

**EXPLORING THE NEXUS BETWEEN BIG DATA
ANALYTICS AND AGRIBUSINESS
COMPETITIVE ADVANTAGE IN CHINA:
THE MEDIATING ROLE OF
DATA-DRIVEN INNOVATION**

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by

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LIST OF ABBREVIATIONS

BDA	Big data analytics
CA	Competitive advantage
Co	Complexity
Com	Compatibility
CP	Competitive Pressure
CuO	Customer Orientation
DDC	Data-driven Culture
DDI	Data-driven innovation
DQ	Data Quality
FA	Firm Age
HR	Human Resource
MU	Market Uncertainty
RA	Relative Advantage
RBV	Resource-Based View
RM	Risk Management
RS	Regulatory Support
TM	Top Management Support
TOE framework	Technology-Organization-Environment framework

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**MENEROKA HUBUNGAN ANTARA ANALITIK DATA RAYA
DAN KELEBIHAN DAYA SAING PERNIAGAAN TANI DI CHINA:
PERANAN PENGANTARAAN INOVASI DIPACU DATA**

ABSTRAK

Kajian ini meneroka hubungan dinamik antara analisis data raya (BDA), inovasi dipacu data (DDI) dan kelebihan daya saing (CA) dalam perniagaan tani China. Menggunakan pendekatan kuantitatif, penyelidikan meneliti kedua-dua hubungan langsung dan pengantara antara konstruk ini, khususnya menyiasat bagaimana BDA mempengaruhi CA secara langsung dan melalui peranan pengantara DDI. Soal selidik tinjauan yang dibangunkan melalui kajian literatur dan temu bual pengamal mengumpul data daripada 287 perniagaan tani, dianalisis menggunakan Pemodelan Persamaan Struktur Separa Kuasa Dua Terkecil (PLS-SEM). Penemuan ini mendedahkan pandangan baru ke dalam dinamik penggunaan teknologi: (1) Kajian ini mempelopori rangka kerja bersepadu yang menggabungkan teori Teknologi-Organisasi-Persekitaran (TOE) dengan Pandangan Berasaskan Sumber (RBV) untuk menjelaskan kelebihan daya saing dipacu data; (2) Meneroka sembilan pemboleh BDA yang ketara (kelebihan relatif, kualiti data, sokongan pengurusan tertinggi, sumber manusia, orientasi pelanggan, pengurusan risiko, tekanan persaingan, budaya dipacu data dan ketidakpastian pasaran) dan satu perencat (kerumitan), sambil mencabar andaian konvensional tentang keserasian dan sokongan kawal selia.

Keputusan menunjukkan bahawa BDA secara positif mempengaruhi CA secara langsung dan tidak langsung melalui pengantaraan DDI, menyumbang 68% daripada varians CA. Penyelidikan ini menyediakan bukti empirikal pertama mekanisme pengantaraan DDI dalam konteks pertanian, menawarkan cerapan yang boleh diambil tindakan untuk meningkatkan daya saing dipacu data. Secara praktikal, ia menyediakan panduan yang boleh diambil tindakan untuk mengoptimumkan keutamaan pelaburan data dan saluran paip inovasi dalam perniagaan tani. Rangka kerja TOE-RBV bersepadu dan faktor penerimaan khusus konteks memajukan pemahaman teori tentang daya saing dipacu data dalam ekonomi sedang pesat membangun.

EXPLORING THE NEXUS BETWEEN BIG DATA ANALYTICS AND AGRIBUSINESS COMPETITIVE ADVANTAGE IN CHINA: THE MEDIATING ROLE OF DATA-DRIVEN INNOVATION

ABSTRACT

This study explores the dynamic relationship between big data analytics (BDA), data-driven innovation (DDI), and competitive advantage (CA) within Chinese agribusinesses. Employing a quantitative approach, the research examines both direct and mediated relationships between these constructs, specifically investigating how BDA influences CA both directly and through the mediating role of DDI. A survey questionnaire developed through literature review and practitioner interviews collected data from 287 agribusinesses, analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings reveal novel insights into technological adoption dynamics: (1) The study pioneers an integrated framework combining the Technology-Organization-Environment (TOE) theory with Resource-Based View (RBV) to explain data-driven competitive advantage; (2) Explores nine significant BDA enablers (relative advantage, data quality, top management support, human resources, customer orientation, risk management, competitive pressure, data-driven culture, and market uncertainty) and one inhibitor (complexity), while challenging conventional assumptions about compatibility and regulatory support. Results demonstrate that BDA positively influences CA both directly and indirectly through

