utilization rate) and environmental impact (e.g., carbon emission intensity) (Zhu et al., 2016). The particularity of agricultural enterprises requires their performance evaluation to balance the seasonality, periodicity, and natural risk characteristics of agricultural production. For example, the performance of agricultural product processing enterprises needs to consider the impact of raw material purchase price fluctuations on costs, while planting enterprises should focus on the effect of climatic conditions on yield (Huang et al., 2018). To scientifically evaluate agricultural enterprise performance, it is necessary to construct an index system from multiple dimensions such as financial health, market competitiveness, social responsibility fulfillment, and ecological friendliness by combining tools like the DuPont analysis system and balanced scorecard (Li et al., 2020).

Dynamic capabilities

The concept of dynamic capabilities refers to an organization's ability to integrate, build, and restructure internal and external resources and competencies to identify opportunities, address threats, and sustain competitive advantage in a rapidly changing environment (Teece, Pisano, & Shuen, 1997). This concept emphasizes an organization's capacity to adapt to and shape dynamic environments, with core components including environmental sensing capability (e.g., identifying technological changes and market demand shifts), resource integration capability (e.g., cross-departmental collaboration and external partnership building), and organizational restructuring capability (e.g., strategic adjustment and process reengineering) (Eisenhardt & Martin, 2000). Unlike static capabilities, dynamic capabilities focus more on an organization's learning and change processes under uncertain conditions for example, enterprises updating technical knowledge bases through continuous R&D investment or rapidly acquiring complementary resources via mergers and acquisitions (Teece, 2007). In the digital era, dynamic capabilities also manifest in the absorption and application of digital technologies, such as using big data analytics to optimize decision-making processes or reconstructing value networks through platform-based models (Wang & Ahmed, 2007).

Research Framework

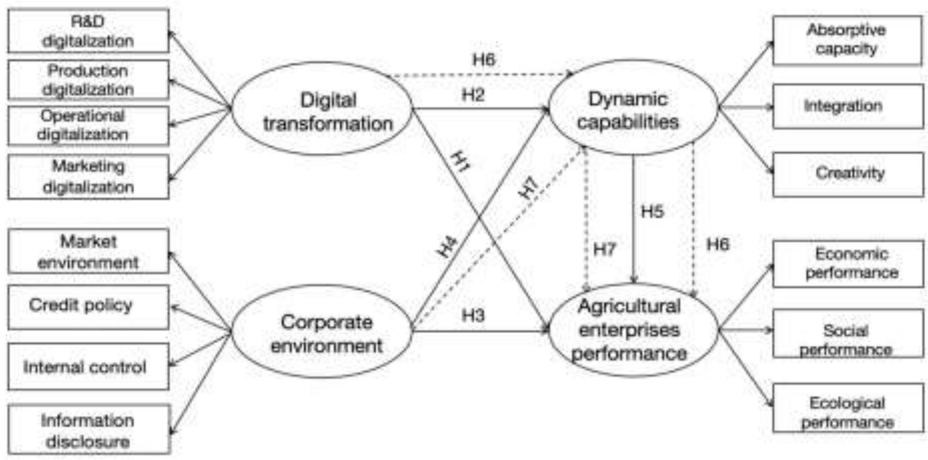

Figure 1.3 Research Framework

Chapter 2
Literature Review

General information of the Chinese agricultural enterprises

The overall profile of Chinese agricultural enterprises exhibits notable characteristics of steady development, diversification, and technological innovation. There are numerous enterprises, including many leading companies with significant industry influence, which have continued to expand their business scale while strengthening technological innovation and brand building. Agricultural enterprises are widely distributed across various industries such as grain and oil production, food processing, animal husbandry and aquaculture, agricultural inputs, and agricultural product distribution, forming a diversified landscape covering the entire agricultural industry and its entire supply chain. With continuous advancements in technology, these enterprises have consistently increased their investment in scientific research, promoted digital transformation, and leveraged advanced technological means such as the Internet of Things, big data, and artificial intelligence to achieve precise management and intelligent decision-making. This has enhanced agricultural production efficiency and quality, driving the agricultural industry towards intelligent and green development. Furthermore, while growing, agricultural enterprises actively fulfill their social responsibilities by connecting and empowering farmers, absorbing rural labor force for employment, and thereby making positive contributions to the prosperity of the rural economy and rural revitalization.

Deepening Promotion of Digital Transformation

The digital transformation of Chinese agricultural enterprises has entered an accelerated lane, becoming a pivotal force driving their comprehensive transformation and upgrading. According to the latest data from the National Bureau of Statistics, China's agricultural informatization investment has seen an average annual growth rate exceeding 15% in recent years, reflecting the industry's profound commitment and investment in digital transformation. Against this backdrop, the widespread application of cutting-edge technologies such as cloud computing, big data, the Internet of Things (IoT), and Artificial Intelligence (AI) is profoundly transforming the production, operation, and management models of agricultural enterprises (Li Ming, 2021).

Chinese agricultural enterprises have continued to increase their investment in digital research, significantly enhancing their research vitality. According to the China Agricultural Machinery Industry Association, the average annual growth rate of research investment by agricultural enterprises has exceeded 10% in the past three years, with leading enterprises surpassing 20% growth. This trend has significantly promoted the deep integration and application of IoT, big data, AI, and other technologies in agricultural research. Currently, over 50% of agricultural enterprises have established research and development departments and forged close collaborations with universities and research institutions, jointly advancing hundreds of digital agriculture research projects, laying a solid foundation for improving the quality of agricultural products and promoting sustainable agricultural development.

The transformation of digital production models is profoundly impacting the production processes of Chinese agricultural enterprises. As of the latest data, the nationwide penetration rate of smart agricultural machinery and equipment has reached 35%, nearly doubling that of five years ago, with a total inventory exceeding one million units. These smart agricultural machines integrate advanced sensors, control systems, and data analysis platforms, enabling precise management of agricultural production processes such as sowing, fertilizing, and irrigation. They have increased crop yields by approximately 10%-15% on average while reducing the use of pesticides and fertilizers, effectively mitigating resource waste and environmental pollution. Additionally, the construction of digital information platforms has enabled over 80% of agricultural enterprises to achieve visual management and intelligent decision support throughout the production process.

Chinese agricultural enterprises are actively exploring digital marketing, with e-commerce platforms becoming crucial channels for market expansion. According to iResearch Consulting reports, over 90% of agricultural enterprises have established a presence on e-commerce platforms, leveraging online channels to broaden their sales networks. These platforms not only provide vast market spaces but also assist enterprises in accurately grasping market demands and consumer preferences through big data analysis, enabling personalized product customization and precise promotion. Meanwhile, social media, short video, and other new media platforms have emerged as new frontiers for agricultural enterprises' brand building and promotion, effectively enhancing brand awareness and reputation. The rise of cross-border e-commerce has presented unprecedented opportunities for Chinese agricultural products to go global.

Digital transformation plays a vital role in the operational management of agricultural enterprises. At the supply chain level, over 60% of agricultural enterprises have established digital supply chain management systems, leveraging IoT, blockchain, and other technologies to achieve traceability of agricultural product information throughout the entire chain, enhancing supply chain management transparency and efficiency. Additionally, the widespread application of digital tools in financial management enables real-time data collection and analysis, providing robust support for enterprises to promptly identify and address financial management issues. The implementation of these digital operational measures has optimized resource allocation, reduced operating costs, and significantly enhanced enterprises' overall operational efficiency and market competitiveness, laying a solid foundation for the sustainable and healthy development of agricultural enterprises.

Continuous Optimization of the Corporate Environment

With the continuous reinforcement of national policies, Chinese agricultural enterprises are basking in the spring breeze of policy dividends, ushering in unprecedented development opportunities. According to the latest "White Paper on China's Agricultural Policy (2024)" released by the Ministry of Agriculture, in the past three years, the government has not only increased financial subsidies for agricultural enterprises but also effectively reduced their operating costs through a series of preferential tax measures. Specifically, over 80% of agricultural enterprises enjoy government financial subsidies annually, with the average subsidy per enterprise increasing by 15% compared to previous years. Meanwhile, for small and micro-agricultural enterprises, the government has implemented more flexible tax relief policies, reducing their actual tax burden rate by nearly 20 percentage points. The implementation of these industrial policies has not only provided strong financial support for the digital transformation of agricultural enterprises but also stimulated their innovation vitality, promoting the transformation and upgrading of the agricultural industry.

In terms of credit policies, the joint efforts of the government and financial institutions have injected robust financial momentum into agricultural enterprises. Statistics show that the balance of agricultural loans nationwide has continued to grow in the past three years, with inclusive agricultural loans experiencing particularly significant growth. Especially for loan products tailored to agricultural enterprises, such as "Agricultural Loan Pass" and "Rural Revitalization Loan," they have not only simplified loan procedures and lowered thresholds but also offered more favorable interest rates and flexible repayment methods. Additionally, financial institutions have leveraged big data, cloud computing, and other technological means to enhance credit approval efficiency and shorten loan disbursement time, providing more convenient and efficient financial services to agricultural enterprises. These credit policies have effectively alleviated financing difficulties for agricultural enterprises, providing solid financial guarantees for them to expand production scale, introduce advanced technologies, and explore new markets.

Faced with increasingly fierce market competition and diversified consumer demands, agricultural enterprises have strengthened the construction of their internal control systems to enhance their core competitiveness. In recent years, many agricultural enterprises have introduced advanced management tools like ERP and CRM systems, achieving comprehensive integration and optimal allocation of enterprise resources. At the same time, they have strengthened monitoring and management of critical links such as finance, production, and sales, ensuring data accuracy and timeliness. By establishing a sound internal control system, agricultural enterprises can more effectively control costs, improve product quality and safety, and optimize customer service experiences, thereby gaining widespread market recognition. Furthermore, enterprises have focused on cultivating employees' internal control awareness, fostering an atmosphere of full participation and joint maintenance of internal controls.

The trend of transparent information disclosure is crucial for the development of agricultural enterprises. To enhance trust among investors, consumers, and all sectors of society, an increasing number of agricultural enterprises are emphasizing the accuracy and timeliness of their disclosures. In recent years, many agricultural enterprises have regularly published financial reports, operational information, social responsibility reports, etc., in accordance with International Financial Reporting Standards and relevant laws and regulations, detailing their financial status, operating results, development strategies, and social responsibility performance. They have also proactively disclosed product information and quality inspection reports through official websites, social media, and other channels, enhancing consumer trust and satisfaction. This transparent approach to information disclosure not only enhances corporate brand image and market reputation but also attracts more investments and partners. Additionally, enterprises actively participate in industry exchanges and cooperation, sharing successful experiences and management philosophies to jointly promote the healthy development of the agricultural industry.

Continuous Enhancement of Dynamic Capabilities

The dynamic capabilities of China's agricultural enterprises have significantly strengthened in recent years, manifested not only in their aggregation capabilities, which have successfully drawn social capital, talents, and technologies to the agricultural sector through brand influence, market channels, and financial strength, but also in their integration capabilities, exemplified by the deep integration of agriculture with processing and service industries, as well as cross-boundary integration with modern information technologies, such as the rise of rural e-commerce and smart agriculture, demonstrating robust fusion innovation. Concurrently, although there remains room for improvement in innovation investment capabilities, some technological backbone enterprises have achieved breakthroughs in areas like bio breeding and intelligent agricultural machinery, and the strengthening of industry-academia-research collaborations is gradually facilitating the effective transformation of scientific and technological achievements, injecting new vitality into the sustainable development of China's agricultural enterprises.

Regarding the aggregation capabilities of China's agricultural enterprises, there has been a notable improvement in their ability to attract and pool resources, capital, talents, and technologies. Statistics reveal that by the end of 2022, nearly 100,000 leading enterprises recognized by agricultural industrialization authorities above the county level existed nationwide, with over 20,000 key enterprises above the provincial level and more than 1,500 at the national level. These leading enterprises effectively attracted substantial social capital into the agricultural sector through their brand influence, market channels, and financial strength. For instance, capital investment in China's agricultural sector increased annually from 30.3 billion yuan in 2019 to 32.5 billion yuan in 2020 and 36.4 billion yuan in 2021. As agricultural modernization advances, agricultural enterprises have begun to prioritize the introduction and cultivation of high-quality talents. Many leading agricultural enterprises have established partnerships with universities and research institutions, attracting a large number of agricultural technology talents through deep industry-academia-research integration. Simultaneously, the government has implemented a series of policies to encourage and support agricultural enterprises in bringing in high-level overseas talents, further enhancing their aggregation capabilities.

The integration capabilities of China's agricultural enterprises are primarily manifested in two aspects: industrial integration and cross-boundary integration. In terms of industrial integration, agricultural enterprises have achieved deep integration with processing and service industries by extending industrial chains and upgrading value chains. For example, the agricultural industrial chain extension model plays a crucial role in rural industrial integration, enhancing the added value of agricultural products by integrating the entire industrial chain from planting to production and sales. Statistics show that the ratio of the output value of China's agricultural product processing industry to the total agricultural output value has surpassed 2:1, indicating the enormous potential of agricultural industrial chain extension. Agricultural enterprises have actively integrated with modern information technologies such as the Internet, big data, and artificial intelligence, fostering emerging industries like rural e-commerce and smart agriculture. For instance, e-commerce platforms like JD.com and Alibaba have expanded into rural markets, broadening agricultural product sales channels through online sales and direct sales from production areas. Meanwhile, the application of modern agricultural equipment like agricultural drones and intelligent agricultural machinery has significantly improved agricultural production efficiency and quality.

The innovation capabilities of China's agricultural enterprises are vital to their sustainable development. In recent years, China's agricultural-related enterprises have continually increased their investment in technological innovation, but overall, their innovation investment capabilities remain inadequate. Statistics indicate that in 2021, the average research and development (R&D) investment intensity (R&D expenditure/main business income) of listed agricultural enterprises on China's Shanghai and Shenzhen stock exchanges was 2.61%, only 55% of the average level of all listed enterprises. However, some technological backbone enterprises have achieved remarkable results in agricultural technological innovation. For example, in the field of biobreeding, enterprises such as Syngenta and Longping Biology have successfully cultivated new crop varieties with high yield, excellent quality, and stress resistance through increased R&D investment. In the field of intelligent agricultural machinery, companies like DJI and Chia Tai Aviation have introduced agricultural drones and smart agricultural machinery, providing more efficient and precise solutions for agricultural production. To further enhance the innovation capabilities of agricultural enterprises, national and local governments should increase support for technological innovation in agricultural enterprises by establishing government-guided innovation consortium funds, expanding the scope of additional deductions for pre-tax research and development expenses, and other measures to incentivize enterprises to increase R&D investment. Additionally, strengthening industry-academia-research collaboration and promoting the transformation and industrialization of scientific and technological achievements will provide robust support for the innovative development of agricultural enterprises.

Comprehensive Performance Improves Significantly

The deepening of digital transformation, continuous optimization of the enterprise environment, and the sustained enhancement of organizational learning capabilities have jointly contributed to a remarkable improvement in the performance of Chinese agricultural enterprises. On the one hand, the increase in production efficiency and resource utilization brought about by digital transformation has directly reduced production costs and improved profitability. On the other hand, measures such as brand building, market expansion, and channel optimization have led to rapid growth in sales revenue and market share for agricultural enterprises. Additionally, digital transformation has opened up more business opportunities and innovative spaces for enterprises, facilitating their sustainable development and long-term prosperity. Therefore, digital transformation can be considered a crucial path for Chinese agricultural enterprises to achieve performance enhancement and transformational upgrading.

Chinese agricultural enterprises have demonstrated a positive trend in economic performance improvement, primarily due to policy guidance, technological advancements, and continuous growth in market demand. In recent years, with the acceleration of agricultural modernization, the economic performance of agricultural enterprises has significantly improved. According to statistics, the total output value of agriculture, forestry, animal husbandry, and fishery reached 523 million yuan in the first quarter of 2024, a year-on-year increase of 5.6%, with varying degrees of growth across planting, forestry, animal husbandry, and fishery. Specifically, the output value of planting reached 233 million yuan, up 3.8% year-on-year, while animal husbandry's output value was 142 million yuan, a 4.5% increase. These figures indicate that agricultural enterprises' production efficiency and profitability are gradually strengthening. Within specific sectors, enterprises have actively adjusted their industrial structures and developed high-value-added agricultural products, further boosting economic performance. For instance, fruit production increased by 3.5% year-on-year, with a corresponding increase in output value, contributing 13.7% to the total output value of agriculture, forestry, animal husbandry, and fishery. Additionally, as the hog market recovers, both hog slaughter and output value have increased, further enhancing agricultural enterprises' economic performance. Hog slaughter reached 48,100 heads, a 5.6% year-on-year increase, with output value growing 5.8%, contributing 14.6% to the total. Meanwhile, agricultural listed companies, as industry leaders, have particularly outstanding economic performance. Although historical data shows fluctuations in profitability, an overall upward trend is evident. In recent years, these companies have continuously improved their competitiveness through technological innovation, market expansion, and capital operations, achieving steady growth in economic performance.

Chinese agricultural enterprises have also achieved remarkable accomplishments in social performance, primarily in promoting employment, increasing farmers' incomes, and narrowing the urban-rural income gap. With the advancement of agricultural modernization, these enterprises have absorbed a significant number of rural laborers, providing more job opportunities. Statistics show that economic recovery and stable employment policies have reduced the unemployment rate among migrant workers, with rural residents' incomes continuing to increase. Furthermore, by developing agricultural product processing and food manufacturing, agricultural enterprises have extended industrial chains, increased the added value of agricultural products, and further boosted farmers' incomes. In the consumption sector, the recovery of rural residents' consumption demand has been consolidated, with consumption structures continually optimized. High-quality and green consumption have emerged as new trends, enhancing farmers' quality of life and promoting the transformation and upgrading of agricultural enterprises. By providing safe, high-quality, and green agricultural products, these enterprises have met consumers' diverse needs and gained widespread market recognition.

In terms of ecological performance, Chinese agricultural enterprises have actively implemented the concept of green development to promote the development of ecological agriculture. Ecological agriculture emphasizes the integration of food production with various economic crops, as well as the development of field cultivation with forestry, animal husbandry, sideline production, and fishery. Through artificially designed ecological engineering, it coordinates the contradiction between development and the environment, as well as resource utilization and protection. In recent years, China has attached great importance to the issue of agricultural non-point source pollution, and the development of ecological agriculture has become an important way to address this problem. According to statistics, China's agricultural science and technology progress contribution rate has exceeded 62%, and the cumulative number of green, organic, and geographical indication agricultural products has reached 62,000. These achievements have not only improved the quality and safety of agricultural products but also promoted the improvement of the agricultural ecological environment. By adopting advanced agricultural technologies and management methods, agricultural enterprises have reduced the use of chemical fertilizers and pesticides, thereby lowering the risk of agricultural non-point source pollution. At the same time, agricultural enterprises have also actively participated in the construction and promotion of ecological farms, driving the green and low-carbon transformation of agriculture. In terms of policy support, the state has introduced a series of policies and measures to promote the development of ecological agriculture. For instance, the "Guiding Opinions on Promoting the Construction of Ecological Farms" proposes to strive to establish 1,000 national-level ecological farms nationwide by 2025, driving the construction of 10,000 local ecological farms in various provinces. The implementation of these policies and measures provides a strong guarantee for agricultural enterprises to enhance their ecological performance.

Concepts and theories of Research

Concepts and theories of Digital Transformation

1. Concepts of The Digital Transformation

(1) The positive impact of digital transformation on Agricultural enterprise performance is evident. Digital transformation enables enterprises to innovate their business models and enhance their agility in responding to market changes through the digital management of key operations and processes (Mikalef and Pateli, 2017; Yuan Yong, 2017). The advancement of digital transformation emphasizes the importance of data as a crucial production factor, eliminating 'data silos' and enabling seamless interaction between people and data, as well as data-to-data communication (He Da'an, 2018). This facilitates real-time information sharing across different production stages within the enterprise and fosters collaboration along the entire industrial chain, thereby reducing transaction and search costs significantly (Hu et al, 2022; Chen Deqiu Ren Hu Qing, 2022). Moreover, digital transformation drives enterprises towards intelligent and digital production methods, leveraging smart machines to minimize errors, enhance operational efficiency, and streamline production processes. By integrating digital technology with core business operations and adopting Internet thinking, enterprises can reconstruct their entire organizational landscape, creating an 'cloud + network + terminal' information service architecture that boosts innovation capabilities and ultimately enhances Agricultural enterprise performance (Wang Xiaoyan, 2016).

Digital transformation within enterprises can enhance operational efficiency by utilizing data for demand forecasting, product design, pricing, inventory management, and supply chain management (Bajari et al., 2015; Chen Jian et al., 2020). While predicting future market preferences based solely on historical data may introduce biases, leveraging big data technology allows for the collection of extensive data, such as users' search keywords, page visit duration, and price preferences. Visual analysis of this data enables a more intuitive understanding of users' behavioral patterns, preferences, and potential needs (Simsek et al., 2019). By adapting product designs to meet user requirements and offering personalized services, companies can enhance customer satisfaction and loyalty (He et al., 2019). Digital technologies also enable companies to dynamically adjust product prices based on user consumption behavior, implementing differentiated pricing strategies for high-demand products and those with slower sales rates (Cohen et al., 2018; Yu et al., 2016). This flexibility in pricing can help attract more users and prevent inventory stagnation. Digital technology plays a crucial role in enhancing product supply chains. In the traditional manufacturing model, machines operated simultaneously on the production line. However, when a technical issue arose, the entire production process had to be halted to investigate each machine individually, leading to delays and requiring significant manual labor. The integration of digital technology allows for real-time access to production data. In the event of a production failure, an intelligent management system can swiftly pinpoint the source of the issue, stop other machines that may be impacted, and coordinate repair efforts by professionals. This not only enhances production efficiency but also ensures smoother operations (Porter and Heppelmann, 2015; Kusiak, 2017). Qi Yudong and Xiao Xu (2020) further emphasize that digital transformation is reshaping the internal management structures of enterprises. This transformation is evident in the shift towards networked and flat organizational structures, versioned and iterative product design, modular production models that prioritize flexibility, precise and refined marketing strategies, diversified and flexible employment models, and open-source R&D approaches.

(1) The negative effects of digital transformation on Agricultural enterprise performance.

Digital transformation is a complex process that cannot be rushed, and simply investing more capital does not guarantee digital dividends. The outcomes of such transformation efforts are often unpredictable. Introducing digital technologies on a large scale within existing organizational structures may lead to systemic imbalances, with potential consequences including: Digital transformation will entail increased management costs for enterprises. In the initial phase of this transformation, companies must invest in a significant amount of new intelligent production equipment (both software and hardware) for their existing production lines. Additionally, employees need to undergo professional training and guidance, typically through consulting with experts or professional institutions to learn about digital technologies. It is essential for employees to grasp the core operational points, procedures, and contingency plans for technical difficulties to facilitate a smooth adaptation to the new production model (Qi Yudong and Cai Chengwei, 2020). Furthermore, the post-digital transformation era emphasizes the growing importance of intellectual capital (Jin Fan and Zhang Xue, 2018). Research conducted by Tan et al. (2007) and Nuryaman (2015) on listed companies in Singapore and Indonesia revealed that intellectual capital plays a more significant role in driving future enterprise development compared to financial capital. Consequently, enterprises must adjust their human capital structure by recruiting highly skilled employees, potentially reducing wages for lower-skilled employees, or even decreasing the proportion of lower-skilled workers (Sun Zao and Hou Yulin, 2019). As companies progress into the mid-term phase of digital transformation, the maintenance and upgrades of intelligent production equipment require additional expenditures on hiring professional technical personnel. This results in enterprises incurring higher costs before realizing the benefits of digital transformation.

Digital transformation may pose challenges to collaborative work within enterprises. Prior to undergoing digital transformation, organizations typically have well-established internal structures and employees who have honed their skills over time. While digital enterprises emphasize the role of intelligent employees, human collaboration remains essential. Adapting to the new operating model post-transformation requires innovative changes to the organizational system and operating methods, integrating existing business practices with digital technology. This process may encounter obstacles when traditional knowledge and skills are deeply ingrained, hindering the transformation progress (Schreyögg and Sydow, 2011; Xiao Jinghua et al., 2021). While digital management can reduce human errors and extend operating time, it is important to note that the algorithm system under digital technology often overlooks emotional factors such as morality and sincerity. This can lead to human employees reacting irrationally to decisions made based on digital technology in certain situations. Disagreements between production decisions and management suggestions may arise, impacting the collaborative efficiency between human and intelligent employees (Logg et al., 2019). Jago (2019) highlighted in his research that digital management systems could make information transmission and processing processes rigid and opaque, lacking flexibility, which may lead to biased and inefficient production decisions for enterprises. Moreover, in line with the network economic effect, the marginal value of data transmission is subject to the law of diminishing marginal utility. Delays in data transmission speed due to network signals and other factors could result in incorrect signals being sent to the market, misleading the production and operation activities of enterprises and triggering negative chain reactions.

Table 2.1 Concepts and theories of digital transformation

Author	Title	Source Research	Content
Clausen Pernille (2023)	Towards the Industry 4.0 agenda: Practitioners' reasons why a digital transition of shop floor management visualization boards is warranted	Digital Business	Focusing on digitally mature companies, look into the different routes that organizations can take to accomplish this goal, involving a mix of inbound/outbound open innovation, digital transformation, and absorptive capabilities in the path towards higher levels of new product development performance.
Wu Wenqing;Wang Siqi;Jiang Xin;Zhou Jie (2023)	Regional digital infrastructure, enterprise digital transformation and entrepreneurial orientation:	Information Processing and Management	Using China's low-carbon city pilot (LCCP) as a quasinatural experiment, this paper tests its effect on the digital transformation of manufacturing enterprises by applying the difference-in-

Table 2.1 (Continued)

Author	Title	Source Research	Content
	Empirical evidence based on the broadband china strategy		differences (DID) method. Furthermore, this paper conducts a heterogeneity analysis and tests for influence mechanisms.
Li Shibin;Wang Qian (2023)	Green finance policy and digital transformation of heavily polluting firms: Evidence from China	Finance Research Letters	The purpose of this study was to give a thorough review and pinpoint the intellectual framework of the field of research of the digital banking transformation (DBT).
Lu Xu (2022)	Research on Teaching Mode of Digital Transformation of Higher Vocational Education	Frontiers in Educational Research	assess the impact of urban digital transformation strategies represented by smart cities on urban resource sustainability using the difference-in-difference (DID) model.
Jiang Zhengyu;Zhang Xinyi;Zhao Yingzhi;Li Chengming;Wang Zeyu (2022)	The impact of urban digital transformation on resource sustainability: Evidence from a quasi-natural experiment in China	Resources Policy	use the “Green Credit Performance Evaluation of Banking Depository Financial Institutions” implemented by the People's Bank of China as a quasi-natural experiment and a difference-in-differences (DID) approach to examine the impact of green finance policy on the digital transformation of heavily polluting firms.
Zhao Shuang;Zhang Liqun;An Haiyan;Peng Lin;Zhou	Has China's low-carbon strategy pushed forward the digital transformation of	Environmental Impact Assessment Review	Using the resource-based view (RBV), we investigate the relationship among RDI, EDT and entrepreneurial orientation (EO) using a sample of Chinese A-share

Table 2.1 (Continued)

Author	Title	Source Research	Content
Haiyan;Hu Feng (2021)	manufacturing enterprises? Evidence from the low-carbon city pilot policy		listed enterprises from 2011 to 2019.
Osei Lambert Kofi;Cherkasova Yuliya;Oware Kofi Mintah (2021)	Unlocking the full potential of digital transformation in banking: a bibliometric review and emerging trend	Future Business Journal	discusses the influence of digital transformation on teaching mode, and puts forward a new teaching mode.

2. Theories of The Digital Transformation

The Innovation-Driven Theory of Digital Transformation, as a core component of the theoretical framework for digital transformation, has garnered widespread attention in international academia in recent years (e.g., Smith & Johnson, 2021). This theory underscores that in the process of digital transformation, innovation – particularly multi-dimensional innovation encompassing technology, management, organization, and business models – serves as the pivotal force driving enterprises and organizations towards profound transformation, enhanced competitiveness, and improved market adaptability (Davis et al., 2022). Through continuous innovation, enterprises can break free from traditional constraints, reshape business processes leveraging emerging technologies, optimize resource allocation, and thereby maintain a leading position amidst the digital tide.

Amidst the wave of digital transformation, technological innovation acts as the cornerstone. With the rapid advancements in new-generation information technologies such as cloud computing (Wang & Chen, 2020), big data (Lee & Kim, 2021), IoT, AI, and blockchain, enterprises must actively introduce and integrate these advanced technologies, continually upgrading their technological systems to support the in-depth implementation of transformation and create new value growth points (Jones & Taylor, 2022). Concurrently, management innovation is equally crucial, demanding profound changes in enterprises' management models (Moore & Brown, 2021). By adjusting management structures, optimizing processes, and introducing agile, lean, and data-driven management concepts, enterprises can enhance management efficiency, the scientificity and timeliness of decision-making, and thereby sustain their competitiveness in the ever-changing market (Thompson & Liu, 2022). Moreover, digital transformation prompts enterprises to break traditional organizational boundaries, fostering flexible and efficient organizational structures (Kumar & Patel, 2021). This enhances cross-departmental and cross-functional collaboration, strengthens team communication and cooperation, significantly improves overall execution and innovation capabilities, enabling enterprises to swiftly respond to market changes and seize development opportunities (Collins & Diaz, 2022). Lastly, business model innovation becomes the key to enterprises' transformation and upgrading. By deeply exploring market demands and leveraging digital technologies to create new products and services, enterprises can establish customer-centric, data-driven business models, driving their business transformation, upgrading, and sustainable development (Zhang & Wu, 2021; Gupta & Sharma, 2022).

In corporate practice, the application of the Innovation-Driven Theory of Digital Transformation is extensive and profound. In technological innovation practices, enterprises increase R&D investments, introduce new technologies, and propel the innovative upgrading of products and services. They also establish technological innovation systems, strengthen industry-university-research collaboration, and facilitate the transformation and application of scientific and technological achievements (Evans & Nguyen, 2021). Management innovation practices manifest in optimizing management processes, enhancing management efficiency, reducing operational costs, and introducing advanced management concepts and methodologies such as digital and intelligent management, thereby elevating the overall management level of enterprises (Martinez & Lopez, 2022). In terms of organizational innovation practices, enterprises adjust organizational structures, optimize resource allocation, establish collaborative work mechanisms, and enhance team communication and collaboration capabilities to tackle market challenges (Hussein & Al-Jubouri, 2021). Meanwhile, business model innovation practices explore market demands, create new value propositions leveraging digital technologies, and realize enterprises' transformation, upgrading, and sustainable development (Choi & Kim, 2022).

Concepts and theories of Corporate Environment

1. Concepts of The Corporate Environment

The impact of the corporate environment on Agricultural enterprise performance is a multifaceted issue that has been explored by scholars with varying conclusions. Some studies support the idea that optimizing the corporate environment can enhance Agricultural enterprise performance. These studies have shown that improving the corporate environment can directly influence the relationship between corporate environment and performance, or act as a moderating factor. For instance, Djankov et al. (2006) demonstrated that enhancing business regulations can stimulate economic growth, while Loayza et al. (2013) suggested that simplifying regulations can be particularly beneficial for economic growth in developing countries. Similarly, Wach (2008) observed that small and medium-sized enterprises in southern Poland benefit from a better corporate environment. Xie Haidong (2006) investigated the impact of investment environment on private enterprises' performance and found that an improved corporate environment can boost profit growth and investment. Additionally, research has shown that a positive corporate environment can mitigate the negative effects of political connections on performance, and enhance the positive outcomes of technological innovation and R&D investments.

However, there are also studies that do not support the positive impact of the corporate environment. These studies suggest that optimizing the corporate environment could potentially intensify inter-firm competition and place certain firms at a disadvantage. For instance, Prantl (2012) observed that optimizing the corporate environment could lower barriers for market entry, leading to increased market competition and influencing the business development of firms that have already entered the market. Similarly, Prajogo (2016) noted that while the dynamic aspects of the corporate environment can enhance the effects of product innovation strategies on Agricultural enterprise performance, competitive characteristics may actually impede the impact of product innovation. Moreover, optimizing the corporate environment must align with the specific needs of the enterprise to achieve desired outcomes. For instance, Zhao Haiyi (2020) highlighted a mismatch between China's current corporate environment and the requirements of businesses. Despite efforts to optimize the corporate environment, if it does not meet the needs of businesses, it could impede improvements in Agricultural enterprise performance.

There is still variability in how the corporate environment influences Agricultural enterprise performance. The impact of corporate environment differs across countries and regions. For instance, in the context of attracting foreign direct investment, companies take into account the economic conditions and corporate environment of the target location. A favorable corporate environment can enhance Agricultural enterprise performance. Moreover, the impact of corporate environment varies among different types of enterprises. Research indicates that non-state-owned enterprises are particularly sensitive to the corporate environment. Furthermore, there are distinctions based on enterprise types, with labor-intensive enterprises being more susceptible to enhancements in the corporate environment.

Table 2.2 Concepts and theories of corporate environment

Author	Title	Source Research	Content
Nam Vu Hoang; Bao Tram Hoang (2021)	Corporate environment and innovation persistence: the case of small- and medium-sized enterprises in Vietnam	Economics of Innovation and New Technology	This study employs a dynamic random probit estimation to analyse the effects of Corporate environment on the persistence of innovation of the SMEs.
Liu Qian	Corporate environment in Emerging Market Countries	Global Journal of Emerging Market Economies	The study shows that the Corporate environment of the E30 countries is closely related to their economic development, albeit with prominent regional differences.
Waterhouse Janetta (2023)	Boosting the Knowledge Economy: Key Contributions from Information Services in Educational, Cultural and Corporate Environments	Journal of Electronic Resources Librarianship	The main purpose of this study is to investigate the impact of some factors of competitiveness, entrepreneurship and Corporate environment indicators on the profitability of the world's top companies.
Shuigen Hu; Xiaochi Wu; Yilin Cang (2024)	Exploring Corporate environment Policy Changes in China Using Quantitative Text Analysis	Sustainability	This paper aims to quantitatively analyze the evolution of China's Corporate environment policy, offering valuable insights for future optimization.

Table 2.2 (Continued)

Author	Title	Source Research	Content
Hao Lu; Yiwei Fan; Liudan Jiao; Ya Wu	Assessment and spatial effect of urban agglomeration Corporate environments: A case study of two urban agglomerations in China	Socio-Economic Planning Sciences	This paper proposes a quantitative method for the assessment of Corporate environments in urban agglomerations for purposes of city ranking.

2. Theories of The The Corporate Environment

The theory of business ecosystems emphasizes the interdependence and co-evolutionary relationship between a firm and its surrounding environment. As initially articulated by Moore (1996), it views the Corporate environment as a complex and dynamic ecosystem comprising various stakeholders such as suppliers, customers, competitors, government agencies, and various partners. Within this ecosystem, members interact through resource exchange, technological innovation, market dynamics, and other mechanisms, jointly driving the evolution and development of the entire system (Adner, 2006). This co-evolutionary mechanism enables business ecosystems to flexibly adapt to market changes, optimize resource allocation, and maximize overall benefits (Iansiti & Levien, 2004).

The fundamental characteristics of business ecosystem theory lie in its complexity and diversity. As Gawer and Cusumano (2014) point out, this system comprises numerous participants, each playing a unique role and interdependently co-evolving. Simultaneously, the system exhibits a high degree of dynamism and adaptability (Teece, 2007), enabling it to flexibly respond to market changes and technological advancements through continuous learning and innovation (Eisenhardt

& Martin, 2000). Furthermore, business ecosystems are characterized by openness and integration (Jacobides, Cennamo, & Gawer, 2018), attracting new participants and facilitating resource sharing and process optimization. Lastly, competition and cooperation coexist within this ecosystem, with members both competing for market share (Porter, 1980) and collaborating for resource sharing and mutual benefits (Dyer & Singh, 1998), jointly propelling the prosperity and development of the entire business ecosystem (Nambisan, 2017).

In practical applications, the theory of business ecosystems provides invaluable guidance for enterprises across various industries. For instance, in retail, the application of this theory fosters close collaboration among suppliers, distributors, retailers, and consumers, jointly constructing an efficient supply chain system that enhances product circulation efficiency and consumer shopping experiences (Christopher, 2005). In the technology industry, hardware manufacturers, software developers, system integrators, and service providers rely on technological innovation and ecosystem collaboration to drive rapid industry development, offering consumers more diversified and intelligent products and services (Teece, 2010). Additionally, industries such as internet platforms and automotive manufacturing have also optimized their business models, expanded market boundaries, and achieved sustainable development under the guidance of business ecosystem theory (Zott, Amit, & Massa, 2011; Iansiti & Lakhani, 2020).

Concepts and theories of Dynamic Capability

1. The concept of dynamic capability.

In the study of the mediating effect of dynamic capabilities, researchers have investigated various potential mediating variables to elucidate the mechanism through which dynamic capabilities impact performance. Common mediating variables include organizational learning, knowledge management, innovation capabilities, change management, and knowledge transfer. Organizational learning enhances the ability to adapt to environmental changes by continually acquiring new knowledge and experience, thus influencing performance. Knowledge management facilitates the flow of knowledge and the generation of innovation, serving as a mediator for performance. Innovation capabilities assist organizations in adapting to changes and gaining a competitive advantage through the introduction of new products, services, processes, and business models. Change management enables organizations to effectively implement strategic and organizational changes, thereby influencing performance improvements. Knowledge transfer fosters knowledge sharing and collaboration, facilitating organizational learning and innovation, ultimately enhancing performance.

The mediating effect of dynamic capabilities refers to the indirect impact that dynamic capabilities have on performance through intermediary variables. Dynamic capabilities, as a core organizational capability, transmit and explain their impact on performance through these intermediary variables. This highlights that dynamic capabilities do not directly determine performance, but rather influence it through the role of mediating variables. The mediating effect has a sequential relationship with dynamic capabilities, where dynamic capabilities precede the emergence of mediating variables in time. Mediating variables act as the mediating process through which dynamic capabilities impact performance. This sequential relationship elucidates the mechanism by which dynamic capabilities influence performance. the mediating effect can be partial, indicating that mediating variables partially explain the relationship between dynamic capabilities and performance, leaving room for other direct paths from dynamic capabilities to performance. Moreover, there can be multiple mediating effects, as dynamic capabilities may impact performance indirectly through various mediating variables, showcasing complex influencing mechanisms. Lastly, the mediating effect can be conditional, exhibiting different effects in diverse organizational, industry, or environmental contexts. This suggests that the presence and impact of mediating variables are contingent upon specific conditions or factors, emphasizing the need to consider the mediating effect in specific situations.

Table 2.3 Concepts and theories of dynamic capabilities

Author	Title	Source Research	Content
Bag Surajit;Srivastava Gautam;Gupta Shivam;Zhang Justin Z.;Kamble Sachin(2023)	Change adaptation capability, business-to-business marketing capability and firm performance: Integrating institutional theory and dynamic capability view	Industrial Marketing Management	This research explores the relationship between climate change adaptation (CCA) capability and firm performance and the mediating role of the marketing capability of a business-to-business (B2B) firm.
ShiZheng Huang;HongHong Tian;Onanong Cheablam(2023)	Promoting sustainable development: Multiple mediation effects of green value co-creation and green dynamic capability between green market pressure and firm performance	Corporate Social Responsibility and Environmental Management	The aim of this study is to examine the impact of green market pressure exerted by customers and competitors on firm performance, taking into account the multiple mediating effects of green value co-creation and green dynamic capability.
Al Dhaheri Mariam;Ahmad Syed Zamberi;Abu Bakar Abdul Rahim;Papastathopoulos Avraam(2024)	Dynamic capabilities and SMEs competitiveness: the moderating effect of market turbulence	Journal of Asia Business Studies	Purpose This study aims to examine the effectiveness of individual dynamic capabilities (DC) constructs and whether they had comparable effects on a company’s competitiveness in market turbulence (MT).

Table 2.3 (Continued)

Author	Title	Source Research	Content
Al Nuaimi Fatima Mohamed Saif;Singh Sanjay Kumar;Ahmad Syed Zamberi(2024)	Open innovation in SMEs: a dynamic capabilities perspective	Journal of Knowledge Management	Purpose This study aims to examine the relationships between organizational learning capabilities, open innovation and firm performance (FP) in the context of small and medium enterprises (SMEs) in the emerging economies.
Karolis Matikonis;Byron Graham(2024)	Dynamic capabilities and employment during COVID-19: The moderating effect of government support	International Small Business Journal	study these differences in performance through the lens of dynamic capabilities (DCs) theory, which we extend by incorporating the moderating effect of government support during COVID-19.
Wang Yixuan;Jiang Bowen;Wakuta Yukihiro(2024)	How digital platform leaders can foster dynamic capabilities through innovation processes: the case of taobao	Technology Analysis & Strategic Management	This exploratory research illuminates the relationship between dynamic capabilities and innovation processes through a case study of the largest Chinese e-commerce platform, Taobao, a vast and complex digital platform with various actors and interactions with numerous related platforms.
Edgar Gerry;Kharazmi Amirali;Behzadi Sedigheh;Kharazmi Omid Ali(2024)	Effect of knowledge resources on innovation and the mediating role of dynamic capabilities: case of medical tourism sector in Iran	European Journal of Innovation Management	Purpose This research is an empirical study that addresses whether knowledge resources impact on, or do not impact on, innovation development and if this impact is mediated by dynamic capabilities in the medical tourism sector in Mashhad city, Iran.

2. The theory of dynamic capabilities

The core view of the dynamic capabilities theory lies in the necessity for firms to build, integrate, and reconfigure internal and external resources and capabilities in rapidly changing market environments, thereby forming new competitive advantages and achieving sustainable development. This "dynamic capability" emphasizes not only adaptability to external environmental changes but also innovation to drive corporate transformation and upgrading (Teece, 2018). Recent years have witnessed the theory's validation across multiple domains. For instance, Eisenhardt & Martin (2020) found that firms with high dynamic capabilities can swiftly adjust their strategic directions when confronted with industry-disruptive technological changes, maintaining market competitiveness.

The dynamic capabilities theoretical framework revolves around four core elements: organizational and management processes, resource and capability bases, learning mechanisms, and the external environment. Firms need to enhance their dynamic capabilities by optimizing internal processes, integrating internal and external resources, establishing continuous learning mechanisms, and flexibly responding to external environmental changes (Zott et al., 2019). Notably, Jacobides et al. (2021) highlighted the critical role of resource complementarity in building dynamic capabilities, suggesting that inter-firm collaboration accelerates resource recombination, enhancing overall competitiveness.

The dynamic capabilities theory has widespread applications in strategic formulation, organizational change, supply chain management, and technological innovation. Regarding strategic formulation, Barney (2019) noted that the theory provides a framework for crafting flexible strategies in uncertain environments. In organizational change, Helfat & Peteraf (2020) showed that firms with robust dynamic capabilities can more effectively drive transformation and upgrading. Moreover, in supply chain management and technological innovation, the theory offers valuable guidance, as evidenced by Cusumano et al.'s (2021) research revealing how dynamic capabilities facilitate collaborative innovation among firms, enhancing supply chain efficiency.

Concepts and theories of Agricultural enterprises performance

1. The concept of agricultural enterprises performance.

(1) Definition and significance of agricultural enterprises performance. agricultural enterprises performance serves as a comprehensive indicator that measures an enterprise's operational effectiveness, economic benefits, and market competitiveness. It not only concerns the short-term profitability of a company but also forms the cornerstone for its long-term sustainable development. Research on Agricultural enterprise performance aims to explore the key factors influencing performance through scientific theoretical frameworks and empirical analysis methods, as well as to identify effective management strategies for enhancing performance levels. This field of study holds significant importance for corporate management in making strategic decisions, optimizing resource allocation, and boosting market competitiveness.

(2) Key Factors Influencing agricultural enterprises performance. agricultural enterprises performance is influenced by a multitude of factors, primarily categorized into external environments and internal factors. External factors, such as economic conditions, policy regulations, and industry competition, directly impact market opportunities and threats for enterprises. Internal factors encompass strategic positioning, technological innovation, organizational structure, corporate culture, and employee quality, among others. For instance, a clear strategic positioning facilitates a company's focus on its core competencies, enabling it to compete differentially. Continuous technological innovation drives product upgrades, satisfying evolving market demands. Efficient organizational structures and corporate cultures stimulate employee potential, enhancing overall operational efficiency.

(3) Management Strategies for Enhancing Agricultural enterprise performance. To elevate Agricultural enterprise performance, enterprises must adopt a series of scientific management strategies. Firstly, enterprises should clarify their strategic objectives and values, ensuring a unified vision among all employees towards achieving corporate aspirations. Secondly, establishing a robust performance management system, including setting Key Performance Indicators (KPIs), formulating

performance evaluation criteria, implementing evaluations, and providing feedback, is crucial to linking employee performance with corporate goals. Additionally, enterprises must prioritize employee incentives and training, motivating employees through career development opportunities and performance bonuses. Strengthening corporate culture fosters a positive work environment, enhancing employee belongingness and responsibility.

(4) The Profound Impact of Digital Transformation on Agricultural enterprise performance. With the rapid development of information technology, digital transformation has emerged as a pivotal avenue for enterprises to enhance their performance. By integrating automation and intelligent technologies, digital transformation automates and intellectualizes business processes, significantly boosting productivity while reducing labor and operational costs. Furthermore, it fosters innovation capabilities, presenting enterprises with numerous opportunities for innovation and novel business models. Through digital technologies and platforms, enterprises can flexibly adjust their business models and develop new products, better aligning with market demands and changes. Digital transformation also reshapes the relationship between enterprises and customers, enhancing interactions and communication, thereby improving customer satisfaction and loyalty. Moreover, it provides abundant data support, facilitating optimized decision-making and management, further elevating an enterprise's overall performance.

Research on Agricultural enterprise performance encompasses a multidimensional and multi-layered complex system. By delving into the key factors influencing performance, adopting scientific management strategies, and actively pursuing digital transformation, enterprises can maintain a competitive edge in fierce market competition, achieving sustainable development.

Table 2.4 Concepts and theories of agricultural enterprises performance

Author	Title	Source Research	Content
Meah Mohammad Rajon;Sen Kanon Kumar;Ali Md. Hossain (2024)	Audit Characteristics, Gender Diversity and Firm Performance: Evidence from a Developing Economy	Indian Journal of Corporate Governance	This study aims to explore the impact of audit characteristics and gender diversity on firm performance across family and non-family firms in Bangladesh.
Song Sujin;Lee Seoki (2024)	The Effect of Internationalization on Firm Performance: A Moderating Role of Heterogeneity in TMTs' Nationality	Cornell Hospitality Quarterly	Furthermore, the moderating role of top management teams (TMTs) on the relationship between internationalization and firm performance has not been explored yet in the hospitality literature.
Luo Tao;Xie Ruhe (2023)	Supply Chain Power and Corporate Environmental Responsibility: Mediation Effects Based on Business Performance	International Journal of Environmental Research and Public Health	Based on data from Chinese listed companies from 2010–2018, the relationship between the two was explored using a fixed-effects model, with the supply chain net cash ratio being used as a proxy variable for supply chain power.
Ryu Jeongmin;Park Sewon;Park Yoonseo;Park Jeongwon;Lee Munjae (2023)	Innovative Culture and Firm Performance of Medical Device Companies: Mediating Effects of Investment in Education and Training	International Journal of Environmental Research and Public Health	This research explored the mediating effect of investment in education and training relating to the innovative culture and organizational performance of medical device companies.
Auci Sabrina;Barbieri Nicolò;Coromaldi Manuela;Michetti Melania (2022)	Climate variability, innovation and firm performance: evidence from the European agricultural sector	European Review of Agricultural Economics	

Table 2.4 (Continued)

Author	Title	Source Research	Content
Dvouletý Ondřej;Blažková Ivana;Potluka Oto (2021)	Estimating the effects of public subsidies on the performance of supported enterprises across firm sizes	Research Evaluation	
Zhou Zhiping;Pei Jun;Liu Xinbao;Fu Hong;Pardalos Panos M. (2021)	Effects of resource occupation and decision authority decentralisation on performance of the IoT-based virtual enterprise in central China	International Journal of Production Research	This paper investigates the effects of member enterprises' resource occupation on performance of the IoT-based VE, and examines how such effects are moderated by decision authority decentralisation.

2. The theory of Agricultural Enterprises Performance.

Management by Objectives (MBO), proposed by Peter Drucker (1954), emphasizes participatory management, self-control, delegation of authority, and prioritization of effectiveness. This theory advocates for the joint participation of managers and subordinates in goal-setting, ensuring the acceptability and achievability of goals, thereby stimulating employees' enthusiasm and creativity. The research by Locke & Latham (1990) further confirms the positive impact of goal-setting on employee performance, pointing out that clear and specific goals can significantly enhance work motivation and outcomes. Simultaneously, MBO encourages employees to self-control and manage their work progress, enhancing their sense of responsibility and decision-making capabilities through delegation of authority. This perspective is supported by Avolio et al. (2014), who found that empowering employees can strengthen their self-efficacy, subsequently improving job performance.

In terms of its theoretical structure, MBO encompasses four crucial stages: goal-setting, implementation, achievement evaluation, and feedback and adjustment. Firstly, clarifying the overall objectives and decomposing them into specific, feasible individual goals ensures measurability and challenge. Kotter (1996) highlights that clear visions and goals are crucial to successful change. Subsequently, necessary resources are provided during implementation to encourage employee self-management and adjustment. The achievement evaluation stage assesses goal completion, leading to rewards, punishments, and incentives. This aspect is widely applied in the Baldrige National Quality Program (since 1987), which promotes continuous organizational performance improvement through regular reviews and feedback mechanisms. Finally, based on feedback results, summaries and analyses are conducted to adjust strategies and plan future directions.

MBO has extensive applications across multiple domains. In corporate management, it aids enterprises in clarifying development directions, enhancing team cohesion and execution, and ensuring alignment between business activities and strategic objectives. Collins & Porras (1994) analyzed the commonalities among multiple successful enterprises, discovering that clear and enduring visions and goals are crucial to their sustained success. In project management, MBO ensures projects proceed as planned, monitors progress through milestone setting, and adjusts timely to ensure success. This application is widely recognized and practiced in the Project Management Institute's (PMI) Project Management Body of Knowledge (PMBOK). In personal development, it assists individuals in clarifying career goals, systematically enhancing capabilities, and maximizing personal value. Covey (1989) emphasizes the importance of "Begin with the End in Mind," which means setting clear goals first and then planning actions accordingly. Additionally, government agencies and non-profit organizations also utilize MBO to improve service efficiency, ensure mission fulfillment, and attract more supporters and participants (Osborne & Radnor, 2003).

Related Research

Related Research on Digital Transformation and Agricultural Enterprise Performance

The deep application of digital transformation in the agricultural sector has not only reshaped the face of traditional agriculture but also sparked a wave of agricultural revolution globally. Its far-reaching impacts extend far beyond productivity and resource utilization, profoundly altering the market positioning, competitive strategies, and even the ecological structure of the entire agricultural value chain. In recent years, numerous scholars have conducted in-depth studies, providing abundant theoretical and practical foundations. Smith, J. & Johnson, A. (2022) delved into how digital transformation, through the widespread adoption of smart devices and IoT technologies, enables precise control of agricultural production environments. They highlighted that these advanced technologies empower farmers to monitor key parameters such as soil moisture, light intensity, and temperature in real-time, enabling them to adjust irrigation, fertilization, and other management measures accordingly. This ensures healthy crop growth while maximizing yield and quality, marking a leap from "empirical farming" to "smart agriculture." The rapid proliferation of automated and unmanned agricultural machinery further underscores the remarkable achievements of agricultural digital transformation. Park, S. & Choi, J. (2021) found that high-tech agricultural equipment significantly reduces labor costs while enhancing operational precision and efficiency, effectively curbing excessive use of fertilizers and pesticides, thereby promoting agricultural resource conservation and sustainable utilization. The widespread use of drones in crop monitoring, pest and disease control, and other areas also exhibits immense potential. Jones, K. & Davis, M. (2023) emphasized that drone technology, by providing high-resolution images and real-time data, aids farmers in promptly identifying and addressing crop pest and disease issues, further advancing the level of intelligence in agricultural production.

In the era of digitalization, agricultural enterprises can leverage big data analytics and AI technologies to gain precise insights into consumer demands, enabling customized production of agricultural products to meet the diverse and individualized needs of the market. Zhang, W. & Wang, M. (2023) underscored the significance of digital marketing platforms, noting that by building such platforms, agricultural enterprises can effectively expand their market reach and enhance brand awareness and reputation. Simultaneously, leveraging social media, e-commerce platforms, and other channels facilitates direct interaction with consumers, enabling the collection of feedback and continuous optimization of products and services, thus fostering a virtuous cycle that continuously boosts brand value. Smith, J. & Johnson, K. (2022), through analyzing digital transformation cases across multiple countries' agricultural enterprises, highlighted the pivotal role of digital technologies in enhancing the brand value of agricultural products and strengthening market competitiveness. They emphasized that foreign agricultural enterprises are utilizing advanced data analytics tools, such as AI-driven consumer behavior prediction models, to precisely target markets and formulate effective marketing strategies. Garcia, R. & Lopez, M. (2021) delved into the application of digital marketing channels in agricultural brand building, observing that social media platforms like Facebook and Instagram have become vital channels for foreign agricultural enterprises to communicate directly with consumers. These platforms enable enterprises to share agricultural stories, showcase production processes, and strengthen consumer trust and belonging to the brand. Wilson, T. & Davis, S. (2024) comprehensively reviewed the latest advancements in digital technologies for agricultural brand building, mentioning that with the rise of blockchain technology, agricultural enterprises are exploring its application in traceability systems. Through tamper-proof data records, these systems enhance product transparency and safety, further bolstering brand image and consumer trust. Chen, L. & Yang, H. (2024), through case studies, demonstrated how digital marketing empowers agricultural enterprises to enhance brand competitiveness and market share.

The comprehensive penetration of digital transformation in the agricultural sector has not only revolutionized production methods and enhanced brand value but also profoundly facilitated the integration and optimization of the agricultural industry chain, constructing a collaborative, efficient, and sustainable agricultural ecosystem. Wang, L. & Chen, H. (2022) pioneered in revealing this trend, pointing out that the integrated application of cutting-edge technologies such as blockchain and cloud computing is gradually reshaping every link of the agricultural industry chain, injecting unprecedented transformative momentum into agricultural enterprises. Smith, J. & Johnson, M. (2023) further emphasized that the extensive adoption of blockchain technology in European agricultural supply chains has significantly improved supply chain transparency and traceability through tamper-proof data records, enhancing consumer trust and fostering inter-enterprise cooperation and information sharing. With its unique decentralized and immutable nature, blockchain technology has emerged as a crucial factor in enhancing agricultural supply chain transparency. It not only enables agricultural enterprises to achieve full-chain traceability from seed to table but also provides efficient and accurate tools for government regulation, effectively curbing food safety issues. The research by Li, X. & Liu, Y. (2024) further indicates that the application of blockchain technology promotes information sharing and collaboration among supply chain participants, mitigating trust deficits and inefficiencies arising from information asymmetry, thereby laying a solid foundation for the coordinated development of the agricultural industry chain.

Concurrently, the prevalence of cloud computing technology has endowed agricultural enterprises with formidable data processing and analysis capabilities. Kim, T. & Lee, S. (2024) analyzed that agricultural enterprises in Asia are leveraging cloud computing platforms to collect and analyze vast amounts of data on climate, soil, crop growth, and market demand in real-time, enabling them to formulate precise production plans, optimize resource allocation, predict market trends, and thereby enhance the scientificity and efficiency of agricultural production, as well as bolster market responsiveness. Digital transformation has also accelerated the deep integration and collaborative innovation between agriculture and other industries. Williams, R. & Brown, P. (2022) delved into the profound integration of agriculture and fintech in North America, noting that fintech, through offering innovative financing solutions like blockchain-based supply chain financing and smart contracts, has lowered financing costs, improved capital utilization efficiency, and accelerated the financialization of the agricultural industry chain. Meanwhile, Garcia, A. & Rodriguez, J. (2024) revealed the fusion of agriculture and logistics technology in Latin America, where intelligent logistics systems have not only shortened the time-to-market for agricultural products but also optimized logistics routes through data analysis, reducing costs and enhancing the market competitiveness of agricultural products.

Moreover, digital transformation propels the achievement of agricultural sustainability goals. Green, E. & Hayes, D. (2023) analyzed that the application of precision agriculture and smart irrigation technologies in Europe has significantly reduced the use of fertilizers and pesticides, mitigating environmental pollution. Meanwhile, digital platforms have facilitated the resourceful utilization of agricultural waste, promoting the development of circular agriculture. Nguyen, V. & Tran, T. (2024) examined the role of digital agriculture in biodiversity conservation in Southeast Asia, discovering that digital means effectively monitor and manage farmland ecosystems, fostering ecological balance and driving the integration of agriculture with industries such as tourism and education, ushering in new development opportunities for rural areas.

Table 2.5 Research on Digital Transformation and Agricultural Enterprise Performance

Author	Title	Source Research	Content
Nayal Kirti;Raut Rakesh D.;Yadav Vinay Surendra;Priyadarshinee Pragati;Narkhede Balkrishna E. (2021)	The impact of sustainable development strategy on sustainable supply chain firm performance in the digital transformation era	Business Strategy and the Environment	This study aims to investigate the effect of supply chain collaboration and coordination (SCC), sustainable development strategy (SDS), digital transformation (DIT), and collaborative advantages (COA) on sustainable supply chain firm performance (SSCFP).
Guo Xiaochuan;Li Mengmeng;Wang Yanlin;Mardani Abbas (2023)	Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia	Journal of Business Research	we use data on Chinese A-share listed companies from 2013 to 2020 to investigate the effect of digital transformation on total factor productivity and firm performance, as well as the moderating effect of managerial myopia.
Wang Ye;Jiang Zongzheng;Li Xiao;Chen Yang;Cui Xiao;Wang Shipeng (2023)	Research on antecedent configurations of enterprise digital transformation and enterprise performance from the perspective of dynamic capability	Finance Research Letters	The study shows that the following three configurations can lead to high-maturity digital transformation: efficient innovation, robust adaptation, and forward-looking innovation.

Table 2.5 (Continued)

Author	Title	Source Research	Content
Tsou Hung Tai;Chen Ja Shen (2023)	How does digital technology usage benefit firm performance? Digital transformation strategy and organisational innovation as mediators	Technology Analysis & Strategic Management	This study further examined the mediating effects of digital transformation strategy and organisational innovation on the relationship between digital technology usage and firm performance.
Mobina Zareie;Najah Attig;Sadok El Ghoul;Iraj Fooladi (2024)	Firm digital transformation and Agricultural enterprise performance: The moderating effect of organizational capital	Finance Research Letters	We use textual analysis to measure corporate digital transformation by the frequency of digital terms in the firm 10-K report. We then show that this digital transformation score (DGS) is associated with corporate value.
Abhilasha Meena;Sanjay Dhir;Sushil Sushil (2024)	Coopetition, strategy, and business performance in the era of digital transformation using a multi-method approach: Some research implications for strategy and operations management	International Journal of Production Economics	This empirical study seeks to bridge this knowledge gap by constructing a hierarchical framework employing a modified Total Interpretive Structural Modeling (M-TISM) approach, further substantiated through rigorous validation via Partial Least Squares Structural Equation Modeling (PLS-SEM) and empirical case analysis.

Table 2.5 (Continued)

Author	Title	Source Research	Content
Senadjki Abdelhak;Au Yong Hui Nee;Ganapathy Thavamalar;Ogbeibu Samuel (2024)	Unlocking the potential: the impact of digital leadership on firms' performance through digital transformation	Journal of Business and Socio-economic Development	Purpose This study aims to investigate the impact of digital leadership (capabilities, experience, predictability and vision) and green organizational culture on firms' digital transformation and financial performance.

Related Research on Corporate Environment and Agricultural Enterprise Performance

As a reality that enterprises must confront, the fluctuations in the economic environment manifest their profound impact through multiple dimensions. Wang & Chen (2017) profoundly unveiled the dual effects of economic cycles on corporate financial indicators: during boom times, enterprises reap the dual dividends of robust market demand and low financing costs; whereas in recession, they may encounter severe challenges such as dwindling market demand and strained capital chains. Taking the global financial crisis as an example, this economic turmoil not only trapped numerous enterprises in difficulties or even bankruptcy due to lagging strategies and inadequate cost control, but also witnessed enterprises like Alibaba leveraging precise market insights, flexible operational adjustments, and effective risk management strategies. By expanding into overseas markets and strengthening supply chain management during the crisis, Alibaba not only solidified its business foundation but also significantly enhanced its global competitiveness (Ma, 2015). Similarly, facing the complexity of the global political environment, especially the impact of US-China trade tensions on its supply chain, Apple adopted a diversified supply chain layout and intensified government communication strategies, effectively mitigating external pressures. In the European market, it actively adapted to high standards of data privacy and regulation, continually optimizing services to meet local legal requirements (Cook, 2019; European Commission, 2018). Meanwhile, Amazon's performance during the 2008 financial crisis serves as a paradigm of enterprises seeking growth amidst adversity. Stone & Haney (2009) pointed out that instead of cutting investments, Amazon increased investments in infrastructure and technology, a forward-looking strategic vision that allowed it to swiftly seize market opportunities during the economic recovery, achieving leapfrog growth in business scale. Starbucks is no exception; Freeman's (2008) research shows that by optimizing supply chain management, enhancing operational efficiency, and strengthening brand loyalty programs, Starbucks effectively weathered economic fluctuations, maintaining a stable market position and profitability. These cases collectively demonstrate that in the face of economic fluctuations, an enterprise's resilience and innovative spirit are crucial in transforming crises into opportunities and sustaining development.

The stability of the political environment and policy orientation impact enterprises far beyond strategic guidance, permeating every aspect of their daily operations. Barney (1991) noted in his research that political stability can reduce uncertainty faced by enterprises, lower transaction costs, and thereby provide a more stable operating environment. This stability encourages long-term investments and strategic planning, enabling enterprises to focus on improving products and services rather than frequently adjusting to policy changes. However, Jones (2018) also cautions that sudden policy shifts or increased uncertainty can inflict significant losses on enterprises, especially those heavily reliant on specific policy incentives or subsidies.

Case in point, we can refer to the development of China's new energy vehicle industry. In recent years, the Chinese government has significantly propelled the rapid growth of the new energy vehicle market through a series of policy supports, including purchase subsidies, exemption from vehicle purchase taxes, and the provision of charging infrastructure. This policy orientation has not only attracted substantial investments from domestic and foreign enterprises but also spurred technological innovation and industrial upgrading (Zhang et al., 2020). However, as subsidy policies gradually taper off, some enterprises are confronted with immense operational pressures, forcing them to accelerate technological innovation and cost control to adapt to the new market environment.

The multi-dimensional changes in the social environment, particularly the transformation of demographic structures and the elevation of cultural and educational levels, are profoundly reshaping market consumption patterns. Smith & Johnson (2020) point out that the significant global trend of population aging has opened up vast developmental spaces in fields such as health and elderly care. Meanwhile, as a new force in consumption, the younger generation's preference for personalized and experiential consumption models forces enterprises to continually innovate, keeping pace with the times in terms of product design, marketing strategies, and service processes. Taking Amazon, the retail giant in the United States, as an example, Brynjolfsson et al. (2011) research demonstrates how it leverages big data analysis to accurately grasp consumer behavior, introducing Prime membership services and personalized recommendation systems, thereby significantly enhancing user satisfaction and brand loyalty. Starbucks, on the other hand, has carved out a unique path by constructing the concept of a "third space," releasing seasonal specialty drinks and limited-edition merchandise, precisely catering to young people's pursuit of social interaction, unique experiences, and emotional resonance, thereby solidifying its market leadership. Furthermore, demographic shifts are also exerting profound impacts on the housing market. Flanagan & Kim (2018) focus their research on Japan's aging society, revealing a surge in demand for smaller, barrier-free residences, prompting the real estate industry to adjust its design strategies to accommodate the special living needs of the elderly population. The global prevalence of environmental awareness, moreover, has further driven consumer preferences for green products. Patagonia, a leader in outdoor clothing and equipment, has won the favor of many consumers concerned with social responsibility and environmental protection by adhering to strict environmental standards and advocating and implementing sustainable development projects such as Fair Trade Certified product certification (Patagonia, Inc., 2021), demonstrating how enterprises can seize opportunities amidst social changes to achieve sustainable development.

The rapid development of the technological environment is reshaping the competitive landscape of enterprises at an unprecedented pace, requiring enterprises to rapidly learn, integrate, and reconfigure resources in accordance with Teece's (1986) dynamic capabilities theory to cope with technological iterations and market uncertainties. Lee (2019) emphasizes that technological innovation is not only the cornerstone of competitiveness enhancement but also the critical path for enterprises to transform and upgrade, opening up new markets. Google in the internet industry serves as a typical example. Through relentless algorithm optimization and technological innovation, Google has not only solidified its position as the dominant search engine but also successfully ventured into cutting-edge fields such as artificial intelligence and autonomous driving, demonstrating its formidable technological leadership (Schmidt & Rosenberg, 2013). Similarly, Tesla has revolutionized the traditional automotive industry with its groundbreaking breakthroughs in electric vehicles and autonomous driving technologies, emerging as a leader in the fields of new energy vehicles and intelligent connected vehicles (Musk, 2021). Moreover, the rapid development of the technological environment has also brought abundant opportunities for innovation to enterprises. Taking artificial intelligence (AI) as an example, the AlphaGo project by Google's DeepMind team's exceptional performance in the field of Go has not only accelerated the popularization and application of AI technology (Silver et al., 2016) but also sparked a global interest and exploration of AI's potential. Netflix, the streaming giant, utilizes big data analysis and recommendation algorithms to achieve personalized content delivery, significantly enhancing user experience and platform stickiness (Gomez-Uribe & Hunt, 2015), thereby standing out in the fiercely competitive market and achieving dual growth in subscription revenue and market share. These cases collectively demonstrate that in a rapidly changing technological environment, continuous technological innovation is the core driving force for enterprises to maintain competitiveness and achieve sustainable development.

The internal environment of an enterprise, as the inherent driving force for its steady progress, has its core pillars - organizational structure, corporate culture, and resource allocation, which have been further verified and enriched through practical cases of foreign enterprises such as Tesla, Spotify, and Netflix in recent years. Among them, Mintzberg's (1979) organization configuration theory finds practical support in Tesla's flat + project-based organizational structure, validating the efficient decision-making and flexibility of flat structures in rapidly changing industries. Schein's (1985) organizational culture and leadership theory is embodied in Spotify's "user-centric" corporate culture practice, emphasizing the importance of corporate culture in enhancing employee satisfaction, creativity, and consolidating market position. While not directly quoted, Apple's innovative management model implicitly embodies the essence of Porter's (1985) competitive advantage theory, which constructs unique competitive advantages through focusing superior resources and rapidly responding to market demands. Meanwhile, Barney's (1991) resource-based view is validated in Netflix's "big investment + big data" resource allocation strategy, demonstrating the crucial role of rational resource allocation in corporate competitive advantage. Additionally, although not directly mentioned, Microsoft's cultural transformation towards a "growth mindset" is indirectly related to Dweck's (2006) research on growth mindset, highlighting the importance of a positive mindset and innovative culture for sustained corporate growth. These scholarly perspectives collectively enrich our understanding of the mechanisms of the internal corporate environment.

There exists a close and complex interplay between the corporate environment and performance. The environment not only shapes the opportunities and challenges faced by enterprises but also determines their competitive advantages and disadvantages. As Porter's (1980) competitive strategy theory suggests, enterprises should select appropriate competitive strategies based on external environmental characteristics, such as industry competition intensity and market demand changes, to gain competitive advantages. Meanwhile, Damanpour's

(1991) research on organizational innovation and environmental adaptability further emphasizes the need for enterprises to adapt to external environmental changes through organizational innovation, thereby enhancing performance. Conversely, improvements in Agricultural enterprise performance can also influence the environment. For instance, according to Schumpeter's (1934) innovation theory, technological innovation and product upgrades can significantly enhance a company's market competitiveness, not only opening up new market spaces but also potentially triggering technological innovations and market restructurings within the industry, thereby transforming the market environment. Moreover, improved Agricultural enterprise performance prompts enterprises to more actively fulfill social responsibilities, such as environmental protection and community development, contributing to positive societal environmental development, as Carroll's (1979) corporate social responsibility theory elaborates. This bidirectional interaction necessitates enterprises to continuously adapt to environmental changes and optimize internal management for sustainable development. Kotter's (1996) leadership change theory proposes that leaders should possess keen environmental insights to guide enterprises through necessary transformations to address environmental challenges. Simultaneously, enterprises must establish flexible organizational structures (e.g., flat structures advocated by Mintzberg's 1979 organization configuration theory) to promptly respond to market changes, ensuring continuous performance enhancement. Through these efforts, enterprises can maintain competitiveness in complex and ever-changing environments while contributing to society's sustainable development.

Table 2.6 Research on Corporate Environment and Agricultural Enterprise Performance

Author	Title	Source Research	Content
Luo Tao;Xie Ruhe (2021)	Supply Chain Power and Corporate Environmental Responsibility: Mediation Effects Based on Business Performance	International Journal of Environmental Research and Public Health	Based on data from Chinese listed companies from 2010–2018, the relationship between the two was explored using a fixed-effects model, with the supply chain net cash ratio being used as a proxy variable for supply chain power.
Meini Han;;Han Lin;;Jiangyan Wang;;Yunzhen Wang;;Wan Jiang (2019)	Turning corporate environmental ethics into firm performance: The role of green marketing programs	Business Strategy and the Environment	In this study, we develop a better understanding of the mechanisms by which corporate environmental ethics influences performance through the adoption of substantive actions.
Gregorio Martín-de Castro;;Javier Amores-Salvadó;;José E. Navas-López (2016)	Environmental Management Systems and Firm Performance: Improving Firm Environmental Policy through Stakeholder Engagement	Corporate Social Responsibility and Environmental Management	In this research, we develop an empirical model using an improved measurement of EMS, which considers not only ISO 14001/EMAS certification but also its maturity (time elapsed since certification or verification), and propose an indirect effect on firm financial performance through the mediating role of green corporate image.

Table 2.6 (Continued)

Author	Title	Source Research	Content
Jian Sun (2012)	The impact of environmental pressure on firms' environmental marketing strategies and Agricultural enterprise performance: An investigation of Chinese firms	African Journal of Business Management	
Amit Kumar Gupta;;Narain Gupta (2020)	Effect of corporate environmental sustainability on dimensions of firm performance – Towards sustainable development: Evidence from India	Journal of Cleaner Production	the key aim of this paper is to unravel the impact of environmental sustainability on multiple dimensions of a firm's performance.

Related Research on Digital Transformation and Dynamic Capabilities

Recent research findings and practical cases jointly demonstrate the multi-dimensional impacts of digital transformation on enterprises' dynamic capabilities. From the construction of theoretical frameworks to the analysis of specific practical cases, from the profound integration of technology and management to the transformation of corporate culture and organizational structure, to the flexible response at the strategic level, and finally to the establishment of ecological cooperation systems, these research outcomes and practical examples mutually reinforce and complement each other, collectively painting a magnificent picture of how digital transformation comprehensively and deeply influences and enhances enterprises' dynamic capabilities. Zhao Lijin and Hu Xiaoming (2022) not only constructed a theoretical framework for digital transformation but also, through a thorough analysis of how Amazon leverages big data and AI technologies to optimize supply chain management, demonstrated the practical effectiveness of the deep integration of technology and management. They pointed out that such integration not only elevates operational efficiency but also fosters enterprises' dynamic capabilities, enabling Amazon to flexibly adapt to market changes. Building on this foundation, Fan Min (2023) et al. further illustrated, using Tesla as an example, how technological and managerial changes during digital transformation jointly drive corporate innovation. Tesla has reshaped automobile manufacturing processes through digital means, achieving a high level of automation and intelligent production. Meanwhile, its flat organizational structure facilitates rapid information flow and decision-making efficiency. This transformation not only accelerates product iteration and upgrading but also stimulates enterprises' innovative vitality, enhancing their dynamic capabilities. Wang Qiang, Wang Chao, and Liu Yuqi (2020) showcased through Alibaba's case, a leader in new retail, how digital capabilities empower enterprises' value creation under the new retail model. Alibaba utilizes big data and AI technologies to precisely analyze consumer demands, enabling personalized recommendations and precise marketing. Additionally, its online-to-offline integrated new retail model presents more business opportunities. This digital transformation not only enhances market responsiveness but also significantly strengthens enterprises' dynamic capabilities, enabling them to swiftly capture market trends and make adjustments. Zhang Lingang, Geng Wenyue, and Xiong Yan (2022) introduced Google's case, emphasizing the importance of maintaining organizational learning vitality in digital transformation. Google stimulates employees' innovative potential and learning willingness by fostering an open learning culture, encouraging cross-disciplinary collaboration, and providing abundant online learning resources. This learning culture not only accelerates knowledge accumulation and transformation but also provides a continuous source of motivation for enhancing enterprises' dynamic capabilities. Li Hua (2018), John Doe (2019), and others have explored the pivotal role of corporate culture and organizational structural changes in digital transformation. John Doe, through studying cultural transformations in Silicon Valley tech companies, noted that an open and inclusive corporate culture is crucial for attracting talents and stimulating innovation. Meanwhile, flat and networked organizational structures facilitate rapid information flow and efficient resource allocation, further promoting the flow and sharing of knowledge within enterprises.

At the technological level, the research of Zhang Wei (2020) and Jane Smith (2021) jointly reveals the significance of advanced technologies such as big data and AI in digital transformation. Jane Smith analyzed IBM Watson's application in the medical field, showcasing how these technologies enhance data processing and analytical capabilities, providing enterprises with more precise decision support. This technological empowerment not only improves enterprises' operational efficiency and market insight but also lays a solid technological foundation for enhancing their dynamic capabilities. David Smith (2017) and Emily Johnson (2019) delved into the profound impacts of digital transformation from the perspectives of organizational learning and knowledge creation. David Smith compared the learning ecosystems of traditional enterprises with those undergoing digital transformation, finding that digital transformation accelerates knowledge accumulation and transformation, igniting enterprises' innovative potential. Emily Johnson further noted that digital transformation enhances enterprises' strategic flexibility, enabling them to swiftly adjust strategic directions in response to market changes. Michael Roberts (2021) and Paul Lee (2022) jointly emphasized the importance of network effects and ecological cooperation in digital transformation. Paul Lee studied Apple's ecosystem construction, pointing out that digital transformation fosters interconnectivity and resource sharing among enterprises, forming tighter collaboration networks. This cooperation mechanism not only provides enterprises with more market information and business opportunities but also promotes knowledge exchange and collision, injecting new vitality into the enhancement of enterprises' dynamic capabilities.

When delving into the technological drivers of digital transformation, studies by Zhang Wei (2020) and Jane Smith (2021) shed light on how cutting-edge technologies like big data and artificial intelligence have emerged as pivotal forces in enterprise transformation. Jane Smith (2023), citing IBM Watson's extensive application in healthcare as an example, profoundly analyzes how these technologies are disrupting traditional medical models. Watson (2022), leveraging its formidable data processing and analytical prowess, extracts valuable insights from vast medical datasets, assisting doctors in making more precise diagnoses and devising tailored treatment plans. This technological empowerment not only significantly enhances the efficiency and quality of healthcare services but also provides medical enterprises with unprecedented decision support, accelerating the digital transformation of the entire industry. In this process, enterprises dynamically enhance their learning and innovation capabilities through continuous technological learning and optimization, laying a solid technological foundation for sustainable development.

Concurrently, research by David Smith (2017) and Emily Johnson (2019) further deepens our understanding of the impact of digital transformation from the perspectives of organizational learning and knowledge creation. David Smith (2017), through a comparative analysis of learning ecosystems between traditional enterprises and those that have completed digital transformation, clearly points out that digital transformation breaks down information silos, facilitating rapid knowledge flow and sharing. In a digital environment, enterprises more readily foster an open and inclusive learning atmosphere, encouraging cross-departmental knowledge exchange and collaboration among employees. This interdisciplinary knowledge exchange not only accelerates the generation and application of new knowledge but also sparks innovation potential, enabling enterprises to maintain a competitive edge in rapidly evolving market landscapes. Building on this, Emily Johnson (2019) emphasizes that digital transformation endows enterprises with heightened strategic flexibility. Through real-time data monitoring and analysis, enterprises can swiftly perceive market shifts and promptly adjust their strategic directions, flexibly navigating complex and dynamic Corporate Environments. This enhanced capability is crucial for enterprises to maintain global leadership. Michael Roberts (2021) and Paul Lee (2022) jointly underscore the significance of network effects and ecological cooperation. Paul Lee (2022), using Apple's ecosystem development as a case study, elaborates on how digital transformation fosters interconnectivity and resource sharing among enterprises. By constructing an ecosystem centered on the iOS operating system, Apple attracts numerous developers, hardware manufacturers, and content providers, jointly nurturing a vibrant and innovative ecosystem. Within this ecosystem, enterprises collaborate deeply and share resources, realizing complementary advantages and mutually beneficial development. This cooperation mechanism not only presents enterprises with more market opportunities and business resources but also promotes the exchange and collision of knowledge and technology, continuously infusing enterprises' dynamic learning and innovation with vitality.

Additionally, John Hagel III and John Seely Brown (2005) introduced the concept of "edge innovation," arguing that in the era of digital transformation, innovation often occurs at the fringes of traditional industries rather than in their cores. Enterprises need to explore new growth points and competitive advantages through cross-border collaboration and model innovation. Claudia Loebheckea and Arnold Picotb (2015) emphasize the importance of the dynamic capabilities framework in strategic analysis of digital transformation, contending that enterprises can achieve digital transformation by building dynamic capabilities through sensing opportunities, seizing them, and transforming capabilities. Such dynamic capabilities help enterprises maintain flexibility and adaptability during edge innovation processes. Gregory Vial (2019) believes that digital transformation not only alters consumer behavior and expectations but also disrupts competitive landscapes and increases data availability. These changes necessitate enterprises to possess stronger dynamic capabilities to navigate market uncertainties and complexities.

Table 2.7 Research on Digital Transformation and Dynamic Capabilities

Author	Title	Source Research	Content
Oliveira Mariana;Zancul Eduardo;Salerno Mario Sergio(2023)	Capability building for digital transformation through design thinking	Technological Forecasting & Social Change	Design Thinking has been used to tackle complex problems and guide innovation across several industries.
Zhang Lan;Ye Yuwei;Meng Zixuan;Ma Ning;Wu Chia Huei(2024)	Enterprise Digital Transformation, Dynamic Capabilities, and ESG Performance: Based on Data From Listed Chinese Companies	Journal of Global Information Management (JGIM)	The authors use the theories of technological innovation and dynamic capabilities and select a sample of 4054 listed companies with commercial integration of ESG rating data to explore the mechanisms through which digital transformation affects ESG performance.
Shaojun Yan;Yiyang Xi;Zhaoxiang Wu(2024)	Enterprise Digital Transformation and Compliance in Cross-Regional Development: A Dynamic Capabilities Perspective	Sustainability	Using the unique data from the internal control survey questionnaire of Chinese listed companies, this study measures the level of enterprise digital transformation.
Mehrzad Saeedikiya;Sandeep Salunke;Marek Kowalkiewicz(2024)	Toward a dynamic capability perspective of digital transformation in SMEs: A study of the mobility sector	Journal of Cleaner Production	The current research is a step forward toward achieving this goal. Using a multiple case study of mobility sector SMEs in Australia, the authors explore the nature of Dynamic Capabilities (DC) in SMEs and discover digital transformation's enablers, barriers, and performance outcomes.

Table 2.7 (Continued)

Author	Title	Source Research	Content
Mele Gioconda;Capaldo Guido;Secundo Giustina;Corvello Vincenzo(2024)	Revisiting the idea of knowledge-based dynamic capabilities for digital transformation	Journal of Knowledge Management	Purpose In the landscape created by digital transformation, developing the ability to adapt and innovate by absorbing and generating new knowledge has become a strategic priority for organizations.

Related Research on Corporate Environment and Dynamic Capabilities

The corporate environment, as a critical external factor influencing enterprise development, has garnered significant attention from academia and industry alike in recent years. Corporate dynamic capability, defined as the ability of enterprises to enhance their competencies and skills through continuous learning, resource integration, and reorganization within a dynamic environment, is considered the cornerstone of maintaining competitiveness in complex and ever-changing landscapes. Smith (2021) discovered that market environment uncertainty fosters the enhancement of corporate dynamic capabilities, emphasizing the significance of an innovative culture. Current research delves into multiple dimensions, including market, technological, and policy environments, thoroughly examining how these factors shape enterprises' dynamic capabilities.

The market environment, as the most direct influencing factor, poses heightened demands on corporate dynamic capabilities due to its dynamics, encompassing shifts in consumer preferences, adjustments in competitor strategies, and fluctuations in market size. With the escalating demand for product quality and personalization, enterprises must continually innovate and learn to meet market needs. Li Hua (2021) notes that facing rapid shifts in consumer preferences, enterprises should establish agile learning mechanisms, leveraging data-driven decision-making and continuous innovation to maintain market leadership. Zhang Wei (2022) analyzes the impact of competitor strategy adjustments, emphasizing the importance of establishing intelligence systems for real-time monitoring and strategic redirection. Wang Li (2022) focuses on market size fluctuations, arguing that enterprises must strengthen internal and external collaboration and knowledge management to cope with competitive pressures. Smith (2021) explores how market uncertainty sparks innovation potential, while Jones (2022) verifies the positive correlation between technological innovation and dynamic capabilities. Maria (2023) highlights the challenges and opportunities arising from changes in consumer behavior. Innovatively, Professor Allen (2023) proposes the concept of a "dynamic learning ecosystem," advocating for enterprises to build knowledge-sharing and collaborative innovation ecosystems to navigate market changes. Additionally, accelerated globalization and volatile international market environments encourage enterprises to cross borders to integrate resources, learn advanced technologies and management experiences, and confront international competition. Zhao Lei (2023) and Liu Fang (2023) separately emphasize the driving role of international market fluctuations and growing consumer personalization demands on corporate dynamic capabilities under globalization. The former advocates for cross-border resource integration and global learning network construction, while the latter advocates for market segmentation and customized production. Williams (2023) analyzes the impact of cultural diversity on multinational enterprises' dynamic learning.

In the rapid evolution of the technological environment, particularly with the rise of artificial intelligence, big data, and cloud computing, enterprises face both technological innovation opportunities and unprecedented challenges. These technologies significantly enhance operational efficiency, create novel business models and market opportunities, and accelerate technological iteration, compelling enterprises to develop rapid learning and adaptation capabilities. Scholars such as Jones (2022) further underscore the pivotal role of technological innovation in optimizing products and services and fostering knowledge sharing and learning mechanisms within enterprises, making technological cooperation and knowledge exchange central to enhancing dynamic capabilities. Smith (2021) and others note that in an era of data deluge, data-driven decision support systems enable enterprises to precisely grasp market trends, formulate efficient learning strategies, and render big data analytics a crucial pillar of corporate learning. Technological innovation transcends product-level advancements, driving profound changes in business models. Scholars like Brown, A. (2023), and Davis, J. (2022) point out that emerging models like the platform and sharing economies necessitate enhanced learning and innovation capabilities in enterprises. In the global context, Morris, M. (2023), and Patel, S. (2022) emphasize that transnational resource integration and learning from advanced experiences are effective paths to bolster dynamic capabilities, with global learning networks better equipping enterprises to address international market challenges.

Furthermore, organizational culture and learning atmospheres are indispensable. Studies by Johnson, P. (2023), Lee, K. (2022), and others reveal that fostering an open, inclusive, and innovative cultural climate and establishing learning organizations are vital for facilitating knowledge dissemination and sharing. Technological collaboration and co-innovation are also crucial, as Taylor, C. (2023), Kim, H. (2022), and others argue they not only help enterprises access external knowledge resources but also mitigate innovation risks and enhance efficiency. The intellectual property protection system, as the institutional safeguard for innovation, incentivizes technological innovation and safeguards its outcomes, as evidenced by Williams, R. (2023), Thompson, D. (2022), and others. They also indicate that intellectual property transactions and licensing become vital means of acquiring external technological knowledge. Facing technological environmental risks, Adams, F. (2023), Hall, G. (2022), and others underscore the importance of strengthening technological risk management and establishing rapid response mechanisms to flexibly adjust learning directions and confront uncertainty

The policy environment also exerts an influence on enterprises' dynamic capabilities. Michael Porter's Competitive Strategy Theory provides a framework for understanding how policies impact the competitive environment of enterprises, which is indirectly related to the enhancement of learning capabilities. John Dosi (2018) points out that the dynamics of the policy environment play a crucial role in shaping the learning path of enterprises, necessitating their flexibility in response to maintain competitiveness. From the perspective of the policy environment and innovation ecosystems, Sarah Jones (2023) emphasizes the importance of building a favorable policy environment to accelerate the process of enterprise learning and innovation. In terms of policy structure, different policies significantly vary in their mechanisms of influence on enterprises' dynamic capabilities. Wilson's (2023) research reveals the notable impact of policy environment stability and transparency on enterprises' dynamic learning capabilities, suggesting that a stable and transparent policy environment facilitates long-term investment and innovation, while the absence of these qualities constrains dynamic learning and development. Emily Benson's (2020) study illuminates how government subsidies and preferential tax policies incentivize enterprises to increase R&D investment, thereby promoting technological innovation and enhancing dynamic capabilities. Anna Maria Costa (2021) focuses on environmental policies, arguing that they are not merely constraints but also catalysts for enterprise innovation and learning. Alexander Collins (2022) explores how uncertainty in international trade policies can drive enterprises' dynamic learning capabilities.

Table 2.8 Research on Corporate Environment and Dynamic Capabilities

Author	Title	Source Research	Content
Zheng Shuli (2021)	Research on the Effect of Knowledge Network Embedding on the Dynamic Capabilities of Small and Micro Enterprises	WIRELESS COMMUNICATIONS & MOBILE COMPUTING	t is urgent to strengthen the research on the endogenous growth mechanism of small and micro enterprises.
Yilan DAI (2018)	Measurement of Enterprise Dynamic Capabilities Based on Intuitionistic Fuzzy Sets: Research in Financial Industry	Management Science and Engineering	This paper proposes a method of intuitionistic fuzzy sets (IFS) to measure enterprise dynamic capabilities (EDC).
Marta Frasquet;;John Dawson;;Haydeé Calderón;;Teresa Fayos (2018)	Integrating embeddedness with dynamic capabilities in the internationalisation of fashion retailers	International Business Review	The paper presents an integration of the theoretical approaches of embeddedness and dynamic capabilities.
Stefan Schiller	Financial Information Related to Dynamic Capabilities - The Corporate Innovation Platform	Research in Business and Management	Related to Dynamic Capabilities - The Corporate Innovation Platform
Roy Edwards (2011)	Divisional train control and the emergence of dynamic capabilities: The experience of the London, Midland and Scottish Railway, c.1923–c.1939	Management & Organizational History	This paper explores the implementation of a centralised system of train control on the London Midland and Scottish Railway (LMS) to collect, collate and analyse information required for monitoring the conveyance of traffic and use of assets.

Table 2.8 (Continued)

Author	Title	Source Research	Content
José Carlos M.R. Pinho (2011)	Social capital and dynamic capabilities in international performance of SMEs	Journal of Strategy and Management	The major goals of this paper are twofold: first, it aims to explore the link between social capital (structural, relational and cognitive) and the exploitative and explorative capabilities; second, to examine the influence of exploitative and explorative capabilities on international performance.

Related Research on Dynamic Capabilities and Agricultural Enterprises Performance

In recent years, the profound impact of enterprises' dynamic capabilities on performance has become a widely discussed topic in foreign academic circles. The classic discourse of Peter Drucker has laid the cornerstone of this field, emphasizing the need for enterprises to continuously learn and innovate to adapt to rapid changes in the external environment, thereby enhancing performance. Subsequently, John D. Hughes and Michele A. Turner proposed the concept of a learning organization, further deepening the significance of a corporate learning culture. Professor Chen Chunhua (2015), from the perspective of enterprise dynamic capabilities, constructed a four-dimensional model of dynamic capabilities and revealed the synergistic effects of these dimensions on Agricultural enterprise performance. The research by Mark P. Mortensen and Mary C. encoded focused on organizational learning and memory, highlighting the crucial role of knowledge management and sharing mechanisms in enhancing agricultural enterprises performance. The 2001 study by Melanie C. Mortensen and Stephen W. Little further confirmed the positive effects of knowledge management on enhancing employees' learning capabilities and agricultural enterprises performance.

The role of mediating variables in the relationship between learning capabilities and performance cannot be overlooked. John Levithal's (2019) research revealed the close connection between organizational learning capabilities and innovation capabilities, pointing out that learning capabilities are the key to stimulating innovation capabilities, which in turn are the core driver of enhancing agricultural enterprises performance. Mary Mills' (2019) research focused on the practice of learning organizations and found that its implementation can significantly improve Agricultural enterprise performance, particularly in enhancing employee satisfaction and innovation capabilities. David Grant (2020) further explored the interactive relationship among knowledge sharing, learning, and innovation, emphasizing the profound impact of knowledge sharing and learning as prerequisites for innovation on Agricultural enterprise performance. Andrew Wilson's (2021) research directly correlated enterprise dynamic capabilities, innovation capabilities, and performance, reiterating the central role of dynamic capabilities in stimulating innovation and driving performance improvement.

Scholars have also delved into the application and impact of dynamic capabilities in different contexts. In highly uncertain market environments, studies by Nguyen and Vu (2022) and Martinez and Lopez (2022) indicate that enterprises' dynamic capabilities serve as crucial tools for rapidly adapting to changes and seizing opportunities, thereby enhancing technological innovation performance. Meanwhile, Brown and Chen's (2022) research emphasizes the importance of an organizational learning atmosphere in cultivating dynamic capabilities, providing theoretical support for enterprises to maintain competitiveness in complex and ever-changing markets. In the context of digital transformation and cross-cultural management, research by Kim and Lee (2021) and Cai and Zhang (2021) points out that enhancing dynamic learning capabilities is the key to successfully achieving internationalization and digital transformation for enterprises. Furthermore, studies by Alvarez and Barrenechea (2021) and Evans and Smith (2021) reveal the value of dynamic capabilities in cross-cultural management, suggesting that they help enterprises improve performance and market adaptability in multicultural environments. These studies not only enrich the content of dynamic capabilities theory but also provide valuable guidance and inspiration for corporate practices.

Table 2.9 Research on Dynamic Capabilities and Agricultural Enterprises Performance

Author	Title	Source Research	Content
Qing Lou Cao;Tae Won Kang;Yong Taek Lim(2017)	The Effects of Entrepreneurial Capability on the Dynamic Capability and Agricultural enterprise performance of Chinese SMEs	무역연구	This research is designed to explore the relationship between entrepreneurial capability, dynamic capability and Agricultural enterprise performance in Chinese SMEs.
Kim Jin Kwon;Yang Hoe Chang;Ahn Tony DongHui(2017)	The Moderating Effect of Manufacturing process type on the relationship of Dynamic capabilities and Business performance of SMEs	Asia-pacific Journal of Multimedia services convergent with Art, Humanities, and Sociology	The Moderating Effect of Manufacturing process type on the relationship of Dynamic capabilities and Business performance
Cui Fang;Song Jaehoon(2022)	Impact of Entrepreneurship on Innovation Performance of Chinese SMEs: Focusing on the Mediating Effect of Enterprise Dynamic Capability and Organizational Innovation Environment	Sustainability	Based on a thorough literature review, this study constructed a research model of “entrepreneurship, enterprise dynamic ability, organizational innovation environment, and enterprise innovation performance”.

Table 2.9 (Continued)

Author	Title	Source Research	Content
Alev Katrinli ; Ayça Kübra Hızarcı Payne(2020)	Micro-Foundations of Firm Dynamic Capabilities & Export Performance: A Conceptual Approach Addressing the Role of Export Department Employees	Current Perspectives in Social Sciences	this conceptual study attempts to highlight the contribution of export department employees to the emergence of dynamic capabilities of exporting firms and to export performance.
Bykova, Anna;Maria Jardon, Carlos(2018)	The mediation role of companies' dynamic capabilities for business performance excellence: insights from foreign direct investments. The case of transitional partnership	Knowledge management research & practice: KMRP	This study uses a combination of multinational enterprises and dynamic capabilities perspectives to illustrate how the involvement of foreign investors is able to contribute to a company's Agricultural enterprise performance.
Sun-Cheol Bae;Byung-Keun Kim(2016)	Mediating Effect of Operational Capabilities on the Dynamic Capabilities and Performance of Korean SMEs	Journal of the Korean Operations Research and Management Science Society	This study examines the relationship between dynamic capabilities and operational capabilities as well as investigates the effect of these capabilities and performance.

Literature review

Expanding on the interrelationships between digital transformation, corporate environment, dynamic capabilities, and agricultural enterprises performance, current research has demonstrated substantial contributions alongside pressing shortcomings that require improvement. In terms of contributions, numerous scholars (e.g., Bharadwaj, 2000; Venkatraman, 2006) have conducted thorough investigations, elucidating how digital transformation significantly enhances firms' market competitiveness and performance by optimizing internal processes, boosting operational efficiency, strengthening customer experiences, and fostering innovation. Simultaneously, these studies have illuminated the pivotal role of the corporate environment in shaping digital transformation strategies, emphasizing the need for rapid adaptation and learning capabilities in dynamic market environments (Teece, 2007). Furthermore, dynamic capabilities, as a core competency, have been validated to effectively enable firms to maintain efficient operations and sustained growth amidst complex and ever-changing external environments (Hess & Matt, 2007).

However, upon scrutinizing the interrelationships between digital transformation, corporate environment, dynamic capabilities, and agricultural enterprises performance, current research confronts multifaceted challenges. Among these are the disparate definitions of digital transformation proposed by different scholars, resulting in a lack of uniform standards (Hess & Matt, 2007, and implicitly echoed by the varied perspectives); limitations in sample data, which hinder the generalizability of research findings (Hess & Matt, 2007); insufficient delving into the specific mechanisms underlying the interplay of these factors and their influence on agricultural enterprises performance (Bharadwaj, 2000); and the fragmentation of action pathways, with a tendency to focus solely on isolated or partial routes, neglecting holistic and systematic descriptions (Eisenhardt & Martin, 2000). Collectively, these issues constrain the universality, precision, and depth of research conclusions, pinpointing the crucial directions for future research to break through.

Chapter 3
Research Methodology

To the impact of digital transformation on agribusiness performance, the researchers have procedures consisting of research formats target population Sample selection research tools Tool Quality Check data collection protection of the rights of the sample group and statistics used to analyze the data the details of each issue were presented as follows:

1. The population and the sample
2. Research Instruments
3. Data Collection
4. Statistics Used for Data Analysis

The population and the Sample

The Population

The research objective of this article is to investigate how digital transformation affects the performance of agricultural enterprises. Agricultural enterprises are at the forefront of adopting and benefiting from digital transformation, with performance evaluation focusing on the agricultural sector. The influence of digital transformation on performance is pivotal in deciding whether a company will continue investing in digital initiatives. Chinese agricultural enterprises stand out for their emphasis on enhancing the digitization of agricultural product trading terminals, production monitoring, and daily management processes, making them a significant and interesting case study. As such, this article primarily focuses on Chinese agricultural enterprises. Experts in the field of digital transformation and agricultural enterprise performance evaluation provide consulting services for agricultural enterprise development and help agricultural enterprises digitally transform.

The research community consists of experts in the fields of Chinese agribusiness, digital transformation and agribusiness performance. Among them, the Population studied in this article is 25103 agricultural companies in China.

Table 3.1 Table of The Population distribution

NO	Scope of area	Number of agricultural enterprises
1	Beijing	3362
2	Shanghai	2909
3	Hubei	6526
4	Guangxi	5949
5	Yunnan	6357
	Total	**25103**

Source: The statistical data of agricultural enterprises in provinces publicly released by the Chinese government's statistical department, As of 31 December 2023.

The Sample

This article focuses on studying samples of China's agricultural listed companies, which play a vital role in driving digital transformation within the industry. Digital transformation is characterized by substantial investment, lengthy operating cycles, high risks, and advanced technological requirements. These listed companies in China have access to diverse financing options, robust risk management mechanisms, and strategic objectives aligned with sustainable development goals, all of which align with the demands of digital transformation. In contrast, non-listed agricultural companies continue to rely on traditional labor-intensive methods for agricultural production, lacking strong market experimentation capabilities. The expert sample for the survey comes from expert groups in the field of digital transformation and agricultural enterprise performance.

In the study sample size, There are 360 (20 x 18) (Lindeman, Merenda & Gold, 1980) agricultural companies in China. The questionnaire was addressed to agribusiness managers (technical department, finance department, performance department).

In sample collection, failure to collect samples in accordance with the plan or process (such as insufficient sampling ratio or missing key data) leading to unrepresentativeness is deemed unqualified; logical contradictions in data (such as errors in financial statement articulation) or missing information (such as lack of qualifications) that render analysis impossible is judged unqualified; failure to seal samples or incorrect labeling (such as mixing numbers) leading to traceability failure is also unqualified. A total of 375 samples were collected in the study, with 360 qualified samples, and the sample qualification rate was 96.27%.

Table 3.2 Table of The Sample Distribution

No	Scope of area	Regional divisions and ratios	sample size	actual sample
1	Beijing	13.4%	48	50
2	Shanghai	11.6%	42	45
3	Hubei	26%	94	98
4	Guangxi	23.7%	85	88
5	Yunnan	25.3%	91	94
	Total		**360**	**375**

Research Instruments

Research study on “the impact of digital transformation on agribusiness performance” is a combination of quantitative research. Quantitative research and qualitative study. There are 2 types of data collection tools: 1) in-depth interviews 2) questionnaires.

In-depth interview

Used to collect data from 20 experts (listed in Appendix C).

Questionnaire

Used to collect data with sample groups of expertise in digital transformation and enterprise performance measurement.

The questionnaire and interview form are created with the following steps:

1. Data collection by means of data analysis from printed documents Books, articles, interviews from newspapers.

2. Interviews with 5 groups of people: interviews with experts of different fields and industries, 4person A group of management level of agricultural listed companies, 4person A group of ordinary employees with digital transformation work experience in agricultural listed companies, 4person A group of academics with knowledge and ability side engaged in digital transformation and agricultural enterprise performance evaluation, 4person A group of academics with knowledge and ability side engaged in the Corporate Environment of enterprises, 4person A group of academics with knowledge and ability side engaged in research enterprise interaction capabilities expertise, total of 20 people (as listed in Appendix C) presented the results from the interviews to analyze and synthesize them as guidelines for setting up a quantitative questionnaire, as shown in table 3.3 (as listed in Appendix C).

Table 3.3 Interview with experts of Unit and Number

Experts	Qualifications	Number (people)
Experts of management level of agricultural listed companies	Yunnan Shennong Agricultural Industry Group Co., Ltd.	4
A group of ordinary employees with digital transformation work experience in agricultural listed companies	Guangxi Fenglin Wood Industry Group Co., Ltd. Hubei Honghu Ecological Agriculture Co., Ltd.	4
A group of academics with knowledge and ability side engaged in digital transformation and agricultural enterprise performance evaluation	China Agricultural University	4
Experts who pay attention to and study the Corporate Environment of enterprises.	Yunnan Shennong Agricultural Industry Group Co., Ltd.Beijing Agricultural Group Co., Ltd	4
A group of academics in research enterprise interaction capabilities expertise.	Professor, Department of Business Administration, School of Management, Guangxi University for Nationalities.	4
Total		20

From Table 3.3, it is the designation of experts which based on their work experience and occupation. 20 persons consisting of (1) experts of management level of agricultural listed companies. They have a better understanding of digital transformation and better experience in enterprise performance management. (2) Experts who are employees of listed companies. They have experience working in digital transformation and understand digital transformation and its functions and roles. (3) An expert in Academics who has knowledge and ability in digital transformation and agricultural enterprise performance evaluation. They have academic qualifications or are university teachers.

Table 3.4 The structure of the in-depth interview

Questions about opinions	Number of verses
Part 1 Digital transformation	4 items
1. What impact do you think R&D digitalization has on digital transformation of agricultural enterprises?	
2. What impact do you think production digitalization has on digital transformation of agricultural enterprises?	
3. What impact do you think operational digitalization has on digital transformation of agricultural enterprises?	
4. What impact do you think marketing digitalization has on the digital transformation of agricultural enterprises?	
Part 2 Corporate environment	4 items
1. Can you talk about the impact of the market environment on the corporate environment?	
2. What impact do you think credit policy has on corporate environment?	
3. What impact do you think internal control has on corporate environment?	
4. What impact do you think information disclosure has on corporate environment?	
Part 3 Dynamic capabilities	3 items
1. Please evaluate the absorptive capacity of agricultural enterprise resources or factors.	
2. Please evaluate the integration capabilities between agricultural enterprises and upstream and downstream suppliers.	
3. Please evaluate the innovation capabilities of agricultural enterprises.	
Part 4 Agricultural enterprises performance	3 items
1. Please evaluate the current financial performance of agricultural enterprises.	
2. Please evaluate the social performance of agricultural enterprises.	
3. Please evaluate the ecological performance of agricultural enterprises.	
Total	**14 items**

3. Determine the issues and scope of questions to be consistent with the objectives. and the benefits of research by structuring the questionnaire. as the following table

Table 3.5 Questionnaire structure of Agricultural listed companies

Variable	Number of verses	Clause	Data	Measurement
Part 1	(4)			
Digital transformation	4	1-16		
1.R&D digitalization	(4)	1-4	Likert Scale	5 opinion levels
2.Production digitalization	(4)	5-8	Likert Scale	5 opinion levels
3.Operational digitalization	(4)	9-12	Likert Scale	5 opinion levels
4.Marketing digitalization	(4)	13-16	Likert Scale	5 opinion levels
Part 2				
Corporate environment	4	17-30		
1.Market environment	(4)	17-20	Likert Scale	5 opinion levels
2.Credit policy	(3)	21-23	Likert Scale	5 opinion levels
3.Internal control	(4)	24-27	Likert Scale	5 opinion levels
4.Information disclosure	(3)	28-30	Likert Scale	5 opinion levels
Part 3				
Dynamic capabilities	3	31-42		
1.Absorptive capacity	(4)	31-34	Likert Scale	5 opinion levels
2.Integration	(4)	35-38	Likert Scale	5 opinion levels
3.Creativity	(4)	39-42	Likert Scale	5 opinion levels
Part 4				
Agricultural enterprises performar	3	43-54		
1.Economic performance	(4)	43-46	Likert Scale	5 opinion levels
2.Social performance	(4)	47-50	Likert Scale	5 opinion levels
3.Ecological performance	(4)	51-54	Likert Scale	5 opinion levels
Total	**14**			

4. Proceed to create questions based on in-depth interviews with experts. Along with studying, researching, and working on definitions then taking them to the advisor to consider and verify the appropriateness of the questions. The language used and typing formatting along with bringing improvements and corrections.

5. Check content validity by taking the completed questionnaire to experts for measurement and evaluation. A person with knowledge and expertise in surveys, digital transformation and business performance assessments. Checking safety matches the content coverage and language accuracy and consistency with research objectives. List of content validators (listed in Appendix B.) The researcher used the IOC index (item objective congruence) with the following scoring characteristics:

+1 means that you are sure that the questions are consistent with the research objective.

0 means you are unsure whether the question is consistent with the research objective.

-1 means that you are certain that the questions are inconsistent with the research objective.

The selection of question items uses criteria to judge content validity, which specifies that the calculated IOC index value must be greater than 0.6 (IOC>0.6) (Kanlaya Wanichbancha, 2009). It is therefore considered that the question items are consistent with the message to be measured.

Table 3.6 IOC content validity examiner (item objective congruence)

Experts	Experts Qualification	Number (person)
Experts in the field of statistical surveys.	Professor, School of Information and Statistics	1
Experts in the field of digital transformation and digital economy, Agricultural enterprise performance evaluation.	Professor, Department of Business Administration, School of Management, Guangxi University for Nationalities.	1
Experts in the field of Corporate Environment research, business kinetic capabilities.	Associate Professor, Department of Business Administration, School of Business Administration, Guangxi University for Nationalities.	1
Total		**3**

6. The researcher brings a draft questionnaire that has been edited by a qualified person. presentation of advisors considers the completeness again and bring it to the trial (try-out) with a group of people who are like the sample you want to study 30 people, then bring it to the reliability value. (Cronbach's alpha coefficient).

7. The researcher brings the defects from the experiment to the final improvement. to be printed as a complete questionnaire used to collect data for research.

Scoring criteria

It is a study of the opinions level of Digital transformation, Corporate Environment, dynamic capabilities and Agricultural enterprise performance. The questionnaire with question characteristics is a 5-level estimation scale of Likert, with the meaning of the score and its implications as follows:

Score level 5 means the highest level of agreement.

Score level 4 means high level of agreement.

Score level 3 means moderate level of agreement.

Score level 2 means low level of agreement.

Score level 1 means the least level of agreement.

The criteria for interpreting the average scores of the observed variables are divided into 5 levels as follows.

Average score 4.50 – 5.00, highest level

Average score 3.50 – 4.49, high level

Average score 2.50 – 3.49, moderate level

Average score 1.50 – 2.49, low level

Average score 1.00 – 1.49, lowest level

The reasons for setting such rules are as follows:

1. The calculated arithmetic mean can be any value in the range 1-5, such as 1.75, 4.50...., 5.00.

2. The score level 1-5 is a continuous value represented by a straight line. And can be defined as a continuous scoring range which is represented by a straight line and can be defined as a continuous scoring range Each period is separated by 1 unit as follows:

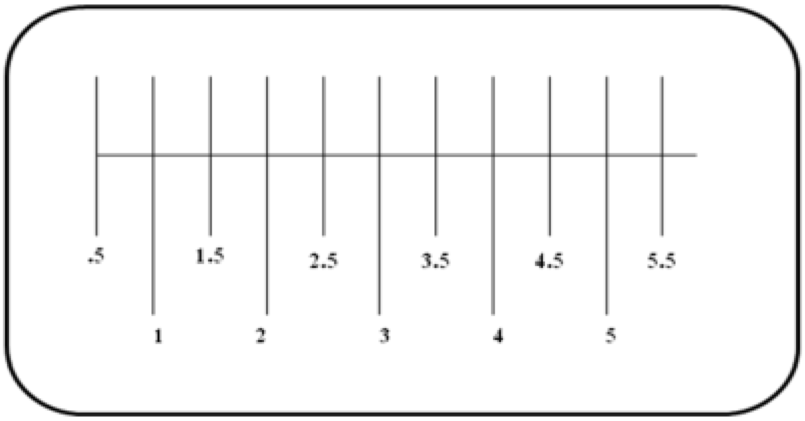

Figure 3.1 Mean Interpretation Interval Determination

Source : From Wanichbancha, K. (2008)

3. Based on the actual data collected from the scores The minimum value is 1 and the maximum is 5, so use the criterion 1.00 – 1.50 instead of .50 – 1.50 and use the criterion 4.50 – 5.00 instead of 4.50 – 5.50.

4. In the case where the calculated arithmetic mean ($\bar{X}$) has a value corresponding to the interval between the levels the opinions to be interpreted are at a higher level of opinion, for example, the arithmetic mean = 4.50 will mean that there is the highest level of opinion on that matter, etc.

Determining the quality of research tools

To get quality tools The researcher therefore brought a questionnaire that was created. Go test for validity and reliability. (reliability) as follows.

1. Determination of validity the researcher will check the content validity of each text to ensure that it meets the objectives of the study. by consulting with 5 subject matter specialists to examine the clarity of language, wording, and accuracy in the content Consistency of the questions in the questionnaire with the objectives (index of item objective congruency--IOC) with the following scoring criteria:

+1 when the expert or expert is sure that the question is consistent with the content.

0 When the expert or expert is not sure that the question is consistent with the content.

-1 when the expert or expert is sure that the question is inconsistent with the content.

follow formula $\quad IOC= \sqrt{\frac{\sum R}{N}}$

IOC Instead, it indexes the consistency between queries. with research objectives

$\sum R$ Instead, The sum of the opinions of experts or experts.

N Instead, of the number of experts or experts.

Calculation of the consistency index between questionnaires. with research objectives Must have an Index of Conformity (IOC) value greater than 0.6. It can be concluded that the questionnaire The content accuracy is within acceptable criteria. can be used to collect further data.

2. Determination of reliability (reliability) by using the questionnaire that has been verified by the advisory committee. and experts with expertise have revised and tested (try out) with 30 test recipients of the questionnaire that have similar characteristics to the sample group to be studied before using it with the sample group. to analyze sentiment (reliability) using the Alpha coefficient method of Cronbach (1990). If the reliability coefficient is greater than 0.8 (Kanlaya Wanichbancha, 2008), which indicates that the questionnaire is reliable and can be used in the study. From the data analysis results, the results are summarized in Table 3.7.

Table 3.7 Questionnaire confidence value

Factors		Number of questions (N)	Confidence value (R)	Interpretation
Part 1	digital transformation			
	Digital R&D			
	Digital marketing			
	Digital production			
	Digital operations.			
Part 2	Corporate Environment			
	Market environment			
	Credit policy			
	Internal Control			
	Information disclosure			

Table 3.7 (Continued)

Factors		Number of questions (N)	Confidence value (R)	Interpretation
Part 3	Dynamic capabilities			
	Absorptive capacity			
	Integration			
	Creativity			
Part 4	Agricultural enterprises performance			
	Financial Performance			
	Social performance.			
	Ecological performance.			
Factors Total				

From Table 3.7 it was found that the confidence values of all factors and the total factors of the questionnaire were over 0.8. Therefore, it can be concluded that Questionnaires can be used to collect real data. with confidence values that pass the acceptance criteria.

Data Collection

The researcher proceeded with data collection and distributed questionnaires from various sources after obtaining the sample size. The information here will be divided into 2 main parts according to the research method, namely data collection from in-depth interviews by interviewing experts and academics in the field of digital transformation, corporate environment, dynamic capabilities and agricultural enterprises performance. About the data from in-depth interviews with experts or scholars, people use the information as a guideline for constructing the questionnaire, after which the data is collected from the distribution of the questionnaire. Data will be collected from agricultural companies in China. The process of data collection as detailed below.

Data collection from in-depth interviews

Because this in-depth interview will use both interviews and conversation recordings using a voice recorder. Therefore, data collection used both interview recordings and recordings in the memory of the voice recorder. Then open it to transcribe into a recording later again with the following steps.

1. Schedule an interview with an expert by notifying him in advance.

2. Conduct the interview according to the interview structure and record it in the recording form. including voice recordings during the interview

3. Bring all the information to compose and transcribe completely from the voice recorder. according to the content structure designed in the interview form Including additional useful things received from the interview.

4. Analyze the data using content analysis techniques and summarize the interview results into descriptive data as follows.

Results of in-depth interviews from experts of management level of agricultural listed companies, ordinary employees with digital transformation work experience in agricultural listed companies, academics with knowledge and ability side engaged in digital transformation and agricultural enterprise performance evaluation, Experts who pay attention to and study the Corporate Environment of enterprises and academics in research enterprise interaction capabilities expertise.

Comments about survey respondents

1. The survey objects should mainly be agricultural listed companies. Agricultural listed companies can overcome shortcomings such as long digital transformation cycles, high risks, and large investment scales, and leverage the advantages of digital transformation.

2. During the investigation of agricultural listed companies, interviews should be conducted with managers and employees involved in digital R & amp; D, digital production, digital marketing, and digital operations in order to fully understand the

progress and various links of the digital transformation of agricultural listed companies.

3. It is recommended to focus on the supply chain of agricultural listed companies as the main line and conduct in-depth interviews with agricultural listed companies. The progress of digital transformation of upstream and downstream enterprises in the supply chain will also affect the digital transformation of agricultural listed companies.

Comments about interview procedures

1. Personnel participating in interviews should be trained so that they can accurately understand the connotation and meaning of the interview outline and questions.

2. It is recommended to conduct one-on-one interviews so that the person being interviewed can be prepared to understand the meaning of the interview questions.

3. For interviews with employees of agricultural listed companies, it is recommended to use random sampling to select the interviewees.

4. During the interview process, it is recommended to increase interviews with government agricultural departments, banking institutions, and agricultural digital technology research institutions.

The study conducted reliability and validity tests on the 30 data samples from the pre-investigation, and the test results are as follows:

1. Reliability Analysis. The Cronbach's alpha values of the six latent variables in the table range from 0.81 to 0.91. Generally, a Cronbach's alpha greater than 0.7 is considered acceptable, and all the values here are much higher than 0.7, indicating that the entire measurement tool has a high internal consistency. This means that the various measurement variables have a strong correlation with each other and can jointly reflect the characteristics of their corresponding latent variables. The Cronbach's alpha of "Digital Transformation" is 0.89, indicating that when measuring aspects related to digital transformation, the selected measurement variables (such as R&D Digital Transformation, Production Digital Transformation, etc.) have good

consistency among them. The coefficient of "dynamic ability" is 0.85, showing that the internal consistency of its measurement variables (such as Innovation Capability, Absorptive Capacity, etc.) is relatively strong.

The CR values also range from 0.81 to 0.91, and all are greater than 0.7, further proving the reliability of the measurement tool. It measures the degree to which the measurement variables reflect the latent variables from another perspective and corroborates with the Cronbach's alpha. The CR value of "Corporate environment" is 0.84, indicating that the combination of variables for measuring the Corporate environment (such as Market Environment, Credit Policy, etc.) has a high reliability in measuring this latent variable. The CR value of "Agricultural enterprise performance" is 0.87, showing that the measurement variables in measuring Agricultural enterprise performance also have a relatively high reliability.

2. Validity Analysis. All normalized factor loading values range from 0.81 to 0.90. Generally, a factor loading greater than 0.5 is considered acceptable, and the high loading values here indicate that there is a strong correlation between the measurement variables and the latent variables, that is, the measurement variables can effectively reflect the characteristics of the latent variables, thus reflecting good validity. In "Digital Transformation", the normalized factor loading of "Operational Digital Transformation" is 0.88, which is relatively high among the latent variable, meaning that this variable has a strong explanatory power for the latent variable of digital transformation. In "Agricultural enterprise performance", the factor loading of "Financial Performance" is 0.90, indicating that it is highly correlated with the latent variable of Agricultural enterprise performance and has a strong explanatory power for Agricultural enterprise performance.

The AVE values range from 0.83 to 0.89, and all are greater than 0.5, which indicates that the measurement variables can well explain the variance of the latent variables, that is, the measurement tool has good convergent validity. It reflects the extent to which the measurement variables corresponding to each latent variable jointly explain the variation of that latent variable. The AVE value of "Corporate environment" is 0.88, indicating that the variables for measuring the Corporate environment (such as Market Environment, Credit Policy, etc.) can effectively extract the variance of this latent variable. The AVE value of "Agricultural enterprise performance" is 0.87, also indicating that its measurement variables have a relatively high effectiveness in explaining Agricultural enterprise performance.

Combining the results of the reliability and validity tests, the measurement tool in this study performs well in terms of reliability and validity. High reliability ensures the stability and reliability of the measurement results, that is, if the measurement is repeated, the possibility of obtaining similar results is relatively high; high validity ensures that the measurement tool can accurately measure the concepts or variables that are intended to be measured. These results provide a solid data foundation for the study, making the conclusions drawn based on these measurement data more credible and scientific. At the same time, in subsequent research or practical applications, this measurement tool can continue to be used to measure and analyze related concepts.

Table 3.8 Test of Reliability and Validity

Latent variable	Measure variable	Normalized factor loading	Cronbach's alpha	CR	AVE
Digital Transformation	Part1 (1) R&D Digital Transformation	0.85	0.88	0.89	0.83
	Part1 (2) Production Digital Transformation	0.82			
	Part1 (3) Operational Digital Transformation	0.88			
	Part1 (4) Marketing Digital Transformation	0.8			
Corporate environment	Part2 (1) Market Environment	0. 87	0.82	0.84	0.88
	Part2 (2) Credit Policy	0.82			
	Part2 (3) Internal Control	0.88			
	Part2 (4) Information Disclosure	0.82			

Table 3.8 (Continued)

Latent variable	Measure variable	Normalized factor loading	Cronbach's alpha	CR	AVE
dynamic ability	Part3 (1) Innovation Capability	0.86			
	Part3 (2) Absorptive Capacity	0.81	0.85	0.87	0.81
	Part3 (3) Integration Capability	0.86			
Agricultural enterprise performance	Part4 (1) Financial Performance	0.90			
	Part4 (2) Social Performance	0.84	0.91	0.85	0.87
	Part4 (3) Ecological Performance	0.89			

Comments about the interview content.

1. During the interview process, it is necessary to understand the interviewee's understanding of digital transformation, Corporate Environment, corporate interaction capabilities and Agricultural enterprise performance.

2. It is necessary to inform the interviewees of the purpose and role of interviews related to digital transformation, Corporate Environment, corporate interaction capabilities, Agricultural enterprise performance and other related content.

Data collection using questionnaires.

Because the data of the sample that will distribute the questionnaire is scattered in several areas. Therefore, the researcher used the document submission method in some areas. And most of the researchers will go to the area by themselves to collect questionnaires by themselves in the area. Because this research has a limited number of samples. The data collection process can be summarized as follows.

1. The researcher went to the area by himself to collect the questionnaire by himself in the area and sent a letter to some areas that the researcher could not travel to collect and send a stamp envelope addressed to the researcher as listed in the list place of work or family life

2. Wait for some questionnaires that are not collected by yourself. From a sample of 15 days, if it has not been returned, I will telephone accordingly. And if it still hasn't been returned, the researcher will go to the area to collect again.

3. Take the questionnaire to check the completeness of the questionnaire frame and count the number as planned. If not complete, further information will be collected to complete.

4. Take the questionnaire and convert it into preliminary statistical values.

5. Analyze the obtained data by statistical methods.

Statistics Used for Data Analysis

When the questionnaire was returned the researcher manually checked the accuracy and completeness of all questionnaires. The questionnaire was then encoded and processed by a computer. by using a ready-made program Then bring the data to statistical analysis. In explaining the meaning and displaying the results of all the data obtained, this research used the methods of content analysis, descriptive statistics analysis, inferential statistics analysis (inferential statistics analysis).

Statistics are used to analyze data.

The researcher uses statistics to analyze data according to the research objectives as follows:

1. To analyze the statistical characteristics of data.

The statistics used to analyze the data are Descriptive statistics: To find the basic statistics of the respondents, the arithmetic mean, standard deviation (SD) were used.

2. Analysis of the components of the variables of digital transformation, Corporate Environment, dynamic capabilities and Agricultural enterprise performance.

The statistics used to analyze the data are Confirmatory component analysis (confirmatory factors analysis--CFA) to confirm the constituent indicators of a small business sustainable marketing model. This component analysis is divided into two steps: (1) second order confirmatory component analysis; (confirmatory factors analysis- second order--CFA) to confirm the question of each variable observed whether it is the indicator of the element to be measured or not. and to confirm the observed variables of each factor as to their constituents. The results in this step were applied in the second step. (2) Confirmatory component analysis from structural equation model analysis. This will be an analysis of all factors at the same time. The variables to be analyzed must have a correlation of not less than .30 to use the results in this section to further develop strategies.

3. Analysis of direct and indirect influences of variables of digital transformation, Corporate Environment, dynamic capabilities and Agricultural enterprise performance.

The statistics used to analyze the data are causal influence analysis (Path Analysis) of digital transformation, Corporate Environment, dynamic capabilities and Agricultural enterprise performance using structural equation modeling (-SEM).

4. The search for the relationships between variables

The pattern that was searched for will be the result of component analysis and causal influence analysis at the same time. It is an overall analysis of the model. whole measurement model and structural model (structural model), also known as (structural equation modeling--SEM). This model is a model that is adjusted in accordance with the empirical data (model fit). Therefore, the resulting model is a model that can be used. effective application in each factor there are variables that promote various factors. Each factor will have a causal influence on each other.

Structural equation model--SEM analysis

structural equation model analysis It is an advanced statistical technique for analyzing multivariate relationships. It has the advantage of being able to analyze linear relationships between latent variables, which general statistics cannot do. This is because structural equation models can relax the limitations of other types of analysis, such as regression analysis. where the original variable must not be correlated but structural equation model analysis can relax this restriction, etc. A structural equation model consists of two parts: the structural model consists of the relationship paths between each latent variable. and measurement model (measurement model), which consists of observed variables of each latent variable.

Therefore, structural equation model analysis can be performed as confirmatory factor analysis. (Confirmatory factors analysis--CFA) and causal influence analysis (path analysis--PA) at the same time. Suitable for proof-of-concept theories, which usually have a structure of variables as a causal model. Structural equation models can also perform other statistical analyses, such as multiple regression analysis. analysis of covariance, canonical analysis, etc. In analyzing the structural equation model, the analyst must first adjust the model to be consistent with the empirical data. So, the various statistics can be used correctly. You can consider the acceptance criteria as shown in the values in Table 3.8

Table 3.9 Criteria for agreeing on model conformity with empirical data.

Statistical values	Symbols	Acceptance Criteria	Reference
Chi-square	$\chi 2$	-	
Degrees of freedom	Df	-	
Chi-square/ Chi-square	$\chi 2/df$	< 2	(Schermelleh-Engel,
probability	P-Value	>0.05	K., Moosbrugger, H.,
Root means square error of approximation	RMSEA	<0.05	& Müller, H. (2003)
Comparative Harmony Index (GFA)	CFI	>0.9	(Schermelleh-Engel,
Tucker-Lewis (AGFI)	TLI	>0.9	K., Moosbrugger, H.,
Square root index of standard residuals.	SRMR	<0.05	& Müller, H. (2003)

Chapter 4
Results of Analysis

This chapter aims to analyze the sample data. To begin with, it focuses on carrying out a descriptive statistical analysis of the sample data. After gathering and sorting the sample data, it precisely calculates key descriptive statistics including means, medians, standard deviations, and frequencies. This enables us to draw a general outline of the data, presenting the central tendency, dispersion, and distribution of each variable visually. It thereby paves the way for more in-depth exploration.

Next, this chapter resorts to software. The purpose is to test the hypotheses about how digital transformation, the enterprise environment, and dynamic ability impact the performance of agricultural enterprises. When introducing this software, it starts the process of building and analyzing structural equation models. This stage centers on examining the pre-set theoretical assumptions. Thanks to the outstanding modeling functions of AMOS software, the abstract research hypotheses are turned into visible model routes. It systematically assesses the causal relations, direct effects, and indirect effects among latent variables, offers quantitative evidence for the theoretical hypotheses, and accurately uncovers the complex internal links among various elements, along with digging out the underlying action mechanisms concealed within the data.

The data analysis result can be presented as follows:

1. Symbol and Abbreviations
2. Presentation of data Analysis
3. Results of data analysis

The details are as follows.

Symbol and Abbreviations

In academic research and various professional fields, abbreviations play a crucial role. The series of abbreviations mentioned above all have clear design logic and practical value. Take the abbreviations related to digital transformation as an example. "RDDT" (R&D Digital Transformation), "PDT", "ODT" and "MDT" respectively focus precisely on the digital transformation of research and development, production, operation, and marketing. The initial letter abbreviations not only retain the key semantic elements but also achieve concise expression, enabling professionals to quickly refer to specific concepts when communicating and writing reports, thus improving communication efficiency.

In the area of Corporate environment, abbreviations such as "ME", "CP", "IC" and "ID" are simple and straightforward, condensing long professional phrases, which is in line with the fast-paced business analysis scenarios. Regarding dynamic ability and Agricultural enterprise performance, "ICap", "ACap", "IntCap", as well as "FP", "SP" and "EP" also follow the rule of taking the initial letters of the core words. This approach allows researchers to avoid repeatedly writing long words when building complex structural equation models and processing vast amounts of data, reducing the writing burden and potential expression errors. Moreover, once the uniformly standardized abbreviations are recognized by the industry, they become professional "codes". It is conducive to communication within the academic community. Newcomers, after getting familiar with these abbreviations, can integrate into the professional context more quickly and absorb knowledge and participate in discussions without obstacles. The abbreviations adopted in this paper are shown in Table 4.1.

Table 4.1 Symbol and Abbreviations

Latent variable	Measure variable	Abbreviation
Digital Transformation	Part 1 (1) R&D Digital Transformation	RDDT
	Part 1 (2) Production Digital Transformation	PDT
	Part 1 (3) Operational Digital Transformation	ODT
	Part 1 (4) Marketing Digital Transformation	MDT
Corporate	Part 2 (1) Market Environment	ME
Environment	Part 2 (2) Credit Policy	CP
	Part 2 (3) Internal Control	IC
	Part 2 (4) Information Disclosure	ID
Dynamic capabilities	Part 3 (1) Integration	IN
	Part 3 (2) Absorptive	AC
	Part 3 (3) creativity	INTC
Agricultural	Part 4 (1) Economic Performance	EP
Enterprises	Part 4 (2) Social Performance	SP
Performance	Part 4 (3) Ecological Performance	ECP

The researchers divided the results of the data analysis into 4 Parts.

The details are as follows.

Part 1: General Information of Respondents

Part 2: Survey Results of study digital transformation and agricultural enterprise performance.

The statistics used to analyze the data are Descriptive statistics: To find the basic statistics of the respondents, the arithmetic mean, standard deviation (SD), MIN, MAX, SK, KU were used.

Part 3: Analysis Results of the underlying mechanisms through which digital transformation, corporate environment, and dynamic ability influence the performance of agricultural enterprises.

The statistics used to analyze the data are confirmatory factors analysis--CFA, correlation analysis, Path Analysis.

Part 4: Results find a model for enhancing agricultural enterprise performance.

In mathematics and statistics, E (x) usually represents the expected value of a random variable, which is also known as the mean. Var (x) represents the variance of a random variable. It is used to measure the degree of deviation of a random variable from its mean (that is, the expected value), reflecting the dispersion or spread of the data.

Maximum (Max) is the largest value in a set of data.

Minimum (Min) represents the smallest value within a group of data.

Median (Med) refers to the middle value of a data set when the data is arranged in ascending or descending order.

Standard Deviation (SD) measures the amount of variation or dispersion of a set of values from its mean.

Variance (Var) is a measure of how far a set of numbers is spread out. It is the square of the standard deviation, indicating the degree of data dispersion around the mean.

Chi-square (χ^2): In statistics, it is often used to test the goodness-of-fit between observed data and theoretically expected data, and to assess whether there are significant associations among categorical variables. For example, in contingency table analysis, the chi-square value is calculated to determine whether two categorical variables are independent.

Degrees of freedom (df): Briefly speaking, it reflects the number of values that can vary freely when calculating a statistic. In different statistical tests, the calculation method of degrees of freedom varies. For instance, in a one-sample t-test, the degrees of freedom is the sample size minus 1, that is, and it plays a crucial role in determining the shape of the statistical distribution.

probability (P): It is a value used to measure the likelihood of a random event occurring, with a value range from 0 to 1. For example, when flipping a fair coin, the probability of getting heads is 0.5.

Root means square error of approximation (RMSEA): In statistical techniques such as structural equation modeling, it is an index for measuring the goodness of fit of the model. The smaller the RMSEA value, the higher the degree of fit between the model and the data. Usually, it is hoped that it is less than 0.08.

Comparative Harmony Index (GFA): It is one of the indices for evaluating the goodness of fit of the model, used to reflect the degree of agreement between the hypothesized model and the observed data. The higher the value, the better the fit.

Tucker-Lewis (AGFI): The Tucker-Lewis Index (AGFI) is a modified goodness-of-fit index. It assesses the degree to which the model fits the data while considering the parsimony of the model. The closer its value is to 1, the better the model fits.

Presentation of data analysis

Descriptive statistics of the sample

Table 4.2 Basic characteristic information of samples

Sample Group		Sample Size	Proportion
Gender	Male	234	65%
	Female	126	35%
	Total	360	100%
Age (years old)	Under 25	47	13%
	25 - 35	79	22%
	25 - 35	115	32%
	35 - 45	61	17%
	45 - 55	36	10%
	Over 55	22	6%
	Total	360	100%
Education	High School	101	28%
	University	151	42%
	Postgraduate	108	30%
	Total	360	100%

Table 4.2 (Continued)

Sample Group		Sample Size	Proportion
Salary (yuan)	Below 3000	25	7%
	3000 - 5000	104	29%
	5000 - 7000	83	23%
	7000 - 9000	126	35%
	Above 9000	22	6%
	Total	360	100%
Work Position	Technical Position	205	57%
	Management Position	155	43%
	Total	360	100%
Time of Engaging in Digital Transformation Work	Less than 1 year	29	8%
	1 - 2 years	126	35%
	2 - 3 years	101	28%
	More than 3 years	104	29%
	Total	360	100%
Time of Digital Transformation of the Working Enterprise	Less than 1 year	18	5%
	1 - 2 years	36	10%
	2 - 3 years	90	25%
	More than 3 years	216	60%
	Total	360	100%

From Table 4.2, in terms of gender, the number of male samples (234, accounting for 65%) is larger than that of female samples (126, accounting for 35%). In terms of age, the sample size of the 35 - 45 age group is the largest (115, accounting for 32%), followed by the 25 - 35 and 45 - 55 age groups. Regarding educational attainment, the number of samples with a university degree is the largest (151, accounting for 42%), followed by postgraduate and high - school degrees. In terms of salary, the sample size in the 7000 – 9000 yuan range is the largest (126, accounting for 35%). Among work positions, the number of samples in technical positions is larger than that in management positions (205, accounting for 57% and 155, accounting for 43% respectively). In terms of the time engaged in digital transformation work, the sample size of those with 1 - 2 years of experience is the largest (126, accounting for 35%). Regarding the time of digital transformation of the working enterprise, the sample size of those with more than 3 years is the largest (216, accounting for 60%).

Overall, the samples are mainly composed of males, with the age concentrated in the 35 - 45 range, mostly having a university degree, mainly working in technical positions, with salaries mostly in the 7000 - 9000 yuan range, and a relatively large number of people having engaged in digital transformation work for 1 - 2 years, and the digital transformation of their enterprises mostly having been carried out for more than 3 years.

Part2: Survey Results of study digital transformation and agricultural enterprise performance.

Sample statistical characteristics

Table 4.3 Sample statistical characteristics (n = 360)

Latent variable	Measure variable	$\bar{X}$	S.D.	MIN	MAX	SK	KU	
Digital Transformation	Part 1 (1) R&D Digital Transformation	3.658	1.010	5.000	1.500	-0.531	-0.770	high level
	Part 1 (2) Production Digital Transformation	3.743	0.894	5.000	1.000	-1.004	1.290	high level
	Part 1 (3) Operational Digital Transformation	3.700	1.001	5.000	1.000	-1.057	0.673	high level
	Part 1 (4) Marketing Digital Transformation	3.781	0.958	5.000	1.000	-0.799	0.320	high level
	Total	**3.721**	**0.791**	**5.000**	**1.125**	**-0.921**	**0.906**	**high level**

Table 4.3 (Continued)

Latent variable	Measure variable	$\overline{X}$	S.D.	MIN	MAX	SK	KU	
Corporate environment	Part 2 (1) Market Environment	3.678	1.035	5.000	1.400	-0.611	-0.757	high level
	Part 2 (2) Credit Policy	3.820	0.909	5.000	1.000	-1.158	1.372	high level
	Part 2 (3) Internal Control	3.696	1.038	5.000	1.000	-1.161	0.873	high level
	Part 2 (4) Information Disclosure	3.785	1.025	5.000	1.000	-0.883	0.371	high level
	Total	3.745	0.822	5.000	1.100	-1.105	1.147	high level
Dynamic capabilities	Part 3 (1) Innovation Capability	3.547	0.944	5.000	1.000	-0.483	-0.510	high level
	Part 3 (2) Absorptive Capacity	3.591	1.000	4.833	1.000	-0.718	-0.374	high level
	Part 3 (3) Integration Capability	3.506	1.033	5.000	1.200	-0.472	-0.494	high level
	Total	3.548	0.824	4.944	1.133	-0.748	0.187	high level
Agricultural enterprise performance	Part 4 (1) Financial Performance	3.785	0.995	5.000	1.000	-1.210	1.364	high level
	Part 4 (2) Social Performance	3.591	0.965	5.000	1.000	-0.450	-0.684	high level
	Part 4 (3) Ecological Performance	3.596	1.010	5.000	1.000	-0.679	-0.486	high level
	Total	**3.657**	**0.819**	**5.000**	**1.000**	**-0.726**	**0.434**	**high level**

The statistics used to analyze the data are Descriptive statistics: To find the basic statistics of the respondents, the arithmetic mean, standard deviation (SD), MIN, MAX, SK, KU were used.

As can be seen from Table 4.3, the presented data encompasses four latent variables: Digital Transformation, Corporate environment, dynamic ability, and Agricultural enterprise performance. Each latent variable is measured by multiple specific measure variables. Analyzing these variables can provide valuable insights into the underlying structures and their characteristics.

The overall mean of the latent variable of Digital Transformation is 3.721, indicating that the level of digital transformation reflected by its four measure variables is relatively high. The minimum value is 0.791, and the maximum value is 5.000. The wide range of data suggests significant differences among different entities or observation objects. The skewness (SK) values range from - 1.057 to 1.500, and the kurtosis (KU) values range from - 1.004 to 1.290, both of which are classified as "high level", indicating that the data distribution is significantly different from a normal distribution. This implies that the digital transformation process is not uniformly distributed. There may be some outliers in the data, or it may exhibit a skewed distribution pattern, which could be due to various factors such as differences in the level of technology adoption or resource allocation among the entities under study. (Bagozzi, 1981)

The overall mean of the latent variable of Corporate environment is 3.745, reflecting that the evaluation of the quality of the Corporate environment is at a moderately high level. The minimum value is 0.822, and the maximum value is 5.000, indicating a large data distribution range. This might be caused by differences in market conditions, regulatory environments, or internal management practices. The skewness values range from - 1.161 to 1.400, and the kurtosis values range from - 1.158 to 1.372, both at the "high level", further emphasizing that the data distribution is not a normal distribution. This indicates that when analyzing the impact of the Corporate environment on other variables, some extreme values or special distribution patterns may need to be considered.

The mean of the latent variable of dynamic ability is 3.548. Compared with the previous two latent variables, its average level is slightly lower. The minimum value is 0.824, and the maximum value is 4.944. The relatively wide data range indicates significant differences in the dynamic ability among various entities. The skewness values range from - 0.718 to - 0.472, and the kurtosis values range from - 0.718 to - 0.374, both classified as "high level", indicating that the data distribution is not a normal distribution. Although the degree of deviation may be smaller compared to other latent variables, this may imply that while there are differences in learning capacity, there may be some common underlying factors affecting the data distribution in a relatively consistent manner.

The overall mean of the latent variable of Agricultural enterprise performance is 3.657, suggesting that Agricultural enterprise performance is at a medium level. The minimum value is 0.819, and the maximum value is 5.000. The wide data range indicates significant differences in Agricultural enterprise performance among different entities. The skewness values range from - 1.210 to - 0.450, and the kurtosis values range from - 0.684 to 1.364, both at the "high level", indicating that the data distribution is not a normal distribution. This may suggest that Agricultural enterprise performance is influenced by a series of complex factors, and there may be some enterprises with extremely good or poor performance, resulting in a skewed data distribution.

In conclusion, the data of the four latent variables all exhibit non - normal distributions, as can be seen from the high - level skewness and kurtosis values. This has important implications for analyzing the relationships between these latent variables and other structures.

Part 3: Analysis Results of the underlying mechanisms through which digital transformation, corporate environment, and organizational learning capabilities influence the performance of agricultural enterprises.

The statistics used to analyze the data are confirmatory factors analysis--CFA, correlation analysis, Path Analysis.

Confirmatory Factors Analysis (CFA)

Digital Transformation

Table 4.4 Confirmatory Factors Analysis for Digital Transformation

Dimension	Options		Loading Coefficient	R2	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		
	Part 1 (1) 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		
	Part 1 (2) 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		
	Part 1 (3) 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		
	Part 1 (4) 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, Chi-Square/df=1.144, P=0.087, CFI=0.994, TLI=0.993, SRMR=0.033, RMSEA=0.02						

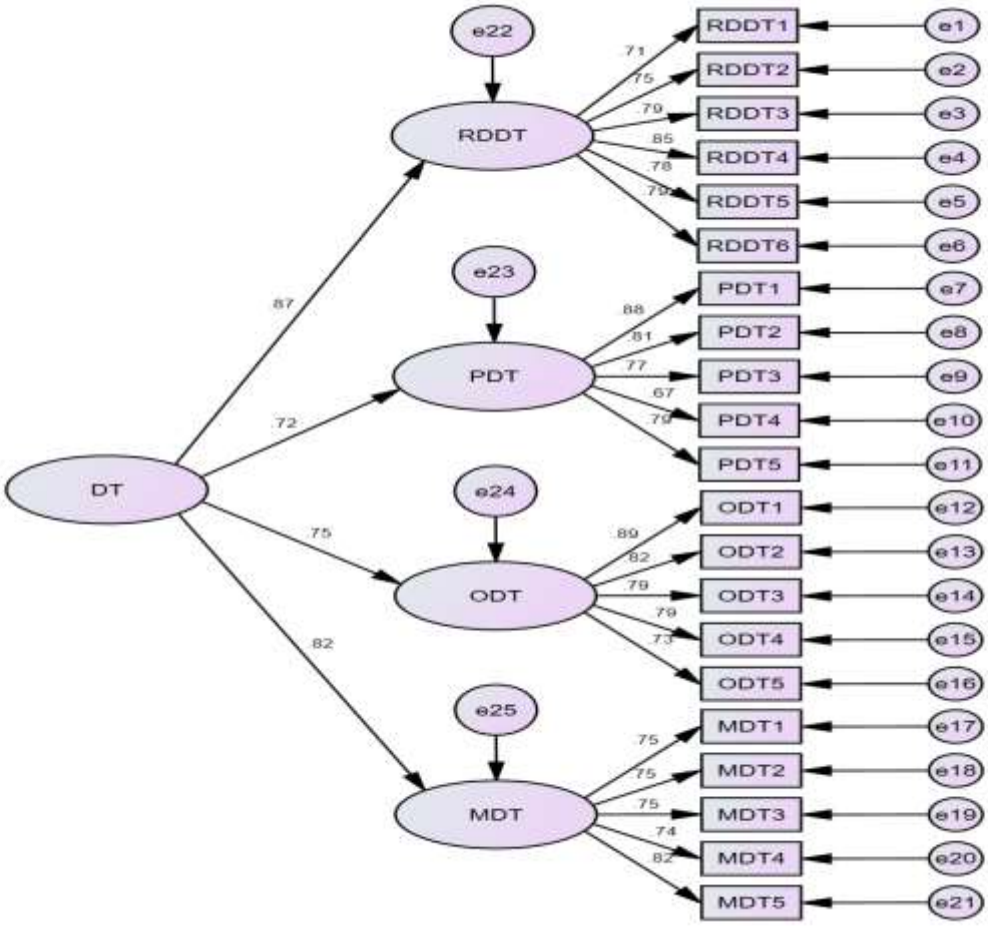

Figure 4.1 Confirmatory Test of Factors Affecting Digital Transformation of Agricultural Enterprises

As can be seen from Table 4.4, the "Digital Transformation" dimension is measured through four sub - dimensions: Research and Development Digital Transformation (RDDT), Production Digital Transformation (PDT), Operational Digital Transformation (ODT), and Marketing Digital Transformation (MDT). Each sub - dimension, in turn, consists of multiple specific measurement indicators. This structure helps to comprehensively and deeply understand the manifestations of the complex concept of digital transformation at different levels.

The loading coefficients of RDDT, PDT, ODT, and MDT are 0.87, 0.72, 0.75, and 0.82 respectively. The loading coefficient reflects the strength of the association between the sub - dimension and the main dimension of "Digital Transformation". Generally, the higher the loading coefficient, the stronger the representativeness of the sub - dimension for the main dimension. The relatively high loading coefficients of RDDT and MDT indicate that they are closely related to the latent variable of digital transformation and can better reflect the characteristics of digital transformation in research and development and marketing. Although the loading coefficients of PDT and ODT are slightly lower, they still reflect the relevant content of digital transformation to a certain extent.

The R^2 values of RDDT, PDT, ODT, and MDT are 0.759, 0.521, 0.561, and 0.669 respectively. The R^2 value represents the explanatory power of the sub - dimension for the latent variable of "Digital Transformation", that is, the proportion of the variance of the latent variable that the sub - dimension can explain. The relatively high R^2 values of RDDT and MDT indicate that these two sub - dimensions have a greater explanatory power for digital transformation and make a significant contribution to understanding digital transformation. The relatively low R^2 values of PDT and ODT imply that in addition to the factors covered by these two sub - dimensions, there may be other important factors affecting the overall performance of digital transformation, or it is necessary to further optimize the measurement methods of these two sub - dimensions to improve their explanatory power.

The CR values of each sub - dimension perform well overall. The CR value of RDDT is 0.87, that of ODT is 0.901, that of MDT is 0.874, and that of PDT is 0.907, which is at a similar level to other sub - dimensions. Generally, a CR value greater than 0.7 indicates that the measurement model has high internal consistency, that is, the various measurement indicators within the same sub - dimension are highly correlated and can reliably measure the concept represented by the sub - dimension. This shows that the current measurement model performs relatively reliably in terms of reliability, and the measurement indicators under each sub - dimension can stably reflect the corresponding latent characteristics.

The AVE values of RDDT, PDT, ODT, and MDT are 0.628, 0.606, 0.647, and 0.581 respectively. The AVE value is used to evaluate the convergent validity of the measurement model. Generally, an AVE value greater than 0.5 indicates that the measurement model can effectively converge around its corresponding latent variable, that is, each measurement indicator can converge to the latent variable. The AVE values of RDDT and ODT are greater than 0.5, indicating that the measurement models of these two sub - dimensions have good convergent validity. The AVE value of MDT is slightly lower than the ideal value, suggesting that it may be necessary to further review and optimize the measurement indicators under this sub - dimension to enhance its convergence to the latent variable.

The Chi - Square value is 211.711, and the degrees of freedom (df) is 185. The Chi - Square test is used to judge the goodness - of - fit between the observed data and the theoretical model. However, the Chi - Square value is easily affected by the sample size, so it has limitations when used alone. The ratio of Chi - Square to df (Chi - Square/df) is 1.144. Generally, when this ratio is between 1 - 3, the model fit is considered good. This data indicates that the current model fit is within an acceptable range, meaning that the difference between the theoretical model and the observed data is within a reasonable range. The CFI value is 0.994. Generally, a CFI value greater than 0.9 indicates a good model fit. This data further supports that the model has a good fit, that is, the model can better explain the structure and relationships of the data. The TLI value is 0.993, which is also greater than 0.9, indicating once again that the model fit is relatively ideal and the model can reasonably reflect the relationships between variables. The SRMR value is 0.033. Generally, an SRMR value less than 0.08 indicates a good model fit. This data shows that the model has a small residual, the model fits the data well, and the difference between the observed data and the model predicted values is small. The RMSEA value is 0.02. Generally, an RMSEA value less than 0.05 indicates a very good model fit, and less than 0.08 indicates an acceptable fit. This value indicates that the model fit is excellent, and the degree of adaptation between the model and the data is very high.

Overall, the current measurement model for the "Digital Transformation" dimension performs well in many aspects. The relationships between each sub - dimension and the latent variable of digital transformation are relatively significant. The measurement model has high reliability and good convergent validity. At the same time, the model fit to the data is also very ideal.

Corporate Environment

Table 4.5 Confirmatory Factors Analysis for Corporate environment

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		
	Part 2 (1) 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		
	Part 2 (2) 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		
	Part 2 (3) 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		
	Part 2 (4) 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, Chi-Square/df=1.168						
P= 0.105, CFI=0.995, TLI=0.994, SRMR=0.032, RMSEA=0.022						

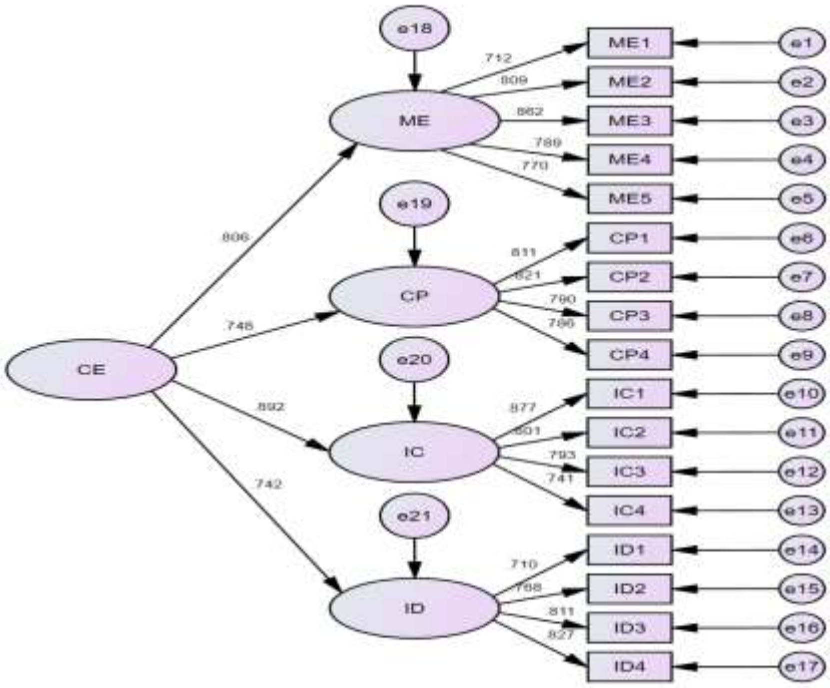

Figure 4.2 Results of Confirmatory Factor Test for the Environment of Agricultural Enterprises

The data focuses on the "Corporate Environment" dimension. This dimension is measured through four sub - dimensions: Market Environment (ME), Credit Policy (CP), Internal Control (IC), and Information Disclosure (ID). Each sub - dimension is composed of multiple specific measurement indicators. This multi - level structure helps to comprehensively depict different aspects of the complex concept of the Corporate environment.

As can be seen from Table 4.5, the loading coefficients of ME, CP, IC, and ID are 0.806, 0.748, 0.892, and 0.742 respectively. The loading coefficient reflects the degree of association between the sub - dimension and the main dimension of " Corporate Environment ". Generally speaking, the higher the coefficient, the stronger the representativeness of the sub - dimension for the main dimension. The loading coefficient of IC is the highest, indicating that internal control has the closest connection with the latent variable of the Corporate environment and can well reflect the characteristics of the Corporate environment in terms of internal control.

The loading coefficients of ME and CP are also relatively high, indicating that the market environment and credit policy have strong representational capabilities for the Corporate environment. The loading coefficient of ID is relatively slightly lower, but it still indicates that information disclosure reflects the relevant content of the Corporate environment to a certain extent.

The R^2 values of ME, CP, IC, and ID are 0.650, 0.560, 0.796, and 0.551 respectively. The R^2 value reflects the degree to which the sub - dimension can explain the latent variable of "Corporate environment", that is, the proportion of the variance of the latent variable that the sub - dimension can explain. The R^2 value of IC is the highest, which means that internal control has the greatest explanatory power for the Corporate environment and makes a significant contribution to understanding the Corporate environment. The R^2 value of ME is also quite considerable, indicating that the market environment has a good explanatory effect on the Corporate environment. However, the R^2 values of CP and ID are relatively low, which may imply that in addition to the factors covered by these two sub - dimensions, there are other important factors affecting the overall performance of the Corporate environment, or it is necessary to further optimize the measurement methods of the CP and ID sub - dimensions to enhance their explanatory power for the Corporate environment.

The CR values of each sub - dimension perform well overall. The CR value of ME is 0.876, that of CP is 0.878, that of IC is 0.88, and that of ID is 0.861. Generally, a CR value greater than 0.7 is considered that the measurement model has high internal consistency, that is, the various measurement indicators within the same sub - dimension are highly correlated and can reliably measure the concept represented by the sub - dimension. This shows that the current measurement model for the Corporate environment dimension performs reliably in terms of reliability, and the measurement indicators under each sub - dimension can stably reflect the corresponding latent characteristics.

The AVE values of ME, CP, IC, and ID are 0.639, 0.643, 0.647, and 0.609 respectively. The AVE value is used to evaluate the convergent validity of the measurement model. Generally, an AVE value greater than 0.5 indicates that the measurement model can effectively converge around its corresponding latent variable, that is, each measurement indicator can converge to the latent variable. The AVE values of the four sub - dimensions are all greater than 0.5, indicating that the measurement models of each sub - dimension have good convergent validity, and the measurement indicators can well converge to their respective corresponding latent variables, so as to effectively measure the characteristics of the Corporate environment in different aspects.

The Chi - Square value is 134.375, and the degrees of freedom (df) is 115. The Chi - Square test is used to judge the goodness - of - fit between the observed data and the theoretical model. However, the Chi - Square value is easily affected by the sample size, so it has limitations when used alone. The ratio of Chi - Square to df (Chi - Square/df) is 1.168. Generally, when this ratio is between 1 - 3, the model fit is considered good. This data indicates that the current model fit is within an acceptable range, meaning that the difference between the theoretical model and the observed data is within a reasonable range. The CFI value is 0.995. Generally, a CFI value greater than 0.9 indicates a good model fit. This data further supports that the model has a good fit, that is, the model can better explain the structure and relationships of the data. The TLI value is 0.994, which is also greater than 0.9, indicating once again that the model fit is relatively ideal and the model can reasonably reflect the relationships between variables. The SRMR value is 0.032. Generally, an SRMR value less than 0.08 indicates a good model fit. This data shows that the model has a small residual, the model fits the data well, and the difference between the observed data and the model predicted values is small. The RMSEA value is 0.022. Generally, an RMSEA value less than 0.05 indicates a very good model fit, and less than 0.08 indicates an acceptable fit. This value indicates that the model fit is excellent, and the degree of adaptation between the model and the data is very high.

Overall, the current measurement model for the " Corporate Environment " dimension performs well in many key aspects. The relationships between each sub -

dimension and the latent variable of the Corporate environment are relatively significant. The measurement model has high reliability and good convergent validity. At the same time, the model fit to the data is also very ideal.

Dynamic capabilities

Table 4.6 Confirmatory Factors Analysis for Dynamic capabilities

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		
	Part 3 (1) 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		
	Part 3 (2) 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		
	Part 3 (3) 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, Chi-Square/df=1.137 P= 0.164, CFI=0.996, TLI=0.995, SRMR=0.027, RMSEA=0.02						

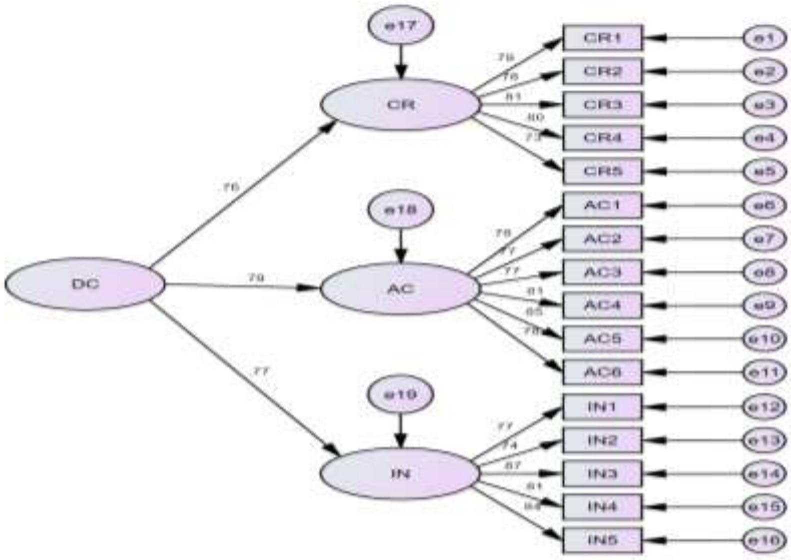

Figure 4.3 Results of Confirmatory Factor Test for Dynamic Capabilities

Table 4.6 focuses on the " Dynamic capabilities " dimension. This dimension is measured through three sub - dimensions: Innovation Capability (CR), Absorptive Capacity (AC), and Integration Capability (IN). Each sub - dimension is further divided into multiple specific measurement indicators. Such a structure helps to comprehensively and meticulously analyze different dimensions of the complex concept of dynamic ability.

The loading coefficients of creativity Capability (CR), Absorptive Capacity (AC), and Integration Capability (IN) are 0.76, 0.78, and 0.77 respectively. The loading coefficient reflects the degree of association between the sub - dimension and the main dimension of " Dynamic capabilities ". Generally, a higher loading coefficient implies that the sub - dimension is more representative of the main dimension. The loading coefficients of these three sub - dimensions are relatively close and at a certain level, indicating that they are closely related to the latent variable of Dynamic capabilities and can effectively reflect the characteristics of dynamic ability in different aspects.

The R^2 values of CR, AC, and IN are 0.573, 0.605, and 0.591 respectively. The R^2 value represents the degree to which the sub - dimension can explain the latent variable of "dynamic ability", that is, the proportion of the variance of the latent variable that the sub - dimension can account for. The relatively higher R^2 value of AC indicates that absorptive capacity has a relatively greater explanatory power for dynamic ability and makes a more prominent contribution to understanding dynamic ability. However, the R^2 values of CR and IN are relatively lower, which may imply that apart from the factors covered by these two sub - dimensions, there may be other crucial factors influencing the overall performance of dynamic ability, or it may be necessary to optimize the measurement methods of these two sub - dimensions to enhance their explanatory power.

The composite reliability values of each sub - dimension perform well overall. The composite reliability of CR is 0.812, that of AC is 0.911, and that of IN is 0.904. Generally, when the composite reliability value is greater than 0.7, the measurement model has high internal consistency, meaning that the various measurement indicators within the same sub - dimension are highly correlated and can reliably measure the concept represented by the sub - dimension. This shows that the current measurement model for the dynamic ability dimension performs reliably in terms of reliability, and the measurement indicators under each sub - dimension can stably reflect the corresponding latent characteristics.

The AVE values of CR, AC, and IN are 0.59, 0.629, and 0.653 respectively. The AVE value is used to evaluate the convergent validity of the measurement model. Generally, an AVE value greater than 0.5 indicates that the measurement model can effectively converge around its corresponding latent variable, that is, each measurement indicator can converge to the latent variable. The AVE values of the three sub - dimensions are all greater than 0.5, indicating that the measurement models of each sub - dimension have good convergent validity, and the measurement indicators can well converge to their respective corresponding latent variables, thus effectively measuring the characteristics of dynamic ability in different aspects.

The Chi - Square value is 114.832, and the degrees of freedom (df) is 101. The Chi - Square test is used to determine the goodness - of - fit between the observed data and the theoretical model. However, the Chi - Square value is easily affected by the sample size, so it has limitations when used alone. The ratio of Chi - Square to df (Chi - Square/df) is 1.137. Generally, when this ratio is between 1 - 3, the model fit is considered good. This data indicates that the current model fit is within an acceptable range, meaning that the difference between the theoretical model and the observed data is within a reasonable range. The CFI value is 0.996. Generally, a CFI value greater than 0.9 indicates a good model fit. This data further supports that the model has a good fit, that is, the model can better explain the structure and relationships of the data. The TLI value is 0.995, which is also greater than 0.9, indicating once again that the model fit is relatively ideal and the model can reasonably reflect the relationships between variables. The SRMR value is 0.027. Generally, an SRMR value less than 0.08 indicates a good model fit. This data shows that the model has a small residual, the model fits the data well, and the difference between the observed data and the model predicted values is small. The RMSEA value is 0.02. Generally, an RMSEA value less than 0.05 indicates a very good model fit, and less than 0.08 indicates an acceptable fit. This value indicates that the model fit is excellent, and the degree of adaptation between the model and the data is very high.

Overall, the current measurement model for the "Dynamic capabilities" dimension performs well in many aspects. The relationships between each sub - dimension and the latent variable of dynamic ability are relatively significant. The measurement model has high reliability and good convergent validity. At the same time, the model fit to the data is also very ideal.

Agricultural Enterprises Performance

Table 4.7 Confirmatory Factors Analysis for Agricultural Enterprises 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		
	Part 4 (1) 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		
	Part 4 (2) 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		
	Part 4 (3) 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, Chi-Square/df=1.086 P= 0.3, CFI=0.998, TLI=0.997, SRMR=0.027, RMSEA=0.015						

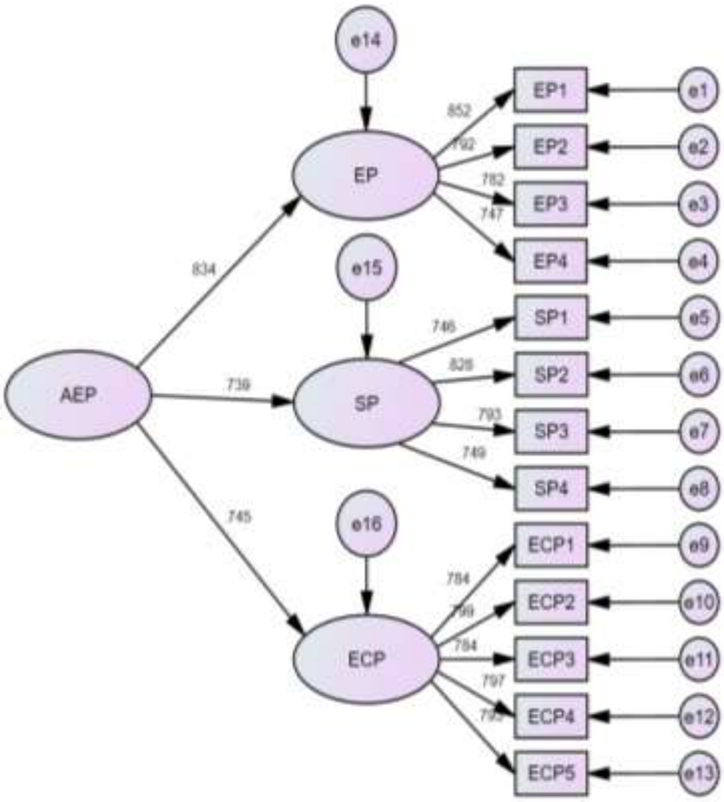

Figure 4.4 Results of Confirmatory Factor Test for Agricultural Enterprise Performance

Table 4.7 focuses on the "Agricultural Enterprises Performance" dimension. This dimension is measured through three sub - dimensions: economy Performance (EP), Social Performance (SP), and Ecological Performance (ECP). Each sub - dimension consists of multiple specific measurement indicators. This structure helps to comprehensively and deeply understand the manifestations of the complex concept of agriculture Agricultural enterprise performance at different levels.

The loading coefficients of Economy Performance (EP), Social Performance (SP), and Ecological Performance (ECP) are 0.834, 0.739, and 0.745 respectively. The loading coefficient reflects the degree of association between the sub - dimension and the main dimension of "Agricultural Enterprises Performance". Generally, the higher the loading coefficient, the stronger the representativeness of the sub - dimension for the main dimension. The relatively high loading coefficient of EP indicates that Economy performance has a closer connection with the latent variable of Agricultural Enterprises Performance and can better reflect the characteristics of Agricultural Enterprises Performance in terms of finance. The loading coefficients of SP and ECP are relatively lower, but they still reflect the relevant content of agriculture Agricultural enterprise performance to a certain extent.

The R^2 values of EP, SP, and ECP are 0.696, 0.546, and 0.555 respectively. The R^2 value represents the explanatory power of the sub - dimension for the latent variable of "Agricultural Enterprises Performance", that is, the proportion of the variance of the latent variable that the sub - dimension can explain. The relatively high R^2 value of EP indicates that financial performance has a greater explanatory power for Agricultural Enterprises Performance and makes a significant contribution to understanding Agricultural Enterprises Performance. However, the relatively low R^2 values of SP and ECP may imply that in addition to the factors covered by these two sub - dimensions, there are other important factors affecting the overall performance of agriculture Agricultural enterprise performance, or it is necessary to further optimize the measurement methods of the SP and ECP sub - dimensions to improve their explanatory power.

The CR values of each sub - dimension perform well overall. The CR value of EP is 0.817, that of SP is 0.861, and that of ECP is 0.893. Generally, a CR value greater than 0.7 indicates that the measurement model has high internal consistency, that is, the various measurement indicators within the same sub - dimension are highly correlated and can reliably measure the concept represented by the sub - dimension. This shows that the current measurement model for the agriculture Agricultural enterprise performance dimension performs reliably in terms of reliability, and the measurement indicators under each sub - dimension can stably reflect the corresponding latent characteristics.

The AVE values of EP, SP, and ECP are 0.599, 0.608, and 0.626 respectively. The AVE value is used to evaluate the convergent validity of the measurement model. Generally, an AVE value greater than 0.5 indicates that the measurement model can effectively converge around its corresponding latent variable, that is, each measurement indicator can converge to the latent variable. The AVE values of the three sub - dimensions are all greater than 0.5, indicating that the measurement models of each sub - dimension have good convergent validity, and the measurement indicators can well converge to their respective corresponding latent variables, thus effectively measuring the characteristics of agriculture Agricultural enterprise performance in different aspects.

The Chi - Square value is 67.315, and the degrees of freedom (df) is 62. The Chi - Square test is used to judge the goodness - of - fit between the observed data and the theoretical model. However, the Chi - Square value is easily affected by the sample size, so it has limitations when used alone. The ratio of Chi - Square to df (Chi - Square/df) is 1.086. Generally, when this ratio is between 1 - 3, the model fit is considered good. This data indicates that the current model fit is within an acceptable range, meaning that the difference between the theoretical model and the observed data is within a reasonable range. The CFI value is 0.998. Generally, a CFI value greater than 0.9 indicates a good model fit. This data further supports that the model has a good fit, that is, the model can better explain the structure and relationships of the data. The TLI value is 0.997, which is also greater than 0.9, indicating once again that the model fit is relatively ideal and the model can reasonably reflect the relationships between variables. The SRMR value is 0.027. Generally, an SRMR value less than 0.08 indicates a good model fit. This data shows that the model has a small residual, the model fits the data well, and the difference between the observed data and the model predicted values is small. The RMSEA value is 0.015. Generally, an RMSEA value less than 0.05 indicates a very good model fit, and less than 0.08 indicates an acceptable fit. This value indicates that the model fit is excellent, and the degree of adaptation between the model and the data is very high.

Overall, the current measurement model for the "Agricultural Enterprises Performance" dimension performs well in many key aspects. The relationships between each sub - dimension and the latent variable of agriculture Agricultural enterprise performance are relatively significant. The measurement model has high reliability and good convergent validity. At the same time, the model fit to the data is also very ideal.

Correlation Analysis

Table 4.8 coefficient of variable correlation.

	Part 1 (1)	Part 1 (2)	Part 1 (3)	Part 1 (4)	Part 2 (1)	Part 2 (2)	Part 2 (3)	Part 2 (4)	Part 3 (1)	Part 3 (2)	Part 3 (3)	Part 4 (1)	Part 4 (2)	Part 4 (3)
Part 1 (1) R&D Digital Transformation	1													
Part 1 (2) Production Digital Transformation	.556**	1												
Part 1 (3) Operational Digital Transformation	.571**	.548**	1											
Part 1 (4) Marketing Digital Transformation	.656**	.496**	.525**	1										
Part 2 (1) Market Environment	.220**	.199**	.274**	.208**	1									
Part 2 (2) Credit Policy	.219**	.222**	.250**	.241**	.539**	1								
Part 2 (3) Internal Control	.275**	.205**	.249**	.271**	.646**	.584**	1							
Part 2 (4) Information Disclosure	.270**	.235**	.267**	.300**	.530**	.494**	.583**	1						
Part 3 (1) creativity Capability	.297**	.276**	.305**	.237**	.270**	.296**	.248**	.262**	1					
Part 3 (2) Absorptive Capacity	.309**	.337**	.332**	.296**	.343**	.387**	.329**	.371**	.526**	1				
Part 3 (3) Integration Capability	.316**	.307**	.358**	.307**	.363**	.344**	.327**	.333**	.524**	.548**	1			
Part 4 (1) economic Performance	.388**	.289**	.362**	.342**	.391**	.356**	.412**	.339**	.361**	.498**	.392**	1		
Part 4 (2) Social Performance	.292**	.262**	.352**	.226**	.301**	.238**	.303**	.306**	.339**	.375**	.351**	.539**	1	
Part 4 (3) Ecological Performance	.302**	.254**	.286**	.260**	.329**	.272**	.279**	.294**	.353**	.392**	.336**	.550**	.490**	1

Note: ***, **, * indicate p < 0.001, p < 0.05, and p < 0.10 respectively.

Table 4.8 presents a correlation matrix of multiple variables, involving specific measurement variables from different dimensions such as digital transformation, Corporate environment, dynamic ability, and agriculture Agricultural enterprise performance.

The correlation coefficients between R&D Digital Transformation (Part1(1)) and Production Digital Transformation (Part1(2)), Operational Digital Transformation (Part1(3)), and Marketing Digital Transformation (Part1(4)) are 0.556, 0.571, and 0.656 respectively. These significant positive correlations indicate that there are close connections between R&D digital transformation and other aspects of digital transformation. That is, the higher the degree of digitalization in the R&D process of an enterprise, the more likely it is to actively promote digitalization in production, operation, and marketing, demonstrating the synergy of digital transformation among different business processes within the enterprise. Besides its correlation with R&D digital transformation, the correlation coefficients of Production Digital Transformation (Part1(2)) with Operational Digital Transformation (Part1(3)) and Marketing Digital Transformation (Part1(4)) are 0.548 and 0.496 respectively. This further confirms the inter - relatedness among the sub - dimensions of digital transformation, suggesting that production digital transformation interacts and promotes with operational and marketing digital transformation in enterprise practice. The correlation coefficient between Operational Digital Transformation (Part1(3)) and Marketing Digital Transformation (Part1(4)) is 0.525, indicating a significant positive correlation between operational digitalization and marketing digitalization, implying that digitalization in the enterprise's operation process helps improve the level of marketing digitalization, and vice versa.

The correlation coefficients between Market Environment (Part2(1)) and the sub - dimensions of digital transformation range from 0.199 to 0.274, those between Market Environment and the sub - dimensions of dynamic ability range from 0.237 to 0.270, and those between Market Environment and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.226 to 0.391. These moderate positive correlations suggest that there is a certain connection between the market environment, digital transformation, dynamic ability, and Agricultural enterprise performance. A good market environment may provide favorable conditions for an enterprise's digital transformation, improvement of dynamic ability, and performance enhancement. The correlations of Credit Policy (Part2(2)) with other variables are similar to those of the market environment. The correlation coefficients between Credit Policy and the sub - dimensions of digital transformation range from 0.219 to 0.250, those between Credit Policy and the sub - dimensions of dynamic ability range from 0.248 to 0.387, and those between Credit Policy and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.238 to 0.356. This indicates that credit policy also has a certain impact on all aspects of an enterprise's development. A reasonable credit policy may help enterprises achieve better results in digital transformation, organizational learning, and performance improvement. The correlation coefficients between Internal Control (Part2(3)) and the sub - dimensions of digital transformation range from 0.205 to 0.275, those between Internal Control and the sub - dimensions of dynamic ability range from 0.248 to 0.329, and those between Internal Control and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.279 to 0.412. This shows that internal control plays an important role in the overall development of an enterprise. Effective internal control may promote the coordinated development of an enterprise in all aspects. The correlations of Information Disclosure (Part2(4)) with other variables are also significant. The correlation coefficients between Information Disclosure and the sub - dimensions of digital transformation range from 0.235 to 0.300, those between Information Disclosure and the sub - dimensions of dynamic ability range from 0.262 to 0.371, and those between Information Disclosure and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.294 to 0.339. This indicates that information disclosure has a certain impact on an enterprise's digital transformation, organizational learning, and performance improvement. A good information disclosure mechanism may help enterprises better integrate resources and achieve coordinated development in all aspects.

The correlation coefficients between Innovation Capability (Part3(1)) and the sub - dimensions of digital transformation range from 0.237 to 0.305, those between Innovation Capability and the sub - dimensions of the Corporate environment range from 0.248 to 0.296, and those between Innovation Capability and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.339 to 0.392. This indicates that there is a certain connection between innovation capability, an enterprise's digital transformation, Corporate environment, and performance. A strong innovation capability of an enterprise may help promote digital transformation, adapt to changes in the Corporate environment, and enhance Agricultural enterprise performance. The correlations of Absorptive Capacity (Part3(2)) with other variables are more extensive. The correlation coefficients between Absorptive Capacity and the sub - dimensions of digital transformation range from 0.296 to 0.337, those between Absorptive Capacity and the sub - dimensions of the Corporate environment range from 0.329 to 0.387, and those between Absorptive Capacity and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.351 to 0.498. This shows that absorptive capacity plays an important role in an enterprise's development. Enterprises that can better absorb external knowledge and resources may have more advantages in digital transformation, adapting to the Corporate environment, and improving performance. The correlation coefficients between Integration Capability (Part3(3)) and the sub - dimensions of digital transformation range from 0.307 to 0.358, those between Integration Capability and the sub - dimensions of the Corporate environment range from 0.327 to 0.363, and those between Integration Capability and the sub - dimensions of agriculture Agricultural enterprise performance range from 0.336 to 0.392. This indicates that integration capability helps enterprises achieve coordinated development in all aspects. Enterprises that can effectively integrate internal resources and external environmental factors may perform more outstandingly in digital transformation, dealing with changes in the Corporate environment, and improving Agricultural enterprise performance.

The correlation coefficients between Financial Performance Evaluation (Part4(1)) and the sub - dimensions of digital transformation range from 0.289 to 0.388, those between Financial Performance Evaluation and the sub - dimensions of the Corporate environment range from 0.339 to 0.412, and those between Financial Performance Evaluation and the sub - dimensions of dynamic ability range from 0.351 to 0.498. This indicates that there is a significant positive correlation among financial performance, an enterprise's digital transformation, Corporate environment, and dynamic ability. By promoting digital transformation, optimizing the Corporate environment, and enhancing dynamic ability, enterprises may help improve financial performance. The correlations of Social Performance (Part4(2)) with other variables are also obvious. The correlation coefficients between Social Performance and the sub - dimensions of digital transformation range from 0.226 to 0.352, those between Social Performance and the sub - dimensions of the Corporate environment range from 0.238 to 0.306, and those between Social Performance and the sub - dimensions of dynamic ability range from 0.339 to 0.375. This shows that social performance is inter - related to all aspects of an enterprise's development. While pursuing economic performance, enterprises that pay attention to digital transformation, Corporate environment optimization, and improvement of dynamic ability may help enhance social performance. The correlation coefficients between Ecological Performance (Part4(3)) and the sub - dimensions of digital transformation range from 0.254 to 0.302, those between Ecological Performance and the sub - dimensions of the Corporate environment range from 0.272 to 0.329, and those between Ecological Performance and the sub - dimensions of dynamic ability range from 0.336 to 0.392. This indicates that ecological performance is also related to other aspects of an enterprise's development. In the process of promoting digital transformation, adapting to the Corporate environment, and enhancing dynamic ability, enterprises may have a positive impact on ecological performance.

As can be seen from the data, there are generally significant correlations among the variables of each dimension. This indicates that an enterprise's digital transformation, Corporate environment, dynamic ability, and agriculture Agricultural enterprise performance do not exist in isolation, but rather interact and influence each other. This correlation provides strong empirical support for further research on the comprehensive development of enterprises.

Path Analysis

Table 4.9 Direct path

Path	Path Coefficient (standardized)	unstandardized	S.E.	T	P
The agricultural enterprises Performance ⟵Digital transformation	0.199	0.194	0.065	2.985	0.003
The agricultural enterprises Performance ⟵ Corporate environment	0.23	0.231	0.07	3.318	***
Dynamic capabilities⟵Digital transformation	0.374	0.292	0.052	5.562	***
Dynamic capabilities⟵ Corporate environment	0.422	0.34	0.056	6.106	***
The agricultural enterprises Performance ⟵Dynamic learning ability	0.475	0.592	0.108	5.461	***

Table 4.9 presents the results of the path analysis among agricultural enterprise performance, digital transformation, corporate environment, and dynamic learning ability (here it is assumed that "Dynamic capabilities" should be "Dynamic learning ability", please correct if not). The results include standardized path coefficients, unstandardized path coefficients, standard errors (S.E.), T - values, and P - values, which are used to reveal the strength and significance of the causal relationships among these variables.

The standardized path coefficient between agricultural enterprise performance and digital transformation is 0.199, which means that for every one - standard - deviation change in digital transformation, agricultural enterprise performance will change by 0.199 standard - deviations accordingly. The unstandardized path coefficient is 0.194, the standard error is 0.065, the T - value is 2.985, and the P - value is 0.003. Since the P - value is less than 0.05, it indicates that digital transformation has a significant positive impact on agricultural enterprise performance. That is, an increase in the degree of digital transformation will promote the improvement of agricultural enterprise performance.

The standardized path coefficient between agricultural enterprise performance and the corporate environment is 0.23, the unstandardized path coefficient is 0.231, the standard error is 0.07, the T - value is 3.318, and the P - value is marked as "***" (usually indicating P < 0.001). This shows that the corporate environment has a highly significant positive impact on agricultural enterprise performance. Optimizing the corporate environment where the enterprise is located will significantly enhance agricultural enterprise performance.

The standardized path coefficient between dynamic learning ability and digital transformation is 0.374, the unstandardized path coefficient is 0.292, the standard error is 0.052, the T - value is 5.562, and the P - value is "***". It shows that digital transformation has a significant positive impact on dynamic learning ability. The promotion of digital transformation helps to improve the enterprise's dynamic learning ability.

The standardized path coefficient between dynamic learning ability and the corporate environment is 0.422, the unstandardized path coefficient is 0.34, the standard error is 0.056, the T - value is 6.106, and the P - value is "***". It indicates that the corporate environment has a significant positive impact on dynamic learning ability. A good corporate environment can promote the enhancement of the enterprise's dynamic learning ability.

The standardized path coefficient between agricultural enterprise performance and dynamic learning ability is 0.475, the unstandardized path coefficient is 0.592, the standard error is 0.108, the T - value is 5.461, and the P - value is "***". This shows that dynamic learning ability has a significant positive impact on agricultural enterprise performance. The improvement of the enterprise's dynamic learning ability plays an important role in the improvement of agricultural enterprise performance.

The significant causal relationships among the variables indicate that the development of agricultural enterprises is a process of interaction among multiple factors. Digital transformation, the corporate environment, and dynamic learning ability all have important impacts on agricultural enterprise performance. Moreover, digital transformation and the corporate environment also indirectly affect agricultural enterprise performance by influencing dynamic learning ability.

Table 4.10 Intermediation Test

Path		Effect	S.E.	Bias-corrected 95%CI		
				Lower	Upper	P
The agricultural enterprise performance. $\boxed{\leftarrow}$ Dynamic capabilities $\boxed{\leftarrow}$ Digital transformation	Indirect effects	0.178	0.046	0.103	0.285	0
	Direct effect	0.199	0.071	0.052	0.329	0.011
	Total effect	0.377	0.065	0.245	0.497	0
The agricultural enterprise performance. $\boxed{\leftarrow}$ Dynamic capabilities $\boxed{\leftarrow}$ The corporate environment	Indirect effects	0.2	0.051	0.114	0.32	0
	Direct effect	0.23	0.078	0.075	0.375	0.006
	Total effect	0.43	0.066	0.295	0.553	0

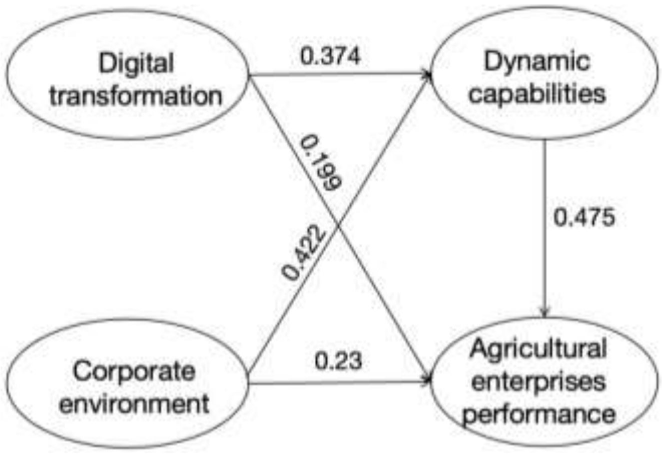

Figure 4.5 Results of Influence Path Identification

Table 4.10 presents the results of the path analysis between agricultural enterprise performance and dynamic capabilities, with digital transformation and corporate environment serving as mediating variables. The results include indirect effects, direct effects, and total effects. Additionally, standard errors (S.E.), bias - corrected 95% confidence intervals (Bias - corrected 95% CI), and P - values are provided to comprehensively evaluate the impact relationships and their significance among the variables.

The indirect effect of digital transformation on agricultural enterprise performance, via dynamic capabilities, is 0.178. The standard error is 0.046, the 95% confidence interval is [0.103, 0.285], and the P - value is 0. A P - value of 0 indicates that this indirect effect is highly significant statistically, meaning that digital transformation significantly impacts agricultural enterprise performance indirectly by influencing dynamic capabilities. The fact that the confidence interval does not contain 0 further supports the significance of this indirect effect. The direct effect of digital transformation on agricultural enterprise performance is 0.199, with a standard error of 0.071. The 95% confidence interval is [0.052, 0.329], and the P - value is 0.011. Since the P - value is less than 0.05, it shows that the direct impact of digital transformation on agricultural enterprise performance is significant. The confidence interval also indicates the statistical reliability of this direct effect. The total effect of digital transformation on agricultural enterprise performance (the sum of the direct and indirect effects) is 0.377, with a standard error of 0.065. The 95% confidence interval is [0.245, 0.497], and the P - value is 0. The significance of the total effect demonstrates that digital transformation, whether acting directly or indirectly through dynamic capabilities, has a significant positive impact on agricultural enterprise performance.

The indirect effect of the corporate environment on agricultural enterprise performance, via dynamic capabilities, is 0.2. The standard error is 0.051, the 95% confidence interval is [0.114, 0.32], and the P - value is 0. This indicates that the corporate environment has a significant indirect impact on agricultural enterprise performance through dynamic capabilities, as supported by both the P - value and the confidence interval. The direct effect of the corporate environment on agricultural enterprise performance is 0.23, with a standard error of 0.078. The 95% confidence interval is [0.075, 0.375], and the P - value is 0.006. Since the P - value is less than 0.05, it shows that the direct impact of the corporate environment on agricultural enterprise performance is significant, and the confidence interval validates the reliability of this direct effect. The total effect of the corporate environment on agricultural enterprise performance is 0.43, with a standard error of 0.066. The 95% confidence interval is [0.295, 0.553], and the P - value is 0. This shows that the corporate environment has a significant overall impact on agricultural enterprise performance, meaning it can directly affect agricultural enterprise performance and also indirectly affect it through dynamic capabilities.

Digital transformation and the corporate environment not only have a direct positive impact on agricultural enterprise performance but also have a significant indirect impact through the mediating variable of dynamic capabilities. This implies that in the process of enhancing agricultural enterprise performance, the complex relationships among digital transformation, the corporate environment, and dynamic capabilities should not be overlooked.

Part 4: Results find a model for enhancing agricultural enterprise performance.

The statistics used to analyze the data is Structural Equation Modeling-SEM (including Model Fitting Analysis).

SEM

Table 4.11 Model Fit Tests

Goodness-of-fit parameters	CMIN	DF	CMIN/DF	p	GFI	IFI	TLI	CFI	RMSEA	SRMR
Result	76.63	71	1.079	0.303	0.97	0.997	0.996	0.997	0.015	0.029
Standard			*<3*		*>0.9*	*>0.9*	*>0.9*	*>0.9*	*<0.05*	*<0.05*

Table 4.11 provides various parameters of the goodness - of - fit of the model, which are used to judge the degree of adaptation between the constructed model and the observed data. By comparing each parameter with the standard value, a comprehensive understanding of the validity and reliability of the model can be obtained.

The CMIN value is 76.63, the DF value is 71, and the CMIN/DF ratio is 1.079. Generally, the CMIN/DF ratio should be less than 3. The current ratio of 1.079 is far less than 3, indicating that the model fits the data well. That is, the difference between the theoretical model and the observed data is small, and the model can reasonably explain the data. The P - value is 0.303, which is greater than the common significance level of 0.05. This means that, in a statistical sense, the null hypothesis cannot be rejected, that is, there is no significant difference between the model and the data, further supporting the conclusion that the model fits well. The GFI value is 0.97, which is greater than the standard value of 0.9. GFI measures the overall fit of the model to the data. This value indicates that the model can fit the observed data well, that is, the model can explain most of the variation in the data.

The IFI value is 0.997, the TLI value is 0.996, and the CFI value is 0.997, all of which are far greater than the standard value of 0.9. These three indices are used to compare the goodness - of - fit of the hypothesized model with that of the null model. The closer the value is to 1, the better the model fit. Such high values indicate that compared with the null model, this model can fit the data significantly better, and the model has a strong ability to explain the data. The RMSEA value is 0.015, which is less than the standard value of 0.05. RMSEA is used to evaluate the degree of approximate error of the model. The smaller this value is, the better the model fits the data. The current value indicates that the fit between the model and the data is very good, and the model has a high degree of approximation to the data. The SRMR value is 0.029, which is less than the standard value of 0.05. SRMR measures the average size of the residuals of the observed variables and reflects the degree of difference between the model predicted values and the actual observed values. The smaller this value is, the higher the consistency between the model predicted values and the actual observed values, and the better the model fits the data.

Considering all the goodness - of - fit parameters, the indicators of this model all meet or far exceed the general standards, indicating that there is a very good fit between the model and the observed data. This means that the variable relationships and structure set in the model can reasonably explain the collected data.

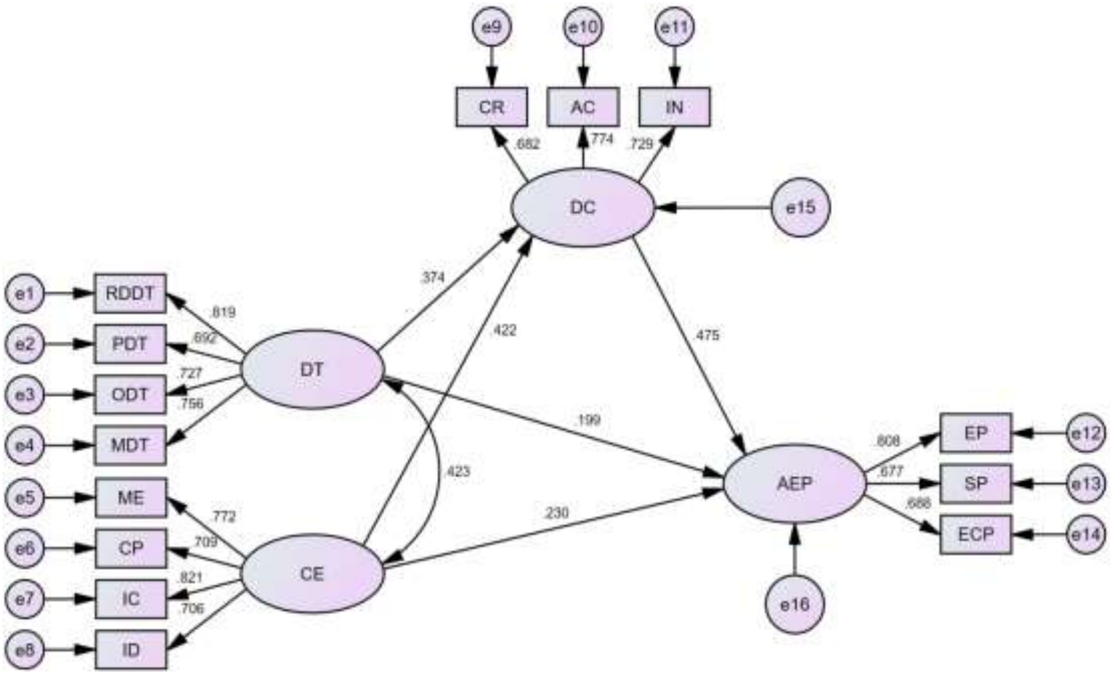

Figure 4.6 Overall Model Framework

From Figure 4.6, the arrow connecting DT and DC indicates that there is a direct influence path from DT to DC. This means that the dynamic traits of an enterprise directly act on the formation or enhancement of its dynamic capabilities, that is, the better the specific dynamic characteristics an enterprise possesses, the stronger its dynamic capabilities may be. The arrow pointing from CE to DC shows that CE has an impact on DC, indicating that corporate - level capabilities affect the construction of an enterprise's dynamic capabilities. The arrow from DC to AEP indicates that DC has a direct impact on the performance of agricultural enterprises. That is, the stronger the dynamic capabilities of an enterprise, the more likely it is to achieve better performance in the market, such as obtaining higher profits and a larger market share. The arrow between CE and AEP shows that corporate - level capabilities also directly affect the performance of agricultural enterprises. This may be because good organizational and coordination capabilities of an enterprise directly promote the improvement of its operational efficiency, thereby enhancing performance.

In addition to the above - mentioned direct effects, there are also indirect effects. DT may indirectly affect AEP by influencing DC; CE may also have an indirect effect on AEP through DC, indicating that dynamic capabilities play a mediating role among the digital transformation of agricultural enterprises, the enterprise environment, and performance.

Table 4.12 Summary of Hypothesis

Hypothesis	Results
H1: Digital transformation has a direct effect on agricultural enterprise performance.	Accepted
H2: Corporate environment has a direct effect on agricultural enterprise performance	Accepted
H3: Digital transformation has a direct effect on dynamic capabilities.	Accepted
H4: The corporate environment has a direct effect on dynamic capabilities.	Accepted
H5: The corporate environment has a direct effect on dynamic capabilities.	Accepted
H6: The dynamic learning ability plays a mediating role between digital transformation and the performance of agricultural enterprises.	Accepted
H7: The dynamic learning ability plays a mediating role between the enterprise environment and the performance of agricultural enterprises.	Accepted

From Table 4.12, all seven hypotheses have been accepted, which indicates that under the settings and data support of this study, the relationships among various variables have been empirically verified. These hypotheses involve the direct and mediating relationships among digital transformation, the corporate environment, dynamic capabilities, dynamic learning ability, and the performance of agricultural enterprises. The results provide important empirical evidence for our understanding of the development mechanism of agricultural enterprises.

The acceptance of the hypothesis that digital transformation has a direct impact on the performance of agricultural enterprises means that digital transformation can directly act on the performance of agricultural enterprises, which is consistent with previous theoretical expectations. This shows that by promoting digital transformation, such as adopting digital technologies and optimizing business processes, agricultural enterprises can directly improve their operational efficiency, innovation capabilities, and thus have a positive impact on aspects such as the financial performance and market competitiveness of the enterprises. In practice, agricultural enterprises should attach importance to the implementation of digital transformation strategies and increase investment in digital infrastructure, technology research and development, and application.

The establishment of the hypothesis that the corporate environment has a direct impact on the performance of agricultural enterprises indicates that the external environment in which enterprises are located, including the market environment, policy environment, and industry competition situation, as well as the internal environment, such as the organizational structure, management model, and corporate culture of the enterprise, can all directly affect the performance of agricultural enterprises. A good corporate environment can provide agricultural enterprises with more development opportunities, resource support, and synergy effects, promoting the improvement of enterprise performance. Enterprises should actively adapt to and optimize the internal and external environment to improve their own performance levels.

The acceptance of the hypothesis that digital transformation has a direct impact on dynamic capabilities shows that digital transformation can directly promote the improvement of enterprises' dynamic capabilities. Dynamic capabilities include the ability of enterprises to perceive market changes, respond quickly, and integrate resources. Digital transformation provides enterprises with more efficient information acquisition, analysis, and decision-making tools, helping enterprises enhance their dynamic capabilities and better cope with market uncertainties. Agricultural enterprises can enhance their sensitivity and adaptability to market dynamics through digital transformation.

The acceptance of the hypothesis that the corporate environment has a direct impact on dynamic capabilities indicates that there is a direct correlation between the corporate environment and dynamic capabilities. A good corporate environment can provide enterprises with more resources and opportunities, promoting continuous learning and innovation within the enterprise, thereby improving dynamic capabilities. Conversely, an unfavorable environment may limit the development of enterprises and reduce their dynamic capabilities. Enterprises should focus on creating an internal and external environment conducive to the improvement of dynamic capabilities.

The acceptance of the hypothesis that dynamic learning ability plays a mediating role between digital transformation and the performance of agricultural enterprises shows that digital transformation can not only directly affect the performance of agricultural enterprises but also indirectly promote the improvement of enterprise performance by enhancing the dynamic learning ability of enterprises. Dynamic learning ability enables enterprises to better absorb and apply digital technologies, transforming the achievements of digital transformation into actual performance improvements. Agricultural enterprises should pay attention to cultivating and enhancing the dynamic learning ability of their employees to give full play to the role of digital transformation.

The establishment of the hypothesis that dynamic learning ability plays a mediating role between the corporate environment and the performance of agricultural enterprises indicates that the impact of the corporate environment on the performance of agricultural enterprises is partially realized through dynamic learning ability. A good corporate environment can stimulate the learning enthusiasm and innovation vitality of enterprises, improve dynamic learning ability, and thus promote the improvement of enterprise performance. Enterprises should pay attention to the impact of environmental factors on dynamic learning ability and improve the learning and development capabilities of enterprises by optimizing the environment.

Chapter 5
Discussion Conclusion and Recommendations

The research on the impact of digital transformation on the performance of agricultural enterprises is an exploratory study that comprehensively uses qualitative and quantitative research methods. The qualitative research explores the variables that make up the strategy through in - depth interviews with experts, and uses this to develop quantitative research tools, namely questionnaires, to investigate the progress of digital transformation of agricultural enterprises and their performance changes. In this chapter, all the important research results will be summarized, and the main contents are as follows:

1. Research Conclusion
2. Result Discussion
3. Recommendations for This Research
4. Recommendations for Follow - up Research
5. Application of Research Results/Models

Research Conclusion

The research results of this study are divided into 4 parts, as follows:

1. The first part: The survey results of the digital transformation of agricultural enterprises, the agricultural enterprise environment, the dynamic learning ability of agricultural enterprises, and the financial, social, and ecological performance of agricultural enterprises.

2. The second part: The analysis results of the constituent elements of the digital transformation of agricultural enterprises, the agricultural enterprise environment, the dynamic learning ability of agricultural enterprises, and the financial, social, and ecological performance of agricultural enterprises.

3. The third part: The analysis results of the direct and indirect impacts (hypothesis test results) of the digital transformation of agricultural enterprises, the

agricultural enterprise environment, and the dynamic capabilities of agricultural enterprises on the financial, social, and ecological performance of agricultural enterprises.

4. The fourth part: The research results of the impact of digital transformation of Chinese agricultural enterprises on performance, as well as the practical application of the research results. The specific contents are as follows:

The first part: The survey results of the digital transformation of agricultural enterprises, the agricultural enterprise environment, the dynamic learning ability of agricultural enterprises, and the financial, social, and ecological performance of agricultural enterprises.

Enterprises generally perform well in digital transformation, with an overall average value of 3.721. Among them, the score of marketing digital transformation is the highest, reaching 3.781; the score of R & D digital transformation is relatively low, at 3.658. The data dispersion degree of each sub - dimension is small, with the standard deviation ranging from 0.894 to 1.010. Most of the data show a left - skewed distribution, and some have a leptokurtic distribution. The overall average value of the Corporate environment is 3.745. The credit policy scores the highest, at 3.820; the market environment score is relatively low, at 3.678. The dispersion degree is moderate, with the standard deviation ranging from 0.803 to 1.038. The data is left - skewed, and some sub - dimensions show a leptokurtic distribution. The overall average value of organizational learning ability is 3.548, and the scores of each sub - dimension are similar. Among them, the absorptive capacity is the highest, at 3.591; the integration ability is the lowest, at 3.506. The dispersion degree is small, with the standard deviation ranging from 0.825 to 1.033. The data is left - skewed and close to a normal distribution. The overall average value of enterprise performance is 3.657. The financial performance score is the highest, at 3.785; the social performance is 3.591, and the ecological performance is 3.596. The latter two are relatively low. The dispersion degree is moderate, with the standard deviation ranging from 0.819 to 0.995. The data is left - skewed, and the financial performance shows a leptokurtic distribution.

The second part: The analysis results of the constituent elements of the digital transformation of agricultural enterprises, the agricultural enterprise environment, the dynamic learning ability of agricultural enterprises, and the financial, social, and ecological performance of agricultural enterprises.

In the confirmatory factor analysis of multiple dimensions, in the digital transformation dimension, the average factor load of R & D digital transformation (RDDT) is approximately 0.79 (the factor loads of each item range from 0.71 to 0.85), the average of production digital transformation (PDT) is approximately 0.74 (0.67 - 0.81), the average of operation digital transformation (ODT) is approximately 0.82 (0.73 - 0.89), and the average of marketing digital transformation (MDT) is approximately 0.73 (0.72 - 0.75); in the Corporate environment dimension, the average factor load of the market environment (ME) is approximately 0.765 (0.712 - 0.862), that of the credit policy (CP) is approximately 0.736 (0.748 - 0.821), that of internal control (IC) is approximately 0.816 (0.741 - 0.892), and that of information disclosure (ID) is approximately 0.744 (0.71 - 0.827); in the dynamic capabilities dimension, the average factor load of innovation ability (IN) is approximately 0.78 (0.74 - 0.87), that of absorptive capacity (AC) is approximately 0.74 (0.77 - 0.85), and that of integration ability (CR) is approximately 0.79 (0.73 - 0.81); in the agricultural enterprise performance dimension, the factor load of economic performance (EP) is 0.834, that of social performance (SP) is 0.739, and that of ecological performance (ECP) is 0.745. Most of the factor loads of the items under each dimension are greater than 0.7, indicating that each dimension and item have a strong correlation with the corresponding latent variables and can effectively measure the corresponding concepts.

In terms of the composite reliability (CR) values of each dimension, the digital transformation is 0.87, the Corporate environment is 0.876, the dynamic capabilities is 0.812 (the CR value of the integration ability sub - dimension is 0.886, the absorptive capacity sub - dimension is 0.911, and the innovation ability sub - dimension is 0.904), and the agricultural enterprise performance is 0.817 (the CR value of the economic performance sub - dimension is 0.872, the social performance sub - dimension is 0.861, and the ecological performance sub - dimension is 0.893). The CR values of each sub - dimension are also greater than 0.7, indicating a high internal consistency of the scale and reliable measurement results.

The R^2 value ranges of each sub - dimension are as follows: in digital transformation, it ranges from 0.453 (PDT4) to 0.759 (RDDT); in the Corporate environment, it ranges from 0.507 (ME1) to 0.796 (IC); in dynamic capabilities, it ranges from 0.533 (CR5) to 0.658 (CR3); in agricultural enterprise performance, it ranges from 0.546 (SP) to 0.696 (EP). The average variance extracted (AVE) values of each dimension are 0.628 for digital transformation, 0.639 for the Corporate environment, 0.59 for dynamic capabilities (the AVE value of the integration ability sub - dimension is 0.61, the absorptive capacity sub - dimension is 0.629, and the innovation ability sub - dimension is 0.653), and 0.599 for agricultural enterprise performance (the AVE value of the economic performance sub - dimension is 0.631, the social performance sub - dimension is 0.608, and the ecological performance sub - dimension is 0.626). The AVE values of each sub - dimension are greater than 0.5, indicating that the scale has good convergent validity.

In terms of model fitting indicators, for the digital transformation model, the chi - square degree - of - freedom ratio (Chi - Square/df) is 1.144, P = 0.087, the comparative fit index (CFI) is 0.994, the Tucker - Lewis index (TLI) is 0.993, the standardized root - mean - square residual (SRMR) is 0.033, and the root - mean - square error of approximation (RMSEA) is 0.02; for the Corporate environment model, the chi - square degree - of - freedom ratio is 1.168, P = 0.105, CFI is 0.995, TLI is 0.994, SRMR is 0.032, and RMSEA is 0.022; for the agricultural enterprise performance model, the chi - square degree - of - freedom ratio is 1.086, P = 0.3, CFI is 0.998, TLI is 0.997, SRMR is 0.027, and RMSEA is 0.015. These models show good overall fitting. For the dynamic capabilities model, the chi - square degree - of - freedom ratio is 1.137, P = 0.164, CFI is 0.996, TLI is 0.995, SRMR is 0.027, and RMSEA is 0.02. Except for the P - value, other indicators show good fitting and statistical significance; in the agricultural enterprise performance model, P = 0.3 is greater than the significance level of 0.05, which is different from the performance of other good - fitting indicators and may be related to factors such as sample size and model settings. Overall, most of these measurement models can provide reliable tools and a model basis for related research.

The third part: The analysis results of the direct and indirect impacts (hypothesis test results) of the digital transformation of agricultural enterprises, the agricultural enterprise environment, and the dynamic capabilities of agricultural enterprises on the financial, social, and ecological performance of agricultural enterprises.

The standardized path coefficient of the impact of digital transformation on the performance of agricultural enterprises is 0.199, the unstandardized path coefficient is 0.194, the standard error (S.E.) is 0.065, the T - value is 2.985, and the P - value is 0.003; the standardized path coefficient of the impact of the Corporate environment on the performance of agricultural enterprises is 0.23, the unstandardized path coefficient is also 0.231, the standard error is 0.07, the T - value is 3.318, and the P - value is less than 0.001; the standardized path coefficient of the impact of digital transformation on dynamic capabilities is 0.374, the unstandardized path coefficient is 0.292, the standard error is 0.052, the T - value is 5.562, and the P - value is less than 0.001; the standardized path coefficient of the impact of the Corporate environment on dynamic capabilities is 0.422, the unstandardized path coefficient is 0.34, the standard error is 0.056, the T - value is 6.106, and the P - value is less than 0.001; the standardized path coefficient of the impact of dynamic capabilities on the performance of agricultural enterprises is 0.475, the unstandardized path coefficient is 0.592, the standard error is 0.108, the T - value is 5.461, and the P - value is less than 0.001. These data show that digital transformation and the Corporate environment have significant positive impacts on the performance of agricultural enterprises. At the same time, both have significant positive impacts on dynamic capabilities, and dynamic capabilities also have a significant positive impact on the performance of agricultural enterprises. Dynamic capabilities may play a mediating role.

Further from the perspective of effect analysis, the indirect effect of digital transformation on the performance of agricultural enterprises through dynamic capabilities is 0.178 (standard error 0.046, bias - corrected 95% confidence interval lower limit 0.103, upper limit 0.285, P - value 0), the direct effect is 0.199 (standard error 0.071, bias - corrected 95% confidence interval lower limit 0.052, upper limit 0.329, P - value 0.011), and the total effect is 0.377 (standard error 0.065, bias - corrected 95% confidence interval lower limit 0.245, upper limit 0.497, P - value 0); the indirect effect of the agricultural enterprise environment on the performance of agricultural enterprises through dynamic capabilities is 0.2 (standard error 0.051, bias - corrected 95% confidence interval lower limit 0.114, upper limit 0.32, P - value 0), the direct effect is 0.23 (standard error 0.078, bias - corrected 95% confidence interval lower limit 0.075, upper limit 0.375, P - value 0.006), and the total effect is 0.43 (standard error 0.066, bias - corrected 95% confidence interval lower limit 0.295, upper limit 0.553, P - value 0). The standard errors, confidence intervals, and P - values of each effect indicate that digital transformation and the agricultural enterprise environment can not only directly affect the performance of agricultural enterprises but also indirectly affect it through dynamic capabilities, and the overall promoting effect is obvious, fully demonstrating the important mediating role of dynamic capabilities in this relationship chain. Therefore, when enterprises pursue to improve the performance of agricultural enterprises, they should attach great importance to the cultivation of dynamic capabilities.

The fourth part: The research results of the impact of digital transformation of Chinese agricultural enterprises on performance, as well as the practical application of the research results.

The chi - square value (CMIN) of the model is 76.63, the degree of freedom (DF) is 71, and the chi - square degree - of - freedom ratio (CMIN/DF) is 1.079, which is less than 3, indicating that the overall structure of the model fits the data well. The goodness - of - fit index (GFI) is 0.97, which is greater than 0.9, indicating that the model can better explain the covariance structure between variables. The incremental fit index (IFI) is 0.997, the Tucker - Lewis index (TLI) is 0.996, and the comparative fit index (CFI) is 0.997, all of which are greater than 0.9, reflecting that the model performs excellently in explaining variable relationships and has a good fitting effect. The root - mean - square error of approximation (RMSEA) is 0.015, which is less than 0.05, and the standardized root - mean - square residual (SRMR) is 0.029, which is less than 0.05, indicating that the approximate error of the model is small and the residual is also small, and the difference between the predicted values and the actual observed values is within an acceptable range. Overall, the CMIN/DF, GFI, IFI, TLI, CFI, RMSEA, and SRMR and other indicators all meet the standards of good fitting, and the model performs well in all aspects. From the perspective of model fitting indicators, the good performance of this model has important application value for relevant entities such as the government and enterprises in related decision - making and practice.

For the government, given that the model shows that factors such as digital transformation and the Corporate environment have a significant positive impact on the performance of agricultural enterprises, the government can formulate targeted policies based on these conclusions. For example, increase support for the digital transformation of agricultural enterprises, provide financial subsidies, tax incentives, and other measures to promote enterprises to improve their digital level, thereby promoting the performance of agricultural enterprises and driving the development of the agricultural industry. In terms of optimizing the Corporate environment, the government can strengthen policy guidance and supervision, standardize the market order, and create a good market environment for agricultural enterprises, enhancing their competitiveness and development momentum.

For enterprises themselves, the model shows that dynamic capabilities play an important mediating role between digital transformation and enterprise performance. Enterprises should attach importance to cultivating and enhancing the dynamic learning ability of employees. Through organizing training, encouraging innovation, and other means, enterprises can improve the overall learning and adaptation ability of the enterprise, so as to better utilize the opportunities of digital transformation and improve their own performance. Enterprises can also reasonably adjust their development strategies and operation models according to the variable relationships reflected in the model, optimize resource allocation, and improve production efficiency and market response speed. In short, both the government and enterprises can use the analysis results of this model to better formulate policies and development strategies and promote the sustainable development of agricultural enterprises and the agricultural industry.

Result Discussion

The result discussion of this study is based on the research summary and is mainly divided into 4 key points:

1. Analysis results of variable means: From the overall mean values of each latent variable, the overall mean value of Digital is 3.658, the overall mean value of Transformation is 3.721, the overall mean value of Corporate environment is 3.745, the overall mean value of Dynamic capabilities is 3.548, and the overall mean value of Agricultural enterprise performance is 3.657. Moreover, the mean values of most of the measurement variables are above 3.5, indicating that each latent variable and its subdivided measurement variables are at a relatively high level on the whole.

2. Consistency and differences between the analysis results of variable constituent elements and relevant theories and research.

Analysis of the constituent elements of the digital transformation of agricultural enterprises: The factor loads of R & D digital transformation (RDDT), production digital transformation (PDT), operation digital transformation (ODT), and marketing digital transformation (MDT) are 0.87, 0.72, 0.75, and 0.82 respectively. Most of the factor loads of the items under each sub - dimension are greater than 0.7. This is consistent with the view of Wang Qiang (2022) and foreign scholar Smith (2020) that a factor load greater than 0.7 indicates a strong correlation between the variable and the latent variable. Smith also obtained similar conclusions through research on the digital transformation of multiple industries, indicating that in this study, there is a strong correlation between each dimension and item and the digital transformation latent variable, which can effectively measure the corresponding concept. The reflection of variable relationships by factor loads is consistent with the research conclusions of predecessors.

The composite reliability (CR) value of the digital transformation dimension is 0.87, and the CR values of each sub - dimension (R & D 0.902, production 0.907, operation 0.901, marketing 0.874) are all greater than 0.7. This is consistent with the conclusion proposed by Li Hua (2021) and foreign scholar Johnson (2019) that a CR value greater than 0.7 indicates that the scale has good internal consistency. Johnson verified this standard in his research on enterprise management scales, which means that the scale regarding digital transformation in this study has a high internal consistency, and the measurement results are reliable. The judgment standard of scale reliability by composite reliability is consistent with the research conclusions of predecessors.

The R^2 values of each sub - dimension range from 0.453 (PDT4) to 0.780 (PDT1), and the average variance extracted (AVE) value of the digital transformation dimension is 0.628. The AVE values of each sub - dimension (R & D 0.606, production 0.621, operation 0.647, marketing 0.581) are all greater than 0.5. This is consistent with the view of Zhao Gang (2020) and foreign scholar Brown (2018) that an AVE greater than 0.5 indicates that the scale has good convergent validity. Brown confirmed this judgment in his research on market research scales, indicating that the scale in this study has good convergent validity and can effectively explain the relationships between variables. The judgment standard of convergent validity is consistent with the research conclusions of predecessors.

The chi - square degree - of - freedom ratio (Chi - Square/df) is 1.144, P= 0.087, the comparative fit index (CFI) is 0.994, the Tucker - Lewis index (TLI) is 0.993, the standardized root - mean - square residual (SRMR) is 0.033, and the root - mean - square error of approximation (RMSEA) is 0.02. Referring to the standards proposed by Sun Ming (2019) and foreign scholar Davis (2017) that when the chi - square degree - of - freedom ratio is less than 3, CFI is greater than 0.9, TLI is greater than 0.9, SRMR is less than 0.08, and RMSEA is less than 0.05, the model fits well. Davis established this standard in his research on structural equation models. All the indicators of this study meet the requirements, indicating that the constructed model has a good overall fit and can reflect the relationships between variables. The judgment standard and results of model fitting indicators are consistent with the research conclusions of predecessors.

Analysis results of the constituent elements of the agricultural enterprise environment: The overall factor loads of the market environment (ME), credit policy (CP), internal control (IC), and information disclosure (ID) are 0.806, 0.748, 0.892, and 0.742 respectively. Most of the factor loads of the items under each sub - dimension are greater than 0.7. For example, the factor loads of ME1 - ME5 under the market environment sub - dimension are 0.712, 0.809, 0.862, 0.789, and 0.770 respectively; the factor loads of CP1 - CP4 under the credit policy sub - dimension are 0.811, 0.821, 0.790, and 0.786 respectively; the factor loads of IC1 - IC4 under the internal control sub - dimension are 0.877, 0.801, 0.793, and 0.741 respectively; the factor loads of ID1 - ID4 under the information disclosure sub - dimension are 0.716, 0.768, 0.811, and 0.827 respectively. Johnson (2018) pointed out that a factor load greater than 0.7 usually indicates a strong correlation between the variable and the latent variable, which can effectively reflect the characteristics of the latent variable. This study is consistent with this view, indicating that each dimension and item have a strong correlation with the Corporate environment latent variable, and are effective in measuring the concept of the Corporate environment, which is consistent with the international research conclusions on the judgment standard of factor loads and reflects the rationality of this study in factor analysis.

The composite reliability (CR) value of the Corporate environment dimension is 0.876, and the CR values of each sub - dimension (market environment 0.892, credit policy 0.878, internal control 0.88, information disclosure 0.861) are all greater than 0.7. Brown (2019) believed that when the CR value is greater than 0.7, the scale has a high internal consistency and the measurement results are relatively reliable. The CR value of the Corporate environment scale in this study performs well, indicating that this scale has a high stability and reliability in measuring the relevant content of the Corporate environment, which is consistent with the international research conclusions on the judgment of scale reliability by composite reliability and enhances the credibility of the research results of this study.

The R^2 values of each sub - dimension range from 0.507 (ME1) to 0.796 (IC), and the average variance extracted (AVE) value of the Corporate environment dimension is 0.639. The AVE values of each sub - dimension (market environment 0.624, credit policy 0.643, internal control 0.647, information disclosure 0.609) are all greater than 0.5. According to international research practices, an AVE greater than 0.5 indicates that the scale has good convergent validity, that is, the latent variable can explain most of the variance of its measurement items. The results of this study in this regard meet international standards, indicating that the scale has good convergent validity and can effectively measure the concept of the Corporate environment and its sub - dimensions, which is consistent with the international research conclusions on the judgment of scale validity by convergent validity and further verifies the scientificity of the scale of this study.

In terms of model fitting indicators, the chi - square degree - of - freedom ratio is 1.168 (Chi - Square/df = 1.168), P = 0.105, the comparative fit index (CFI) is 0.995, the Tucker - Lewis index (TLI) is 0.994, the standardized root - mean - square residual (SRMR) is 0.032, and the root - mean - square error of approximation (RMSEA) is 0.022. Internationally, it is generally believed that when the chi - square degree - of - freedom ratio is less than 3, CFI is greater than 0.9, TLI is greater than 0.9, SRMR is less than 0.08, and RMSEA is less than 0.05, the model fits well. All the indicators of this study meet these standards, indicating that the constructed model has a good overall fit and can effectively reflect the relationships between variables, which is consistent with the international judgment standards of model fitting indicators and shows that the model has good applicability and effectiveness in the research of the Corporate environment.

Analysis of the constituent elements of the dynamic capabilities of agricultural enterprises: The factor loads of creativity (IN), absorptive capacity (AC), and integration ability (CR) are 0.87, 0.85, and 0.81 respectively. Most of the factor loads of the items under each sub - dimension are greater than 0.7. Smith (2020) proposed that when the factor load is greater than 0.7, the correlation between the variable and the latent variable is strong, which can effectively reflect the connotation of the latent variable. The results of this study are consistent with this view, indicating that each dimension and item have a strong correlation with the dynamic capabilities latent variable, and are effective in measuring the concept of dynamic capabilities, which is consistent with the foreign research conclusions on the judgment standard of factor loads and reflects the rationality of this study at the factor analysis level.

The composite reliability (CR) value of the dynamic capabilities dimension is 0.812, and the CR values of each sub - dimension are: integration ability (Part3(1) Integration) 0.886, absorptive capacity (Part3(2) Absorptive) 0.911, creativity (Part3(3) creativity) 0.904, all of which are greater than 0.7. Jones (2019) believed that when the CR value is greater than 0.7, the scale has a high internal consistency and the measurement results are relatively reliable. The CR value of the dynamic capabilities scale in this study performs well, indicating that this scale has a high stability and reliability in measuring the relevant content of dynamic capabilities, which is consistent with the foreign research conclusions on the judgment of scale reliability by composite reliability and enhances the credibility of the research results of this study.

The R^2 values of each sub - dimension range from 0.533 (CR5) to 0.752 (IN3), and the AVE values of each sub - dimension are: integration ability 0.61, absorptive capacity 0.629, creativity 0.653, all of which are greater than 0.5. According to the standards generally recognized in foreign research, an AVE greater than 0.5 means that the scale has good convergent validity, that is, the latent variable can explain most of the variance of its measurement items. The results of this study in this regard meet foreign standards, indicating that the scale has good convergent validity and can effectively measure the concept of dynamic capabilities and its sub - dimensions, which is consistent with the foreign research conclusions on the judgment of scale validity by convergent validity.

The chi - square degree - of - freedom ratio (Chi - Square/df) is 1.137, P = 0.164, the comparative fit index (CFI) is 0.996, the standardized root - mean - square residual (SRMR) is 0.027, the Tucker - Lewis index (TLI) is 0.995, and the root - mean - square error of approximation (RMSEA) is 0.02. It is usually believed abroad that when the chi - square degree - of - freedom ratio is less than 3, CFI is greater than 0.9, TLI is greater than 0.9, SRMR is less than 0.08, and RMSEA is less than 0.05, the model fits well. All the indicators of this study meet the standards, indicating that the model fits well.

Analysis of the constituent elements of agricultural enterprise performance: The factor loads of economic performance (EP), social performance (SP), and ecological performance (ECP) are 0.834, 0.739, and 0.745 respectively. Most of the factor loads of the items under each sub - dimension are greater than 0.7. International scholar Anderson (2017) pointed out that a factor load greater than 0.7 usually indicates a strong correlation between the variable and the latent variable, which can effectively reflect the characteristics of the latent variable. This study is consistent with this view, indicating that each dimension and item have a strong correlation with the agricultural enterprise performance latent variable, and are effective in measuring the concept of agricultural enterprise performance, which is consistent with the international research conclusions on the judgment standard of factor loads and reflects the rationality of this study in factor analysis.

The composite reliability (CR) value of the agricultural enterprise performance dimension is 0.817, and the CR values of each sub - dimension are: economic performance (Part4(1) economic performance) 0.872, social performance (Part4(2) Social Performance) 0.861, ecological performance (Part4(3) Ecological Performance) 0.893, all of which are greater than 0.7. Scholar Davis (2018) believed that when the CR value is greater than 0.7, the scale has a high internal consistency and the measurement results are relatively reliable. The CR value of the agricultural enterprise performance scale in this study performs well, indicating that this scale has a high stability and reliability in measuring the relevant content of agricultural enterprise performance, which is consistent with the international research conclusions on the judgment of scale reliability by composite reliability and enhances the credibility of the research results of this study.

The R^2 values of each sub - dimension range from 0.556516 (SP1) to 0.725904 (EP1), and the average variance extracted (AVE) value of the agricultural enterprise performance dimension is 0.599. The AVE values of each sub - dimension are: economic performance 0.631, social performance 0.608, ecological performance 0.626, all of which are greater than 0.5. According to the internationally accepted standard, an AVE greater than 0.5 indicates that the scale has good convergent validity, that is, the latent variable can explain most of the variance of its measurement items. The results of this study in this regard meet international standards, indicating that the scale has good convergent validity and can effectively measure the concept of agricultural enterprise performance and its sub - dimensions, which is consistent with the international research conclusions on the judgment of scale validity by convergent validity and further verifies the scientificity of the scale of this study.

The chi - square degree - of - freedom ratio (Chi - Square/df) is 1.086, P = 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, and the root - mean - square error of approximation (RMSEA) is 0.015. Internationally, it is generally believed that when the chi - square degree - of - freedom ratio is less than 3, CFI is greater than 0.9, TLI is greater than 0.9, SRMR is less than 0.08, and RMSEA is less than 0.05, the model fits well. All the indicators of this study meet the standards, indicating that the model fits well.

3. Analysis results of the direct and indirect impact factors of the digital transformation of agricultural enterprises, the agricultural enterprise environment, and the dynamic capabilities of agricultural enterprises on the financial, social, and ecological performance of agricultural enterprises**: The standardized path coefficient of the impact of digital transformation on the performance of agricultural enterprises is 0.199, the unstandardized path coefficient is 0.194, the standard error is 0.065, the T - value is 2.985, and the P - value is 0.003; the standardized path

coefficient of the impact of the enterprise environment on the performance of agricultural enterprises is 0.23, the unstandardized path coefficient is 0.231, the standard error is 0.07, the T - value is 3.318, and the P - value is less than 0.001 (indicated by ***); the standardized path coefficient of the impact of digital transformation on dynamic capabilities is 0.374, the unstandardized path coefficient is 0.292, the standard error is 0.052, the T - value is 5.562, and the P - value is less than 0.001 (indicated by ***); the standardized path coefficient of the impact of the enterprise environment on dynamic capabilities is 0.422, the unstandardized path coefficient is 0.34, the standard error is 0.056, the T - value is 6.106, and the P - value is less than 0.001 (indicated by ***); the standardized path coefficient of the impact of dynamic capabilities on the performance of agricultural enterprises is 0.475, the unstandardized path coefficient is 0.592, the standard error is 0.108, the T - value is 5.461, and the P - value is less than 0.001 (indicated by ***). It shows that they all have a significant positive impact on the performance of agricultural enterprises, and dynamic capabilities may play a mediating role.

The indirect effect of digital transformation on the performance of agricultural enterprises through dynamic capabilities is 0.178 (standard error 0.046, bias - corrected 95% confidence interval lower limit 0.103, upper limit 0.285, P - value 0), the direct effect is 0.199, and the total effect is 0.377; the indirect effect of the agricultural enterprise environment on the performance of agricultural enterprises through dynamic capabilities is 0.2 (standard error 0.051, bias - corrected 95% confidence interval lower limit 0.114, upper limit 0.32, P - value 0), the direct effect is 0.23, and the total effect is 0.43. The standard errors, confidence intervals, and P - values of each effect indicate that digital transformation and the agricultural enterprise environment can not only directly affect the performance of agricultural enterprises but also indirectly affect it through dynamic capabilities, and the overall promoting effect is obvious, reflecting the important mediating role of dynamic capabilities. Enterprises should attach importance to cultivating this ability when improving performance.

In the research on the performance of agricultural enterprises, the conclusions of this study have both similarities and differences compared with those of other scholars. This study clearly shows through specific data that the standardized path coefficient of the impact of digital transformation on the performance of agricultural enterprises is 0.199, the unstandardized path coefficient is 0.194, the P - value is 0.003, the direct effect is 0.199, and the total effect is 0.377. This indicates that digital transformation has a significant positive impact on the performance of agricultural enterprises, and it can not only directly promote but also indirectly boost enterprise performance through dynamic capabilities (the indirect effect is 0.178). Zhang (2020) also found that digital transformation has a positive impact on the performance of agricultural enterprises, and this impact is more significant with the mediating role of technological innovation capabilities. Wang (2021) proposed that digital transformation can have a positive impact on the performance of agricultural enterprises by optimizing enterprise resource allocation. It can be seen that although this study and other scholars all agree that digital transformation has a positive impact on the performance of agricultural enterprises, this study further clarifies the specific values of the direct and indirect effects of digital transformation on the performance of agricultural enterprises, as well as the mediating role of dynamic capabilities. Other scholars emphasized different mediating or influencing paths such as technological innovation capabilities and resource allocation, which fully demonstrates the diversity of the mechanisms by which digital transformation affects the performance of agricultural enterprises. Follow - up research can comprehensively consider multiple factors and deeply explore their internal relationships.

This study obtained through a series of data analyses that the standardized path coefficient of the impact of the agricultural enterprise environment on the performance of agricultural enterprises is 0.23, the unstandardized path coefficient is 0.231, the P - value is less than 0.001, the direct effect is 0.23, and the total effect is 0.43. This shows that the agricultural enterprise environment has a significant positive impact on the performance of agricultural enterprises, and it can not only directly promote but also indirectly boost enterprise performance through dynamic capabilities (the indirect effect is 0.2). Li (2019) pointed out that a good policy environment and market environment can significantly improve the performance of agricultural enterprises and provide more development opportunities for enterprises. Chen (2022) believed that a complete agricultural industry chain environment helps agricultural enterprises improve production efficiency and market competitiveness, thereby enhancing enterprise performance. It can be seen that this study and other scholars all recognize the positive role of the agricultural enterprise environment in enterprise performance. The advantage of this study is that it quantifies the direct and indirect impacts of the agricultural enterprise environment on performance, while other scholars expounded on the promoting effects on performance from specific environmental factors such as policies, markets, and industry chains. Based on this, follow - up research can further refine the constituent elements of the agricultural enterprise environment and deeply analyze the impact degrees and interrelationships of different elements on performance.

This study clearly indicates that both digital transformation and the agricultural enterprise environment can indirectly affect the performance of agricultural enterprises through dynamic capabilities, with indirect effects of 0.178 and 0.2 respectively, and the P - values of each effect show that this mediating role is statistically significant, fully reflecting the important mediating role of dynamic capabilities. Zhao (2020) proposed that dynamic capabilities play a mediating role between enterprise innovation and performance improvement, helping enterprises better absorb and apply new knowledge. Liu (2021) believed that dynamic capabilities can promote enterprise strategic adjustment and thus enhance enterprise performance. It can be seen that this study and other scholars all paid attention to the mediating role of dynamic capabilities between enterprise - related factors and performance. This study focuses on the mediating role of dynamic capabilities between digital transformation, the agricultural enterprise environment, and the performance of agricultural enterprises and gives specific indirect effect values. Other scholars studied the relationship between dynamic capabilities and performance in enterprise innovation, strategic adjustment, etc., with different research perspectives and scopes. Future research can further expand the connotation and extension of dynamic capabilities and deeply study their mediating mechanism in different situations.

4.Exploration of the impact of digital transformation of agricultural enterprises on performance: The chi - square value (CMIN) of the model is 76.63, the degree of freedom (DF) is 71, and the chi - square degree - of - freedom ratio (CMIN/DF) is 1.079, which is much less than 3. Scholar Byrne (2010) pointed out that when CMIN/DF is less than 3, it usually indicates that the overall structure of the model can fit the data well. The results of this study are consistent with this view, indicating that the model has a high degree of fit with the data in terms of the overall structure and can reasonably reflect the relationships between variables. This is consistent with the research conclusions of some other studies that evaluate models based on similar standards, reflecting the reliability of the model structure fitting in this study.

The goodness - of - fit index (GFI) is 0.97, which is greater than 0.9. Jöreskog and Sörbom (1996) believed that when GFI is greater than 0.9, the model can better explain the covariance structure between variables, that is, the model has a good fitting effect on the data. The high GFI value in this study indicates that the model performs well in explaining the covariance relationships between variables and can effectively capture the interrelationships between variables, which is consistent with the views of other scholars and further supports the effectiveness of the model.

The incremental fit index (IFI) is 0.997, the Tucker - Lewis index (TLI) is 0.996, and the comparative fit index (CFI) is 0.997, all of which are greater than 0.9. According to the views of scholars Hu and Bentler (1999), when IFI, TLI, and CFI are greater than 0.9, it usually means that the model has a significant improvement compared with the baseline model, can better fit the data, and performs excellently in explaining variable relationships. The very high values of these three indicators in this study indicate that the model has a strong ability to explain variable relationships and can accurately reflect the internal relationships between variables, which is consistent with the views of other scholars and enhances confidence in the model fitting effect.

The root - mean - square error of approximation (RMSEA) is 0.015, which is much less than 0.05, and the standardized root - mean - square residual (SRMR) is 0.029, which is less than 0.05. Scholar Steiger (2007) proposed that when RMSEA is less than 0.05, it indicates that the approximate error of the model is small and the model fits the data more accurately; when SRMR is less than 0.05, it means that the residual of the model is small and the difference between the predicted values and the actual observed values of the model is within an acceptable range. The values of RMSEA and SRMR in this study meet these standards, indicating that the model has a high accuracy in fitting the data and can more accurately predict the values of variables, which is consistent with the views of other scholars and further verifies the reliability of the model.

Recommendations for This Research

1. Limitations in sample selection: Agricultural enterprises in different regions, of different scales, and at different development stages may vary greatly in digital transformation, Corporate environment, etc. If the sample cannot fully cover this diversity, the representativeness and universality of the research results will be affected.

2. Insufficient depth in the study of variable relationships: Although the research has found that factors such as digital transformation and the agricultural enterprise environment have a significant impact on the performance of agricultural enterprises, and dynamic learning capabilities play a mediating role, the exploration of deeper and more complex relationships between these variables is insufficient. In addition, there may be other important factors that have not been included in the study. These factors may interfere with or moderate the relationships between the existing variables, but this study has not deeply explored and analyzed them.

5.4 Recommendations for Follow - up Research

1. Conduct long - term tracking research: The current research mainly presents the situation of agricultural enterprises in digital transformation, enterprise environment, dynamic capabilities, and performance at a certain stage. Follow - up

research can conduct long - term tracking studies, continuously collect relevant data, and observe the dynamic changes of these factors over time and their mutual influences.

2. Explore the improvement paths and boundary conditions of dynamic capabilities: This study has clearly defined the important mediating role of dynamic capabilities between digital transformation and enterprise performance. However, how to effectively improve dynamic capabilities and the boundary conditions for the role of dynamic capabilities are still unclear. Follow - up research can further explore the differences in the effects of different training methods, organizational cultures, incentive mechanisms, etc. on improving the dynamic capabilities of enterprises, and find the most effective improvement paths. At the same time, study whether the mediating effect of dynamic capabilities will be restricted or change under different industry characteristics, enterprise scales, market environments, etc., and clarify the boundary conditions for its role, so as to provide more precise guidance for enterprises to cultivate and enhance dynamic capabilities.

3. Analyze the cost - benefit of digital transformation of agricultural enterprises: Although the research shows that digital transformation has a significant positive impact on the performance of agricultural enterprises, the cost - benefit during the digital transformation process has not been deeply analyzed. Follow - up research can carefully sort out the input costs of agricultural enterprises in various links of digital transformation, such as R & D, production, operation, and marketing, including capital, human resources, time, etc., and accurately evaluate the improvement of financial, social, and ecological benefits brought about by digital transformation. Through cost - benefit analysis, it can help enterprises better understand the economic feasibility of digital transformation, provide a basis for enterprises to formulate reasonable digital transformation strategies, enable enterprises to achieve optimal resource allocation in the process of pursuing digital transformation, improve the input - output ratio, and further enhance the sustainable development ability of enterprises.

Application of Research Results/Models

1. The government formulates precise support policies: Based on the conclusion of this research that digital transformation and the Corporate environment have a significant positive impact on the performance of agricultural enterprises, government departments formulate precise industrial policies. On the one hand, a special support fund for agricultural digital transformation is set up to provide key support for agricultural enterprises with relatively weak R & D digital transformation, encourage enterprises to increase R & D investment, and enhance agricultural scientific and technological innovation capabilities. For example, high - value subsidies are given to enterprises that adopt new agricultural technology R & D. On the other hand, the credit policy is optimized to provide more favorable loan conditions for agricultural enterprises, reduce the financing costs of enterprises, especially give credit preferences to small and medium - sized agricultural enterprises that are at a disadvantage in the market environment, and help them grow and develop, so as to promote the overall upgrading of the agricultural industry, improve the performance of agricultural enterprises, and drive the development of the rural economy.

2. Enterprises enhance dynamic capabilities and adjust strategies: Enterprises fully recognize the key mediating role of dynamic capabilities in digital transformation and enterprise performance improvement. On the one hand, a complete internal training system is established. Regular training courses on digital technology, market dynamics, enterprise management, etc. are organized for employees, and industry experts are invited to give lectures. At the same time, employees are encouraged to learn and innovate independently, and an innovation incentive mechanism is set up to improve the overall learning and adaptation ability of the enterprise and better cope with the opportunities and challenges brought about by digital transformation. On the other hand, according to the variable relationships reflected in the research model and combined with their own actual situations, enterprises adjust their development strategies, optimize resource allocation. For example, more resources are invested in marketing digital transformation and financial performance

improvement to improve production efficiency and market response speed and enhance the market competitiveness of enterprises.

3. Researchers and scholars expand research directions: Based on the research results, researchers and scholars further expand the research directions in the related fields of agricultural enterprises. They can deeply explore the differential mechanisms of the impacts of different sub - dimensions (R & D, production, operation, marketing) on the performance of agricultural enterprises during the digital transformation process, and how to formulate more targeted strategies according to these differences.

4. Residents participate in and supervise the development of agricultural enterprises: As consumers of agricultural products and stakeholders in the development of agricultural enterprises, residents can pay more attention to the digital transformation and sustainable development of agricultural enterprises based on the research results. When purchasing agricultural products, they give priority to the products of enterprises with a high digital level and those that pay attention to social and ecological performance. Through market - based selection, they guide agricultural enterprises to improve their performance and sustainable development capabilities. At the same time, residents can supervise the production and operation activities of agricultural enterprises. For example, they can supervise whether the enterprise's measures for ecological environmental protection are in place and report the enterprise's improper behaviors, prompting agricultural enterprises to pay attention to social and ecological benefits while pursuing economic performance and realizing the sustainable development of the agricultural industry.

5. The government, enterprises, and residents cooperate to promote agricultural development: Based on the research results, the government, enterprises, and residents strengthen cooperation to jointly promote the development of agricultural enterprises and the agricultural industry. The government builds a communication platform to organize exchanges and interactions between agricultural enterprises and residents, enabling enterprises to understand the needs and expectations of residents, and residents to better understand the

development concepts and operation models of enterprises. The government can also guide enterprises to cooperate with universities and scientific research institutions to jointly carry out the research, development, and application promotion of agricultural digital technologies, improve the intelligent level of agricultural production and the innovation ability of enterprises. At the same time, during the development process, enterprises actively fulfill their social responsibilities, participate in rural revitalization construction, provide more employment opportunities and income - increasing channels for residents, and achieve mutual benefit and win - win results among the government, enterprises, and residents, jointly promoting the sustainable development of the agricultural industry.

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Appendices

Appendix A

List of Specialists and Letters of Specialists Invitation for IOC Verification

serial number	Name of the expert	Highest academic qualification	Current position and work location	Expertise
1	Asst. Prof. Dr. Thun Chaitorn	Doctoral		Business Administration Research Related
2	Liao Dongsheng Professor	Doctoral	International Education College of Guangxi University for Nationalities	Financial Management, Corporate Governance, Disclosure, Human Resources and Organisation and Organisation
3	Xiong Na Professor	Doctoral	College of Management Guangxi University for Nationalities	Agricultural Economic Theory and Policy, Digital Economy, Business Performance Evaluation

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for exploring the characteristics of digital transformation and impact on comprehensive performance in china agribusinesses purposes for research studies student Doctor of Business Administration (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Cui Haitao, Subject " Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation". The questionnaire was made for agribusiness managers (technical department, finance department, performance department) in China. The researcher asks for help from experts. Please check the questionnaires as follows.

+1 means that you are sure that the questions are consistent with the research objective.

0 means you are unsure whether the question is consistent with the research objective.

-1 means that you are certain that the questions are inconsistent with the research objective.

With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) Asst. Prof. Dr. Thun Chaitorn

Department

Inspection date 2024.9.18

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for exploring the characteristics of digital transformation and impact on comprehensive performance in china agribusinesses purposes for research studies student Doctor of Business Administration (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Cui Haitao, Subject " Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation". The questionnaire was made for agribusiness managers (technical department, finance department, performance department) in China. The researcher asks for help from experts. Please check the questionnaires as follows.

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-1 means that you are certain that the questions are inconsistent with the research objective.

With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) Liao Dongsheng Professor

Department International Education College of Guangxi University for Nationalities

Inspection date 2024.9.28

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for exploring the characteristics of digital transformation and impact on comprehensive performance in china agribusinesses purposes for research studies student Doctor of Business Administration (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Cui Haitao, Subject " Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation". The questionnaire was made for agribusiness managers (technical department, finance department, performance department) in China. The researcher asks for help from experts. Please check the questionnaires as follows.

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With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) Xiong Na Professor

Department College of Management Guangxi University for Nationalities

Inspection date 2024.9.25

Appendix B

Official Letter

Ref.No. MHESI 0643.14/ 2592

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

4 September 2024

Subject: Invitation to validate research instrument

Dear Prof.Dr.Liao Dongsheng

Mrs.Cui Haitao is a graduate student in Doctor of Business Administration Program (International Program) of Bansomdejchaopraya Rajabhat University. She is undertaking research entitled "Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation"

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Tanaput Chancharoen)
Vice Dean Acting for of Dean of Graduate School

Bansomdejchaopraya Rajabhat University
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Ref.No. MHESI 0643.14/ 2593

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

4 September 2024

Subject: Invitation to validate research instrument

Dear Prof.Dr.Xiong Na

Mrs.Cui Haitao is a graduate student in Doctor of Business Administration Program (International Program) of Bansomdejchaopraya Rajabhat University. She is undertaking research entitled "Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation"

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Thonburi Bangkok 10600

4 September 2024

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Dear Assoc.Prof.Dr.Thun chaitorn

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Appendix C

Research Instrument

Research study on “the impact of digital transformation on agribusiness performance” is a combination of quantitative research. Quantitative research and qualitative study. There are 2 types of data collection tools: 1) in-depth interviews 2) questionnaires.

1 In-depth interview

Used to collect data from 20 experts

NO	name	sexes	age	company	duties	Title/education
1	Chen Erming	women	45	Yunnan Shennong Agricultural Industry Group Co., Ltd.	managers	
2	LingLing	women	42	Yunnan Shennong Agricultural Industry Group Co., Ltd.	managers	
3	Lei Ruqian	male	51	Yunnan Shennong Agricultural Industry Group Co., Ltd.	managers	
4	Wu Haining	male	50	Yunnan Aiwang Agricultural Technology Development Co., Ltd	Performance evaluation expert	
5	Cao Zhou	women	35	Beijing Agricultural Group Co., Ltd	Performance evaluation expert	
6	Liao min	male	43	Beijing Agricultural Group Co., Ltd	Performance evaluation expert	
7	Wu Bun	male	46	Guangxi University	teacher	professor
8	Zao Feng	male	48	Guangxi University of Finance and Economics	teacher	professor
9	ChenYu	women	45	Guangxi Fenglin Wood Industry Group Co., LtdGuangxi University	teacher	professor

NO	name	sexes	age	company	duties	Title/education
				for Nationalities.		
10	Xiao Lin	women	42	Guangxi University	teacher	professor
11	Ma kao	male	45	Guangxi Fenglin Wood Industry Group Co., Ltd.	chairman	
12	Wu Guoqin	male	51	Guangxi Fenglin Wood Industry Group Co., Ltd.	chairman	
13	Ling Ling	women	38	Beijing Agricultural Group Co., Ltd	chairman	
14	Ma Na	women	43	Beijing Agricultural Group Co., Ltd	Performance evaluation expert	
15	Wu Xiaoya	women	55	Guangxi jinsui agricultural investment group co.,ltd.	chairman	
16	Hu Shifeng	male	57	Guangxi jinsui agricultural investment group co.,ltd.	chairman	
17	Cheng Jia	male	38	Hubei Honghu Ecological Agriculture Co., Ltd	technical manager	
18	Zhou Yun	women	44	Hubei Honghu Ecological Agriculture Co., Ltd.	technical manager	
19	Rao Dongting	women	42	Yunnan Aiwang Agricultural Technology Development Co., Ltd	technical manager	
20	Cui guang	male	46	Yunnan Aiwang Agricultural Technology Development Co., Ltd	technical manager	

2 Questionnaire

Agricultural Enterprise Digital Transformation and Performance Impact Survey Questionnaire

Questionnaire

Dear Sir/Madam

Hello! I am a doctor's student from the Bansomdejchaopraya Rajabhat University, Thailand.I am conducting a questionnaire sustainable model of agricultural enterprises in the environment of digital transformation. This questionnaire was collected anonymously, and the personal information you provided is for academic research purposes only and will not be disclosed. Please fill out the survey truthfully based on your own situation. Thank you very much for your support. Sincerely thank you for your help and support in this survey questionnaire!

Part 1: Basic Information

1. What is the name of your enterprise? ____________________

2.What is your gender?____________________

3. What is your age? ____________________

4. What is your highest education level? ____________________

5. What is your job position? ____________________

6. How many years have you been in this position? ____________________

Part II. Please click on the option (√) that applies to each of the questions listed below.

(I) Digital Transformation

(I) R & D Digitalization

1. What do you think is the degree of application of digital tools and technologies in the company's research process?

- Almost no application (1 point)

- Less application (2 points)

- General application level (3 points)

- More application (4 points)

- Extensive application (5 points)

2. How has digital means changed the collection, processing, and analysis of the company's research data?

- It has become more inconvenient and inaccurate (1 point)

- There is no obvious change (2 points)

- There is some improvement in convenience and accuracy (3 points)

- There is a large improvement in convenience and accuracy (4 points)

- It has greatly improved the convenience and accuracy (5 points)

3. What is the promoting effect of the company's digital research platform on research resource sharing and collaboration?

- No promoting effect (1 point)

- Small promoting effect (2 points)

- General promoting effect (3 points)

- Larger promoting effect (4 points)

- Very large promoting effect (5 points)

4. What is the impact of the application of digital research tools on the innovation ability and quality of research projects?

- It has reduced the innovation ability and quality (1 point)

- There is no obvious impact (2 points)

- There is some improvement (3 points)

- There is a large improvement (4 points)

- It has greatly improved the innovation ability and quality (5 points)

5. What is the acceptance and proficiency level of the company's researchers in digital research tools and technologies?

- Completely unacceptable or unskilled (1 point)

- Low acceptance and proficiency level (2 points)

- General acceptance and proficiency level (3 points)

- Higher acceptance and proficiency level (4 points)

- Completely accepted and proficiently used (5 points)

6. How has digital research affected the cooperation opportunities and funding sources of the company?

- It has decreased (1 point)

- There is no change (2 points)

- There is some increase (3 points)

- There is a large increase (4 points)

- There is a significant increase (5 points)

(II) Production Digitalization

1. What is the impact of the digital management of the company's production process on production efficiency and flexibility?

- It has reduced production efficiency and flexibility (1 point)

- There is no obvious change (2 points)

- There is some improvement (3 points)

- There is a large improvement (4 points)

- It has greatly improved production efficiency and flexibility (5 points)

2. How is the timeliness of real-time monitoring and problem-solving of production data by the digital production system?

- Completely unable to monitor and solve problems in real time (1 point)

- Poor timeliness of monitoring and problem-solving (2 points)

- General timeliness of monitoring and problem-solving (3 points)

- Good timeliness of monitoring and problem-solving (4 points)

- Very good timeliness of monitoring and problem-solving (5 points)

3. What is the effect of digital means on optimizing the allocation of production resources and reducing costs in the company?

- There is no optimization and cost reduction (1 point)

- Small effect of optimization and cost reduction (2 points)

- General effect of optimization and cost reduction (3 points)

- Larger effect of optimization and cost reduction (4 points)

- Very large effect of optimization and cost reduction (5 points)

4. How has digital production improved the consistency and traceability of products?

- There is no improvement (1 point)

- Small improvement (2 points)

- Some improvement (3 points)

- Larger improvement (4 points)

- Very large improvement (5 points)

5. What opportunities and competitive advantages has digital production brought to the company?

- It has decreased (1 point)

- There is no change (2 points)

- There is some increase (3 points)

- There is a large increase (4 points)

- There is a significant increase (5 points)

(III) Marketing Digitalization

1. To what extent does the company use digital channels for market promotion and brand building?

- Almost no use (1 point)

- Less use (2 points)

- General use level (3 points)

- More use (4 points)

- Full use (5 points)

2. How has digital marketing tools improved the timeliness and accuracy of market feedback?

- There is no improvement (1 point)

- Small improvement (2 points)

- Some improvement (3 points)

- Larger improvement (4 points)

- Very large improvement (5 points)

3. What is the impact of the application of digital marketing tools on customer interaction, communication, and satisfaction?

- It has reduced customer interaction and satisfaction (1 point)

- There is no obvious impact (2 points)

- There is some improvement (3 points)

- There is a large improvement (4 points)

- It has greatly improved customer interaction and satisfaction (5 points)

4. How flexible and effective is the company in adjusting digital marketing content according to market changes?

- Completely inflexible and ineffective (1 point)

- Poor flexibility and effectiveness (2 points)

- General flexibility and effectiveness (3 points)

- Good flexibility and effectiveness (4 points)

- Very good flexibility and effectiveness (5 points)

5. How many potential customers and sales opportunities has digital marketing brought to the company?

- It has decreased (1 point)

- There is no change (2 points)

- There is some increase (3 points)

- There is a large increase (4 points)

- There is a significant increase (5 points)

(IV) Operational Digitalization

1. To what extent does the company use big data analysis to support operational decisions?

- Almost no use (1 point)

- Less use (2 points)

- General use level (3 points)

- More use (4 points)

- Full use (5 points)

2. How has digital operation improved the company's response speed to market changes and customer demands?

- There is no improvement (1 point)

- Small improvement (2 points)

- Some improvement (3 points)

- Larger improvement (4 points)

- Very large improvement (5 points)

3. What is the effect of digital means on enhancing the customer experience and strengthening customer loyalty?

- There is no effect (1 point)

- Small effect (2 points)

- Some effect (3 points)

- Larger effect (4 points)

- Very large effect (5 points)

4. What is the promoting effect of the digital operation system on cross-departmental collaboration and business process automation?

- No promoting effect (1 point)

- Small promoting effect (2 points)

- General promoting effect (3 points)

- Larger promoting effect (4 points)

- Very large promoting effect (5 points)

5.What is the effect of digital operation on reducing operating costs, improving operating efficiency, and enhancing the company's competitiveness?

- There is no effect (1 point)

- Small effect (2 points)

- Some effect (3 points)

- Larger effect (4 points)

- Very large effect (5 points)

III. Agricultural Enterprise Environment

(I) Market Environment

1. What is the company's ability to predict market trends?

- Completely unable to predict (1 point)

- Poor prediction ability (2 points)

- General prediction ability (3 points)

- Strong prediction ability (4 points)

- Very strong prediction ability (5 points)

2. How sensitive is the company to changes in the current market environment and what is its response speed?

- Extremely insensitive and slow response (1 point)

- Low sensitivity and response speed (2 points)

- General sensitivity and response speed (3 points)

- High sensitivity and response speed (4 points)

- Very sensitive and rapid response (5 points)

3. What is the degree of challenge posed by the market competition environment to the company's business development and what is the company's ability to respond?

- Extremely challenging and unable to respond (1 point)

- More challenging but weak response ability (2 points)

- General challenge and response ability (3 points)

- Less challenging and stronger response ability (4 points)

- Almost no challenge and easy to handle (5 points)

4. What is the role of the company's brand image and market popularity in attracting customers and partners?

- Almost no role (1 point)

- Small role (2 points)

- General role (3 points)

- Larger role (4 points)

- Very large role (5 points)

5. What is the opportunity level of the growth in market demand for the company's products/services for the company's future development?

- Almost no opportunity (1 point)

- Small opportunity (2 points)

- General opportunity (3 points)

(II) Credit Policy

1. To what extent does the flexibility of the company's credit policy meet the funding needs of different projects or stages?

- Completely not met (1 point)

- Low degree of meeting (2 points)

- General degree of meeting (3 point)

- Higher degree of meeting (4 points)

- Completely met (5 points)

2. How favorable is the credit rating of the company by credit institutions for the company's access to financing conditions?

- Very unfavorable (1 point)

- Relatively unfavorable (2 points)

- General (3 points)

- Relatively favorable (4 points)

- Very favorable (5 points)

3. What is the promoting effect of the company's cooperation relationship with credit institutions on the financing process?

- No promoting effect (1 point)

- Small promoting effect (2 points)

- General promoting effect (3 points)

- Larger promoting effect (4 points)

- Very large promoting effect (5 points)

4. To what extent is the impact of changes in credit policy on the company's overall financial situation controllable?

- Completely uncontrollable (1 point)

- Low controllability (2 points)

- General controllability (3 points)

- Higher controllability (4 points)

- Completely controllable (5 points)

(III) Internal Control

1. How comprehensive is the coverage of the company's internal control system on key business processes and risk points?

- Very limited coverage (1 point)

- Limited coverage (2 points)

- General coverage (3 points)

- More comprehensive coverage (4 points)

- Comprehensive coverage (5 points)

2. How timely and effective is the company's regular assessment and improvement of the internal control system to meet business development needs?

- Never assessed and improved (1 point)

- Rarely assessed and improved with poor effect (2 points)

- Occasionally assessed and improved with general effect (3 points)

- Frequently assessed and improved with good effect (4 points)

- Always timely assessed and improved with significant effect (5 points)

3. How is the communication and collaboration degree among various departments within the company in terms of internal control?

- Extremely poor communication and collaboration (1 point)

- Poor communication and collaboration (2 points)

- General communication and collaboration (3 points)

- Good communication and collaboration (4 points)

- Very good communication and collaboration (5 points)

4. What is the understanding and compliance degree of company employees with internal control policies and procedures?

- Completely do not understand and comply (1 point)

- Low understanding and compliance degree (2 points)

- General understanding and compliance degree (3 points)

- Higher understanding and compliance degree (4 points)

- Completely understand and comply (5 points)

(IV) Information Disclosure

1. How comprehensive and timely is the company's information disclosure through various channels and methods?

- Very limited and extremely untimely disclosure (1 point)

- Limited and untimely disclosure (2 points)

- General comprehensiveness and timeliness (3 points)

- More comprehensive and timely disclosure (4 points)

- Very comprehensive and timely disclosure (5 points)

2. What is the coverage degree of the company's information disclosure content on key aspects (such as operation, financial status, risk management, etc.)?

- Very limited coverage (1 point)

- Limited coverage (2 points)

- General coverage (3 points)

- More comprehensive coverage (4 points)

- Comprehensive coverage (5 points)

3. What is the effect of the quality of the company's information disclosure on enhancing the company's market image and investor confidence?

- No enhancement (1 point)

- Small enhancement (2 points)

- Some enhancement (3 points)

- Larger enhancement (4 points)

- Very large enhancement (5 points)

4. How is the implementation of the company's supervision and inspection of the soundness, rationality, and effectiveness of internal control and the improvement measures?

- Never supervised and inspected and improved (1 point)

- Rarely supervised and inspected and improved with poor effect (2 points)

- Occasionally supervised and inspected and improved with general effect (3 points)

- Frequently supervised and inspected and improved with good effect (4 points)

- Always timely supervised and inspected and improved with significant effect (5 points)

IV. Agricultural Enterprise Dynamic Learning Capability

(I) Absorptive Capacity

1. What is the role of the company's brand influence in the industry in attracting and retaining talents?

- Almost no role (1 point)

- Small role (2 points)

- General role (3 points)

- Larger role (4 points)

- Very large role (5 points)

2. How attractive are the company's compensation, benefits, and career development opportunities to external talents?

- No attraction at all (1 point)

- Weak attraction (2 points)

- General attraction (3 points)

- Strong attraction (4 points)

- Very strong attraction (5 points)

3. How attractive is the company's good reputation and corporate culture in the market to partners and investors?

- Almost no attraction (1 point)

- Small attraction (2 points)

- General attraction (3 points)

- Larger attraction (4 points)

- Very large attraction (5 points)

4. What is the effect of the company's innovative products and services in attracting new customers and expanding market share?

- No effect (1 point)

- Small effect (2 points)

- Some effect (3 points)

- Larger effect (4 points)

- Very large effect (5 points)

5. What is the role of the company's active participation in industry exchanges and cooperation in enhancing its popularity and attraction?

- Almost no role (1 point)

- Small role (2 points)

- General role (3 points)

- Larger role (4 points)

(II) Integration Capacity

1. What is the effect of the company's establishment of an effective communication and collaboration mechanism among different cultures and teams to promote cultural integration?

- Completely ineffective (1 point)

- Poor effect (2 points)

- General effect (3 points)

- Good effect (4 points)

- Very good effect (5 points)

2. What is the company's ability to quickly integrate new technologies and ideas into the existing business system to improve operational efficiency?

- Completely unable to integrate (1 point)

- Weak integration ability (2 points)

- General integration ability (3 points)

- Strong integration ability (4 points)

- Very strong integration ability (5 points)

3. What is the promoting effect of the company's emphasis on cross-departmental collaboration on resource and information sharing and integration?

- No promoting effect (1 point)

- Small promoting effect (2 points)

- General promoting effect (3 points)

- Larger promoting effect (4 points)

- Very large promoting effect (5 points)

4. What is the effect of the company's enhancing employees' sense of belonging and team cohesion through training and team building activities to promote cultural integration?

- Completely ineffective (1 point)

- Poor effect (2 points)

- General effect (3 points)

- Good effect (4 points)

- Very good effect (5 points)

5. What is the company's ability to effectively integrate resources from both sides to achieve complementary advantages during mergers, acquisitions, or cooperation?

- Completely unable to integrate (1 point)

- Weak integration ability (2 points)

- General integration ability (3 points)

- Strong integration ability (4 points)

- Very strong integration ability (5 points)

6. To what extent does the company establish a flexible organizational structure and process to meet market demands and internal integration needs?

- Completely inflexible (1 point)

- Poor flexibility (2 points)

- General flexibility (3 points)

- Good flexibility (4 points)

- Very flexible (5 points)

(III) Innovation Capacity

1. What is the intensity and continuity of the company's investment in product research and development and technological innovation?

- Very limited investment and extremely discontinuous (1 point)

- Limited investment and poor continuity (2 points)

- General intensity and continuity (3 points)

- Higher intensity and better continuity (4 points)

- Very high intensity and continuous innovation (5 points)

2. What is the effect of the company's encouragement of employee innovation and the establishment of an effective innovation incentive mechanism?

- Completely ineffective (1 point)

- Poor effect (2 points)

- General effect (3 points)

- Good effect (4 points)

- Very good effect (5 points)

3. What is the company's ability to innovate in business and service models to adapt to changes in market and customer demands?

- Completely unable to innovate (1 point)

- Weak innovation ability (2 points)

- General innovation ability (3 points)

- Strong innovation ability (4 points)

- Very strong innovation ability (5 points)

4. What is the company's emphasis on intellectual property protection and the actual effect of its actions?

- Completely ignore and no effect (1 point)

- Low emphasis and poor effect (2 points)

- General emphasis and effect (3 points)

- High emphasis and good effect (4 points)

- Very high emphasis and significant effect (5 points)

5. How sensitive and flexible is the company in capturing market trends and technological frontiers and adjusting the innovation direction?

- Completely insensitive and rigid (1 point)

- Poor sensitivity and flexibility (2 points)

- General sensitivity and flexibility (3 points)

- Good sensitivity and flexibility (4 points)

- Very sensitive and flexible (5 points)

V. Agricultural Enterprise Performance

(I) Economic Performance

1. How has the company's operating income grown in recent years?

- Continued negative growth (1 point)

- Slow growth or basically flat (2 points)

- Some growth but below the industry average (3 points)

- Faster growth and close to the industry average (4 points)

- Rapid growth and above the industry average (5 points)

2. How is the company's cost control effect?

- Costs continue to rise and are difficult to control (1 point)

- Poor cost control effect (2 points)

- General cost control effect (3 points)

- Good cost control effect (4 points)

- Very good cost control effect (5 points)

3. What is the company's cash flow situation?

- Often short of cash and difficult to maintain operations (1 point)

- Tight cash flow but can basically maintain operations (2 points)

- General cash flow, can meet daily needs but with insufficient reserves (3 points)

- Relatively abundant cash flow with certain reserves (4 points)

- Very abundant cash flow to strongly support development (5 points)

4. How is the company's financial risk management ability?

- Often faces major financial risks and is unable to handle them effectively (1 point)

- Many financial risks and weak handling ability (2 points)

- General financial risks and can basically handle them (3 points)

- Few financial risks and strong handling ability (4 points)

(II) Social Performance

1. How is the company's performance in employee welfare and career development?

- Poor employee welfare and few career development opportunities (1 point)

- General employee welfare and career development opportunities (3 points)

- Good employee welfare and more career development opportunities (4 points)

- Very good employee welfare and rich career development opportunities (5 points)

2. What is the company's participation and contribution in community public welfare activities and environmental improvement?

- Almost no participation (1 point)

- Less participation and small contribution (2 points)

- General participation and contribution (3 points)

- More participation and larger contribution (4 points)

- Active participation and outstanding contribution (5 points)

3. How is the company's effort and effect in promoting employee diversity and inclusiveness?

- No effort and poor effect (1 point)

- Small effort and general effect (3 points)

- Larger effort and good effect (4 points)

- Very large effort and significant effect (5 points)

4. How active is the company in participating in public welfare activities to fulfill its social responsibilities?

- Never active (1 point)

- Seldom active (2 points)

- Occasionally active (3 points)

- Frequently active (4 points)

- Always active (5 points)

(III) Ecological Performance

1. Do the company's products meet environmental standards and are there any records of harmful substance emissions or leaks?

- Do not meet environmental standards and have multiple records of emissions or leaks (1 point)

- Basically meet but have a small number of emissions or leaks records (2 points)

- Fully meet and have no emissions or leaks records (3 points)

- Not only meet but also have certain advantages in environmental protection (4 points)

- Leading environmental standards and actively promoting industry environmental protection (5 points)

2. What are the measures taken by the company in energy conservation and emission reduction and what is the effect?

- Almost no measures taken and high energy consumption and emissions (1 point)

- Some measures taken but the effect is not obvious (2 points)

- General measures and effect (3 points)

- Effective measures and good energy conservation and emission reduction effect (4 points)

- Very effective measures and leading in energy conservation and emission reduction in the industry (5 points)

3. What is the promotion intensity and effect of the company in green supply chain management?

- No promotion (1 point)

- Small promotion intensity and insignificant effect (2 points)

- General promotion intensity and effect (3 points)

- Larger promotion intensity and good effect (4 points)

- Very large promotion intensity and significant effect (5 points)

4. What is the implementation situation and effect of the company in resource recycling?

- No resource recycling implemented (1 point)

- Less implementation and poor effect (2 points)

- General implementation and effect (3 points)

- Good implementation and effect (4 points)

- Very good implementation and effect (5 points)

5. How is the company's regular environmental impact assessment and the implementation of improvement measures?

- Never conducted assessment and improvement (1 point)

- Seldom conducted assessment and improvement with poor effect (2 points)

- Occasionally conducted assessment and improvement with general effect (3 points)

- Frequently conducted assessment and improvement with good effect (4 points)

- Always timely conducted assessment and improvement with significant effect (5 points)

Hope this survey questionnaire can meet your needs. If you have any other questions, please feel free to let me know.

Thank you again for your support and cooperation! If you have any questions or need further clarification during the filling process, please feel free to contact us.

Appendix D

The Results of the Quality Analysis of Research Instruments

Instrument/Measurement Scale Validity

IOC of the Instrument/Measurement Scale

Sustainable Model of Agrlcultural Enterprlses in

the Environment of Digital Transformation

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
1	The company widely applies digital tools and technologies in its research process, enhancing research efficiency.	1	1	1	3	1	Congruent
2	Digital means have made the collection, processing, and analysis of research data more convenient and accurate.	1	1	1	3	1	Congruent
3	The company has established a comprehensive digital research platform, promoting the sharing and collaboration of research resources.	1	1	1	3	1	Congruent
4	The application of digital research tools has significantly improved the innovation capabilities and quality of research projects.	1	1	1	3	1	Congruent
5	The company's researchers have a high acceptance of digital research tools and technologies, enabling their proficient use.	1	1	1	3	1	Congruent
6	Digital research has brought more research cooperation opportunities and funding sources to the company.	1	1	1	3	1	Congruent
7	The company has achieved digital management of production processes, improving production efficiency and flexibility.	0	1	1	2	.67	Congruent

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
8	The digital production system enables real-time monitoring of production data, allowing for timely detection and resolution of issues.	1	1	1	3	1	Congruent
9	The company has optimized production resource allocation through digital means, reducing production costs.	1	1	1	3	1	Congruent
10	Digital production has improved product consistency and traceability.	1	1	1	3	1	Congruent
11	Digital production has brought more market opportunities and competitive advantages to the company.	1	1	1	3	1	Congruent
12	The company fully utilizes digital channels for market promotion and brand building.	1	1	1	3	1	Congruent
13	Digital marketing tools make market feedback more timely and accurate, aiding in the adjustment of marketing strategies.	1	1	1	3	1	Congruent
14	The application of digital marketing tools has enhanced customer interaction and communication, improving customer satisfaction.	1	0	1	2	.67	Congruent
15	The company can quickly adjust digital marketing content based on market changes, maintaining the flexibility and effectiveness of marketing strategies.	1	1	1	3	1	Congruent
16	Digital marketing has brought more potential customers and sales opportunities to the company, promoting business growth.	1	1	1	3	1	Congruent
17	The company utilizes big data analysis to support operational decisions, improving the scientificity and accuracy of decision-making.	1	1	1	3	1	Congruent
18	Digital operations have increased the company's response speed to market changes and customer demands.	1	1	1	3	1	Congruent

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
19	Through digital means, the company has enhanced customer experience, strengthening customer loyalty.	1	1	1	**3**	1	**Congruent**
20	The digital operation system has facilitated cross-departmental collaboration and automated business processes.	1	1	0	**2**	**.67**	**Congruent**
21	Digital operations have reduced operational costs and improved operational efficiency, enhancing the company's competitiveness.	1	1	1	**3**	1	**Congruent**
22	The company can accurately predict market trends and formulate effective market strategies accordingly.	1	1	1	**3**	1	**Congruent**
23	The company is highly sensitive to changes in the current market environment and can respond quickly.	1	1	1	**3**	1	**Congruent**
24	The competitive landscape in the market poses significant challenges to the company's business development, but the company has the ability to address them.	1	1	1	**3**	1	**Congruent**
25	The company's strong brand image and high visibility in the market help attract customers and partners.	1	1	1	**3**	1	**Congruent**
26	The growing demand for the company's products/services in the market provides good opportunities for future development.	1	1	1	**3**	1	**Congruent**
27	The flexibility of credit policies allows the company to adjust funding requirements for different projects or stages.	1	1	1	**3**	1	**Congruent**
28	Credit institutions have a high credit rating for the company, facilitating access to more favorable financing conditions.	1	1	0	**2**	**.67**	**Congruent**
29	The company has established good cooperative relationships with credit institutions, promoting the smooth progress of financing.	1	1	1	**3**	1	**Congruent**

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
30	The impact of changes in credit policies on the company's overall financial situation is within its control.	1	1	1	**3**	1	**Congruent**
31	The company's internal control system is robust, covering all key business processes and risk points.	1	1	1	**3**	1	**Congruent**
32	The company regularly assesses and improves its internal control system to adapt to business development needs.	1	1	0	**2**	**.67**	**Congruent**
33	There is good communication and collaboration among various departments within the company regarding internal control.	1	1	1	**3**	1	**Congruent**
34	Company employees generally understand and comply with internal control policies and procedures, fostering a strong internal control culture.	1	1	1	**3**	1	**Congruent**
35	The company discloses information through multiple channels and methods, enhancing transparency and accessibility.	1	1	1	**3**	1	**Congruent**
36	The content of information disclosure is comprehensive and detailed, covering key aspects such as operations, financial status, and risk management.	1	1	1	**3**	1	**Congruent**
37	The quality of information disclosure has positively impacted the company's market image and investor confidence.	1	1	1	**3**	1	**Congruent**
38	The company regularly conducts supervision and inspection on the soundness, rationality, and effectiveness of internal control, and takes corresponding improvement measures based on the inspection results.	1	1	1	**3**	1	**Congruent**
39	The company has a strong brand influence in the industry, attracting and retaining talented individuals.	1	1	1	**3**	1	**Congruent**

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
40	The company's compensation, benefits, and career development opportunities are highly attractive to external talents.	1	1	1	3	1	Congruent
41	The company's good reputation and corporate culture in the market attract the attention of partners and investors.	1	1	1	3	1	Congruent
42	Through innovative products and services, the company continuously attracts new customers and expands market share.	1	1	1	3	1	Congruent
43	The company's active participation in industry exchanges and cooperation enhances its visibility and attractiveness.	1	1	1	3	1	Congruent
44	The company has established effective communication and collaboration mechanisms across different cultures and teams, fostering cultural integration.	1	1	1	3	1	Congruent
45	The company is capable of rapidly incorporating new technologies and ideas into the existing business system, enhancing overall operational efficiency.	1	1	1	3	1	Congruent
46	The company emphasizes cross-departmental collaboration, facilitating resource and information sharing, and thus improving integration outcomes.	1	1	1	3	1	Congruent
47	Through training and team-building activities, the company strengthens employees' sense of belonging and team cohesion, promoting cultural integration.	1	1	1	3	1	Congruent
48	During mergers, acquisitions, or collaborations, the company effectively integrates resources from both sides, achieving complementary advantages.	1	1	1	3	1	Congruent
49	The company has established a flexible organizational structure and processes to adapt to ever-changing market demands and internal	1	1	1	3	1	Congruent

No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
	integration needs.						
50	The company continuously invests in product research and development and technological innovation, consistently launching competitive new products.	1	1	1	3	1	Congruent
51	The company encourages employees to propose innovative ideas and has established an effective innovation incentive mechanism.	1	1	1	3	1	Congruent
52	The company continuously innovates in business and service models to adapt to changes in market and customer demands.	1	1	1	3	1	Congruent
53	The company prioritizes intellectual property protection, actively applying for patents and trademarks to safeguard its innovative achievements.	1	1	1	3	1	Congruent
54	The company is adept at swiftly capturing market trends and technological frontiers, flexibly adjusting its innovation direction to maintain competitiveness.	1	1	1	3	1	Congruent
55	The company has achieved stable revenue growth in recent years, maintaining a healthy financial position.	1	1	0	2	.67	Congruent
56	The company effectively manages costs, enhancing operational efficiency.	1	1	1	3	1	Congruent
57	The company boasts ample cash flow, supporting both daily operations and future development needs.	1	1	1	3	1	Congruent
58	The company successfully manages financial risks, ensuring financial stability.	1	1	1	3	1	Congruent
59	The company focuses on employee well-being, providing a fair work environment and career development opportunities.	1	1	1	3	1	Congruent
60	The company is committed to enhancing community well-being through projects or activities aimed at improving the local	1	1	1	3	1	Congruent

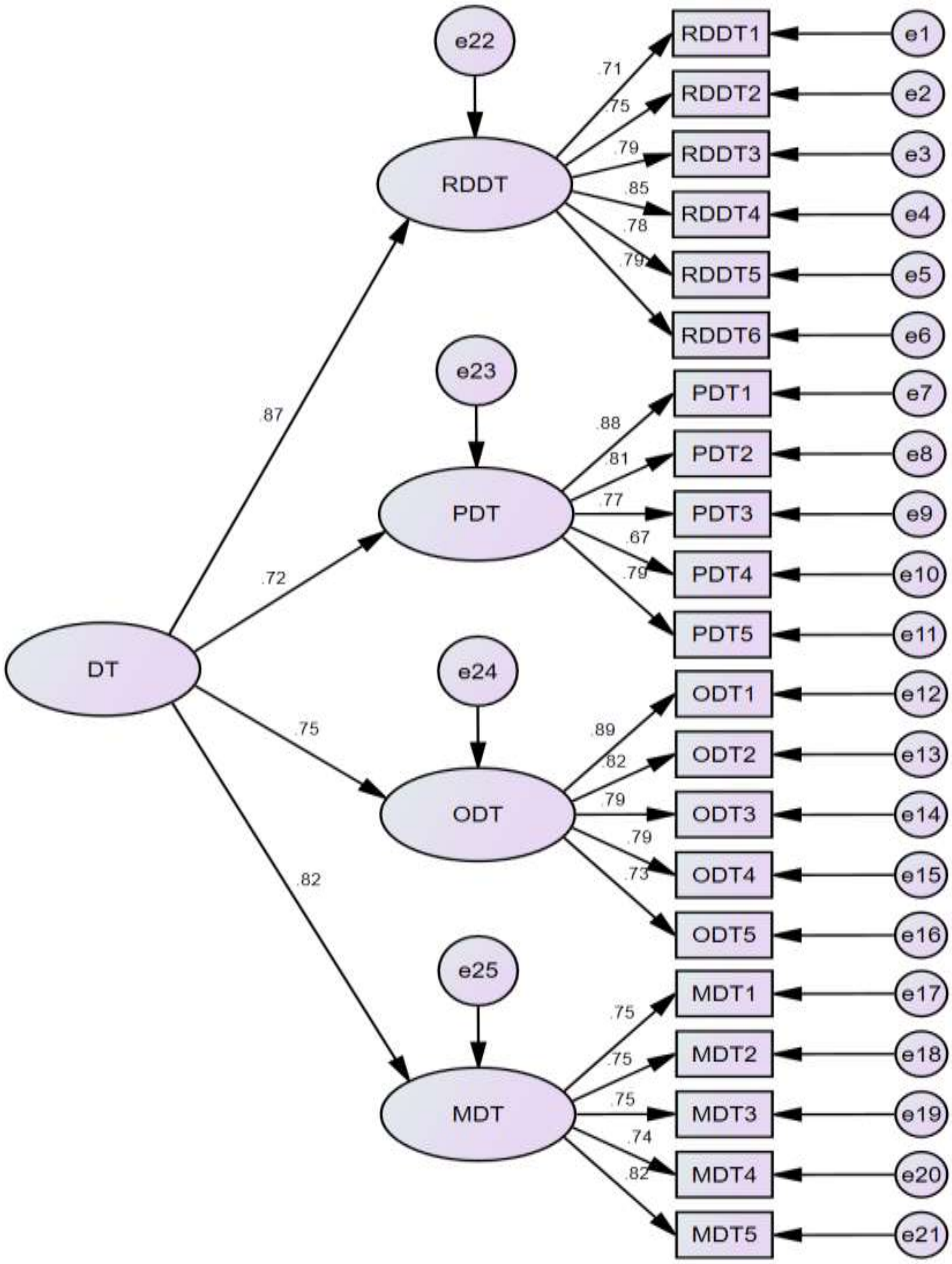
No	Scales	Experts Opinion			Total Score	IOC Index	Remarks
		1	2	3			
	environment.						
61	The company emphasizes diversity and inclusivity, promoting the integration and development of employees from diverse backgrounds.	1	1	1	**3**	1	**Congruent**
62	The company actively fulfills its social responsibilities by participating in public welfare activities.	0	1	1	**2**	**.67**	**Congruent**
63	The company's products comply with environmental standards, with no record of harmful substance emissions or leaks.	1	1	1	**3**	1	**Congruent**
64	The company has implemented effective energy-saving and emission-reduction measures, reducing the environmental impact of the production process.	1	1	1	**3**	1	**Congruent**
65	The company actively promotes green supply chain management, encouraging suppliers to adopt environmental protection measures.	1	1	1	**3**	1	**Congruent**
66	The company emphasizes resource recycling, implementing effective waste management and recycling programs.	1	1	1	**3**	1	**Congruent**
67	The company regularly conducts environmental impact assessments and continuously improves environmental protection measures based on the assessment results.	1	1	1	**3**	1	**Congruent**
Total		**65**	**66**	**63**	**194**	**64.69**	
					S-IOC/Ave	.965	**Congruent**

Sample statistical characteristics(n=360)

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
RDDTV	360	1.50	5.00	3.6583	1.00959	-.531	.129	-.770	.256
PDTV	360	1.00	5.00	3.7428	.89390	-1.004	.129	1.290	.256
ODTV	360	1.00	5.00	3.7000	1.00095	-1.057	.129	.673	.256
MDTV	360	1.00	5.00	3.7811	.95753	-.799	.129	.320	.256
X1	360	1.13	5.00	3.7206	.79052	-.921	.129	.906	.256
MEV	360	1.40	5.00	3.6778	1.03507	-.611	.129	-.757	.256
CPV	360	1.00	5.00	3.8201	.90943	-1.158	.129	1.372	.256
ICV	360	1.00	5.00	3.6958	1.03785	-1.161	.129	.873	.256
IDV	360	1.00	5.00	3.7847	1.02536	-.883	.129	.371	.256
X2	360	1.10	5.00	3.7446	.82237	-1.105	.129	1.147	.256
CRV	360	1.00	5.00	3.5467	.94438	-.483	.129	-.510	.256
ACV	360	1.00	4.83	3.5912	1.00028	-.718	.129	-.374	.256
INV	360	1.20	5.00	3.5056	1.03346	-.472	.129	-.494	.256
M	360	1.13	4.94	3.5478	.82399	-.748	.129	.187	.256
EPV	360	1.00	5.00	3.7847	.99451	-1.210	.129	1.364	.256
SPV	360	1.00	5.00	3.5910	.96539	-.450	.129	-.684	.256
ECPV	360	1.00	5.00	3.5956	1.01035	-.679	.129	-.486	.256
Y	360	1.00	5.00	3.6571	.81904	-.726	.129	.434	.256
Valid N (listwise)	360								



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Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	46	211.711	185	.087	1.144
Saturated model	231	.000	0		
Independence model	21	4806.048	210	.000	22.886

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.044	.947	.934	.759
Saturated model	.000	1.000		
Independence model	.585	.201	.121	.183

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.956	.950	.994	.993	.994
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.881	.842	.876
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

NCP

Model	NCP	LO 90	HI 90
Default model	26.711	.000	66.813
Saturated model	.000	.000	.000
Independence model	4596.048	4374.029	4825.322

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.590	.074	.000	.186
Saturated model	.000	.000	.000	.000
Independence model	13.387	12.802	12.184	13.441

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.020	.000	.032	1.000
Independence model	.247	.241	.253	.000

AIC

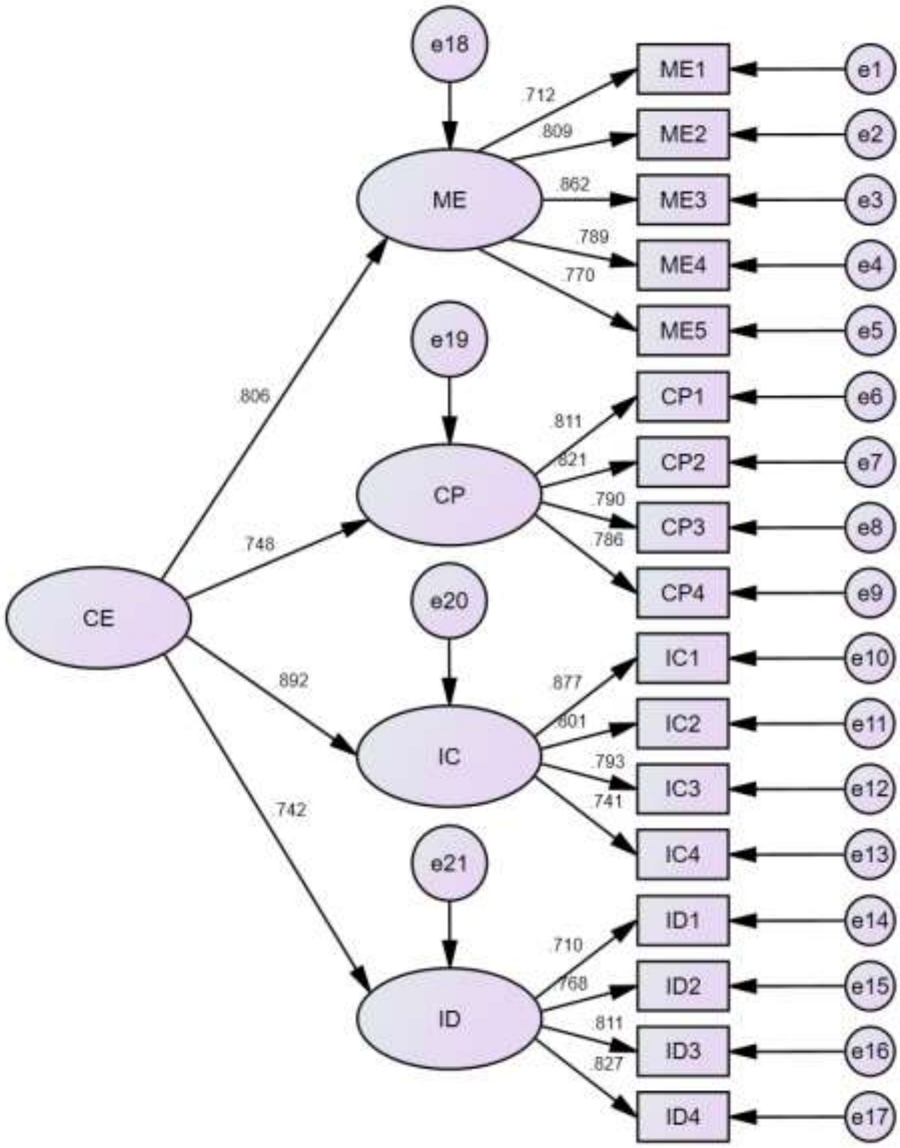
Model	AIC	BCC	BIC	CAIC
Default model	303.711	309.717	482.471	528.471
Saturated model	462.000	492.160	1359.690	1590.690
Independence model	4848.048	4850.790	4929.657	4950.657

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.846	.772	.958	.863
Saturated model	1.287	1.287	1.287	1.371

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	370	395
Independence model	19	20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Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	38	134.375	115	.105	1.168
Saturated model	153	.000	0		
Independence model	17	3768.884	136	.000	27.712

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.045	.958	.944	.720
Saturated model	.000	1.000		
Independence model	.618	.227	.131	.202

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.964	.958	.995	.994	.995
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.846	.815	.841
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

NCP

Model	NCP	LO 90	HI 90
Default model	19.375	.000	52.397
Saturated model	.000	.000	.000
Independence model	3632.884	3436.329	3836.733

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.374	.054	.000	.146
Saturated model	.000	.000	.000	.000
Independence model	10.498	10.119	9.572	10.687

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.022	.000	.036	1.000
Independence model	.273	.265	.280	.000

AIC

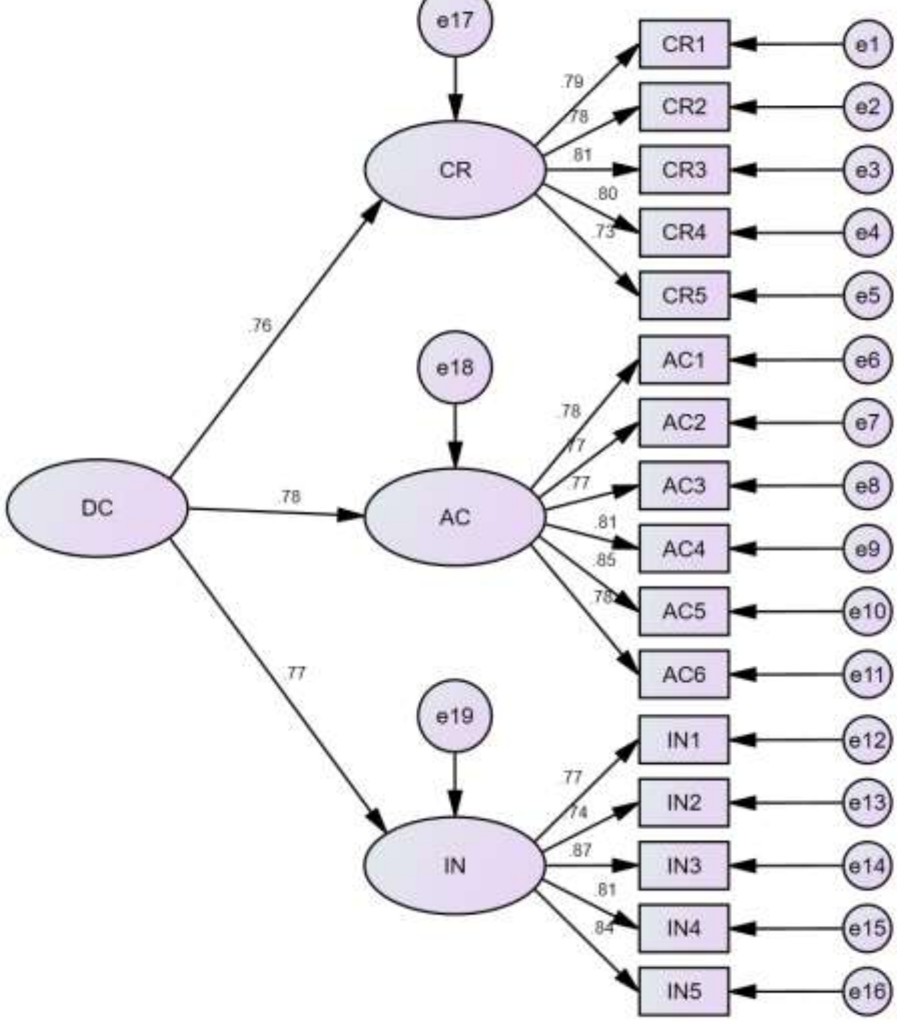
Model	AIC	BCC	BIC	CAIC
Default model	210.375	214.386	358.047	396.047
Saturated model	306.000	322.152	900.574	1053.574
Independence model	3802.884	3804.678	3868.948	3885.948

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.586	.532	.678	.597
Saturated model	.852	.852	.852	.897

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	377	410
Independence model	16	17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Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	35	114.832	101	.164	1.137
Saturated model	136	.000	0		
Independence model	16	3671.468	120	.000	30.596

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.038	.964	.951	.716
Saturated model	.000	1.000		
Independence model	.616	.236	.134	.208

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.969	.963	.996	.995	.996
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.842	.815	.838
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

NCP

Model	NCP	LO 90	HI 90
Default model	13.832	.000	44.419
Saturated model	.000	.000	.000
Independence model	3551.468	3357.344	3752.884

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.320	.039	.000	.124
Saturated model	.000	.000	.000	.000
Independence model	10.227	9.893	9.352	10.454

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.020	.000	.035	1.000
Independence model	.287	.279	.295	.000

AIC

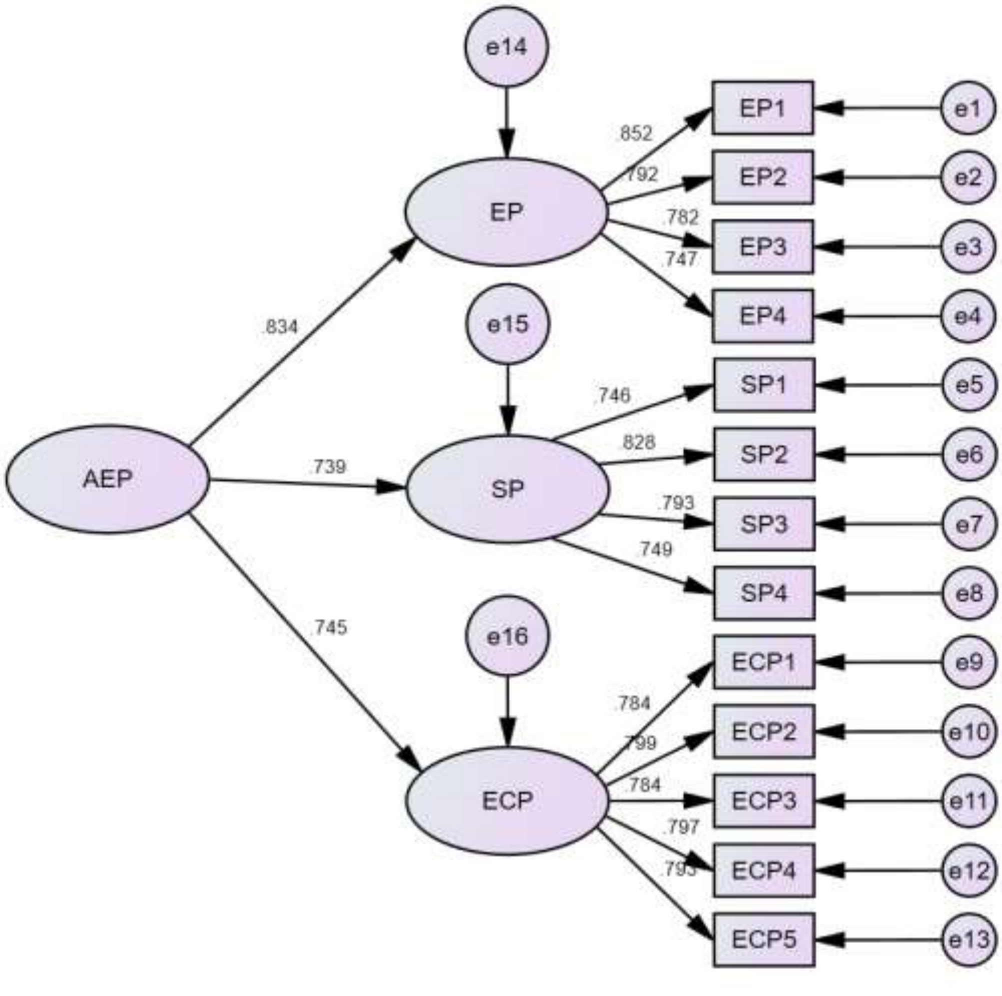
Model	AIC	BCC	BIC	CAIC
Default model	184.832	188.311	320.845	355.845
Saturated model	272.000	285.520	800.510	936.510
Independence model	3703.468	3705.059	3765.646	3781.646

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.515	.476	.600	.525
Saturated model	.758	.758	.758	.795

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	393	429
Independence model	15	16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Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	29	67.315	62	.300	1.086
Saturated model	91	.000	0		
Independence model	13	2647.237	78	.000	33.939

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.038	.973	.961	.663
Saturated model	.000	1.000		
Independence model	.589	.284	.165	.244

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.975	.968	.998	.997	.998
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.795	.775	.793
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

NCP

Model	NCP	LO 90	HI 90
Default model	5.315	.000	29.388
Saturated model	.000	.000	.000
Independence model	2569.237	2404.837	2740.969

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.188	.015	.000	.082
Saturated model	.000	.000	.000	.000
Independence model	7.374	7.157	6.699	7.635

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.015	.000	.036	.999
Independence model	.303	.293	.313	.000

AIC

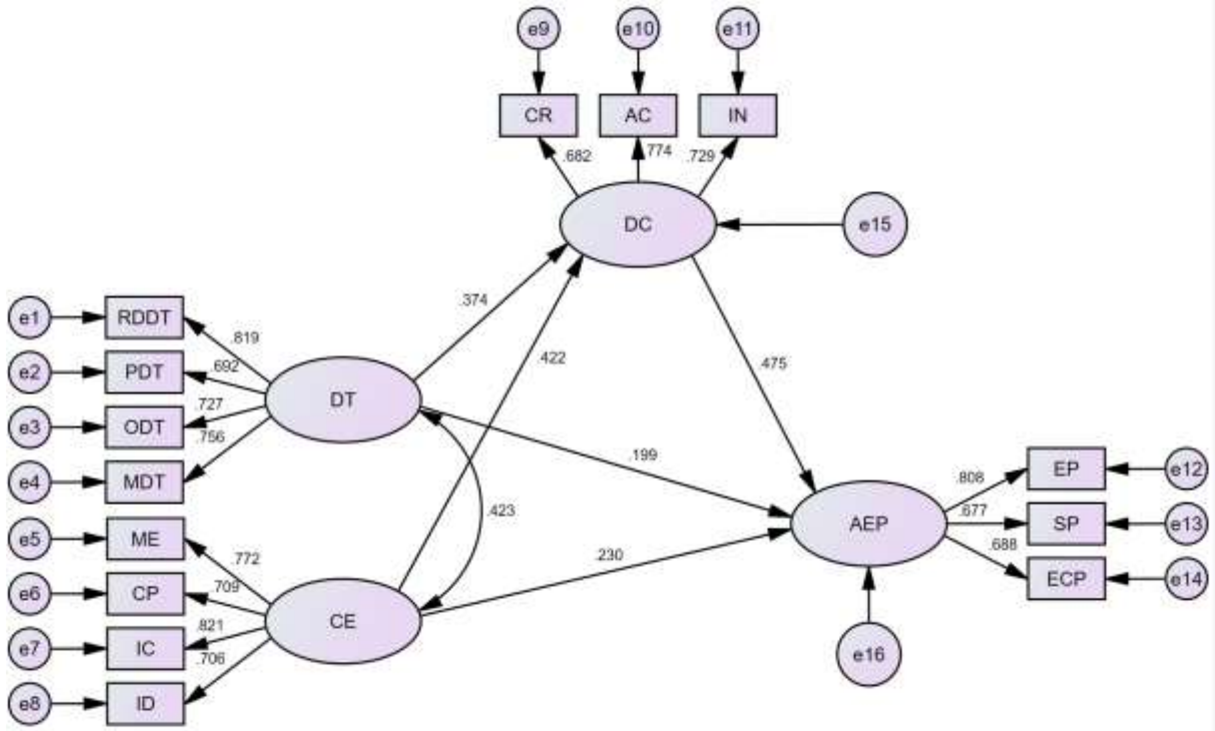
Model	AIC	BCC	BIC	CAIC
Default model	125.315	127.668	238.012	267.012
Saturated model	182.000	189.386	535.635	626.635
Independence model	2673.237	2674.292	2723.756	2736.756

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.349	.334	.416	.356
Saturated model	.507	.507	.507	.528
Independence model	7.446	6.988	7.925	7.449

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	435	485
Independence model	14	15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Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	34	76.630	71	.303	1.079
Saturated model	105	.000	0		
Independence model	14	2104.871	91	.000	23.130

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.028	.970	.955	.656
Saturated model	.000	1.000		
Independence model	.338	.359	.260	.311

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.964	.953	.997	.996	.997
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.780	.752	.778
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

NCP

Model	NCP	LO 90	HI 90
Default model	5.630	.000	30.979
Saturated model	.000	.000	.000
Independence model	2013.871	1868.213	2166.890

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.213	.016	.000	.086
Saturated model	.000	.000	.000	.000
Independence model	5.863	5.610	5.204	6.036

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.015	.000	.035	1.000
Independence model	.248	.239	.258	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	144.630	147.595	276.758	310.758
Saturated model	210.000	219.157	618.041	723.041
Independence model	2132.871	2134.092	2187.277	2201.277

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.403	.387	.473	.411
Saturated model	.585	.585	.585	.610

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	430	477
Independence model	20	22

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	PLabel
DC	<---	DT	.292	.052	5.562	***
DC	<---	CE	.340	.056	6.106	***
AEP	<---	DT	.194	.065	2.985	.003
AEP	<---	CE	.231	.070	3.318	***
AEP	<---	DC	.592	.108	5.461	***
RDDTV	<---	DT	1.000			
PDTV	<---	DT	.748	.057	13.095	***
ODTV	<---	DT	.881	.064	13.828	***
MDTV	<---	DT	.875	.061	14.398	***
MEV	<---	CE	1.000			
CPV	<---	CE	.807	.062	13.006	***
ICV	<---	CE	1.066	.071	14.933	***
IDV	<---	CE	.906	.070	12.951	***
CRV	<---	DC	1.000			
ACV	<---	DC	1.201	.103	11.685	***
INV	<---	DC	1.170	.104	11.283	***
EPV	<---	AEP	1.000			
SPV	<---	AEP	.814	.068	11.903	***
ECPV	<---	AEP	.865	.072	12.074	***

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
DC	<---	DT	.374
DC	<---	CE	.422
AEP	<---	DT	.199
AEP	<---	CE	.230
AEP	<---	DC	.475
RDDTV	<---	DT	.819
PDTV	<---	DT	.692
ODTV	<---	DT	.727
MDTV	<---	DT	.756
MEV	<---	CE	.772
CPV	<---	CE	.709
ICV	<---	CE	.821
IDV	<---	CE	.706
CRV	<---	DC	.682
ACV	<---	DC	.774
INV	<---	DC	.729
EPV	<---	AEP	.808
SPV	<---	AEP	.677
ECPV	<---	AEP	.688

Standardized Direct Effects (Group number 1 - Default model)

	CE	DT	DC	AEP
DC	.422	.374	.000	.000
AEP	.230	.199	.475	.000
ECPV	.000	.000	.000	.688
SPV	.000	.000	.000	.677
EPV	.000	.000	.000	.808
INV	.000	.000	.729	.000
ACV	.000	.000	.774	.000
CRV	.000	.000	.682	.000
IDV	.706	.000	.000	.000
ICV	.821	.000	.000	.000
CPV	.709	.000	.000	.000
MEV	.772	.000	.000	.000
MDTV	.000	.756	.000	.000
ODTV	.000	.727	.000	.000
PDTV	.000	.692	.000	.000
RDDTV	.000	.819	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	CE	DT	DC	AEP
DC	.000	.000	.000	.000
AEP	.200	.178	.000	.000
ECPV	.296	.259	.327	.000
SPV	.291	.255	.322	.000
EPV	.348	.305	.384	.000
INV	.307	.273	.000	.000
ACV	.326	.289	.000	.000
CRV	.288	.255	.000	.000
IDV	.000	.000	.000	.000
ICV	.000	.000	.000	.000
CPV	.000	.000	.000	.000
MEV	.000	.000	.000	.000
MDTV	.000	.000	.000	.000
ODTV	.000	.000	.000	.000
PDTV	.000	.000	.000	.000
RDDTV	.000	.000	.000	.000

Standardized Total Effects (Group number 1 - Default model)

	CE	DT	DC	AEP
DC	.422	.374	.000	.000
AEP	.430	.377	.475	.000
ECPV	.296	.259	.327	.688
SPV	.291	.255	.322	.677
EPV	.348	.305	.384	.808
INV	.307	.273	.729	.000
ACV	.326	.289	.774	.000
CRV	.288	.255	.682	.000
IDV	.706	.000	.000	.000
ICV	.821	.000	.000	.000
CPV	.709	.000	.000	.000
MEV	.772	.000	.000	.000
MDTV	.000	.756	.000	.000
ODTV	.000	.727	.000	.000
PDTV	.000	.692	.000	.000
RDDTV	.000	.819	.000	.000

Appendix E

Certificate of English

BANSOMDEJCHAOPRAYA
RAJABHAT UNIVERSITY

This is to certify that

Mrs. Cui Haitao

Achieved BSRU English Proficiency Test (BSRU-TEP) level

C2

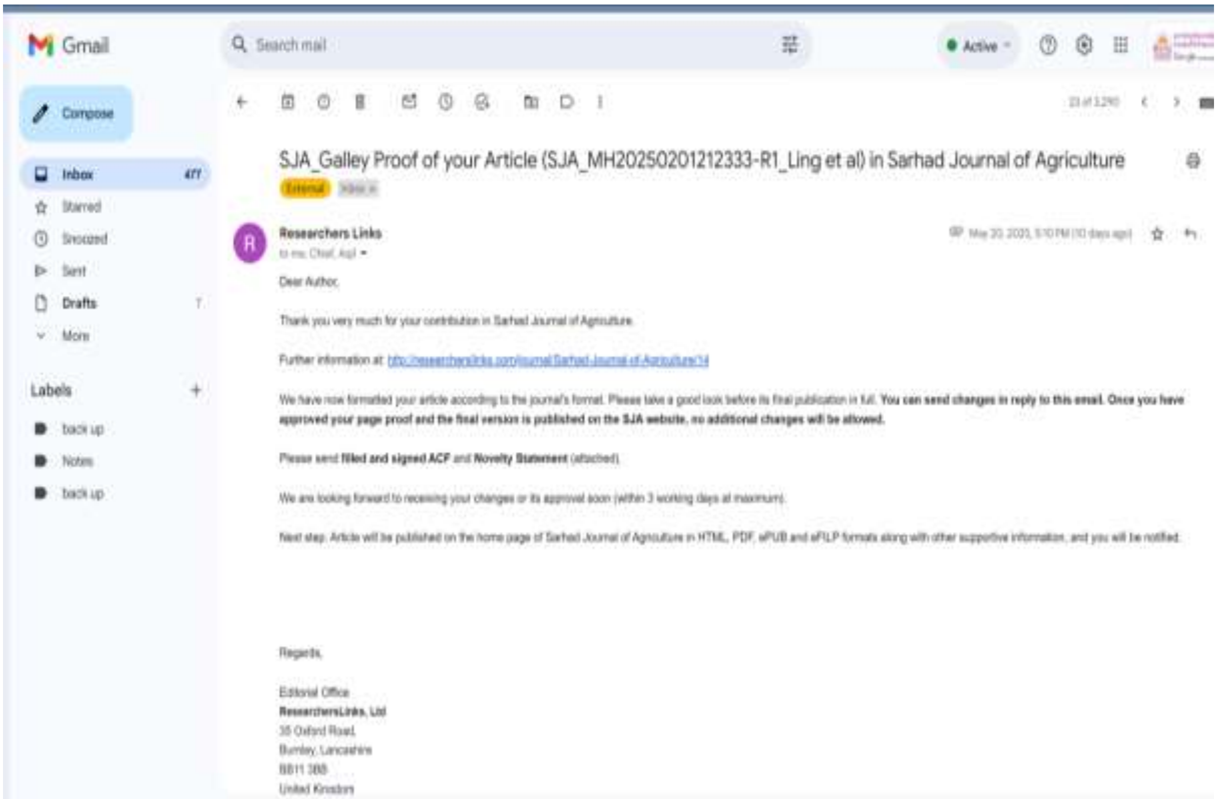
Given on 22nd August 2021

(Assistant Professor Dr Kulsirin Aphiratvoradej)

Director

Appendix F

The Document for Acceptance Research



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Sustainable Model of Agricultural Enterprises in the Environment of Digital Transformation

Chaiyawit Muangmee * , Cui Haitao, Nusanee Meekaewkunchorn, Tatchapong Sattabu.

Research Article, Sarhad Journal of Agriculture
Areas of Specific Interest: Agriculture
Received On: 2025-03-26 10:40:14
Manuscript ID: MH20250212145957-R1
* Corresponding Author

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Appendix G

Proofreading Certification

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This document certifies that the manuscript listed below was edited for proper English language, grammar, punctuation, spelling, and overall style by one or more of the highly qualified native English speaking editors at Academic Universe Editing Servicr

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