DDI mediation, accounting for 68% of CA variance. This research provides the first empirical evidence of the DDI mediation mechanism in agricultural contexts, offering actionable insights for enhancing data-driven competitiveness. Practically, it provides actionable guidance for optimizing data investment priorities and innovation pipelines in agribusinesses. The integrated TOE-RBV framework and context-specific adoption factors advance theoretical understanding of data-driven competitiveness in emerging economies.

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter centres on the study of competitive advantage (CA), its essential role in agribusiness, and the primary objective of the present research: to investigate how agribusinesses can leverage big data analytics (BDA) through data-driven innovation (DDI) as a mediator to strengthen their competitive advantage (CA). This part offers an analysis of the current condition of agribusinesses in China and explores the correlation between BDA and Cloud CA, along with emphasizing the significance of DDI. Following that, this study emphasizes the problems that are being addressed, and next presents the study objectives and its significance. The research also includes definitions of essential terms. The part closes by providing a concise overview of the organizations that will be discussed in the next sections of this research.

1.2 Background of the Study

In the rapidly evolving landscape of global agribusiness, competitive advantage has emerged as a critical objective for companies striving to optimize operations and enhance market positioning. The agribusiness sector, particularly in China, faces significant challenges and opportunities due to the increasing complexity of supply chains, advancements in technology, and intensified global competition. The convergence of these factors underscores the need for agribusinesses to leverage

innovative strategies to maintain sustainable competitive advantages in the market (Sahputra & Nendi, 2024).

Big data analytics represents a substantial opportunity within this context, enabling agribusinesses to harness vast amounts of data generated across various stages—from production and processing to distribution and retailing. BDA facilitates deeper insights into market trends, consumer preferences, and operational efficiencies, thereby supporting informed decision-making at all operational levels (Gao & Sarwar, 2022). For instance, the integration of weather data through BDA enables farmers to make more informed decisions regarding crop management, thus adapting to changing climatic conditions and optimizing agricultural practices (Judijanto, 2023). The use of BDA can lead to the identification of new business opportunities, improved risk management, and enhanced resource allocation, ultimately contributing to increased efficiency and productivity within agribusiness operations (Alghamdi & Agag, 2023).

Particularly vital to the relationship between BDA and CA is the concept of data-driven innovation (DDI). As agribusinesses increasingly incorporate BDA into their workflows, DDI serves as a mediator, transforming raw data into actionable knowledge that informs strategic innovations (Kusumah et al., 2024). This innovation is not limited to technological advancements but encompasses the development of new business models and value propositions tailored to respond effectively to market demands.

Research has shown that the potential of BDA is closely tied to an organization's capability to manage knowledge effectively (Ferraris et al., 2019). Moreover, effective deployment of BDA can aid in enhancing innovation performance, thereby reinforcing competitive advantage (Alghamdi & Agag, 2024). The agribusiness environment in China is characterized by unique traits such as a large and diverse agricultural output, a rapidly growing domestic market, and significant government influences on market dynamics (Sadiku et al., 2020). Despite these advantages, the sector faces pressures such as environmental constraints, evolving consumer needs, and international competition, necessitating a strategic focus on harnessing advanced technologies like BDA alongside DDI (Lassoued et al., 2021).

To facilitate this transformation, agribusiness stakeholders must develop internal capabilities that enable effective data utilization and foster innovation. The need for comprehensive strategies that integrate BDA with traditional agribusiness practices underscores the evolving nature of strategic management within the sector. Studies suggest that embedding BDA into existing operations can significantly enhance business performance and dynamic capabilities, which are crucial for adapting to market changes (Wang et al., 2024). The successful integration of BDA into agricultural operations can align with precision agriculture practices, leading to reduced environmental impacts while improving profitability (J. Y. Chen et al., 2024).

In summary, the intersection of big data analytics, data-driven innovation, and competitive advantage presents a valuable opportunity for agribusinesses to navigate

the complexities of modern markets. By focusing on these areas, this research aims to elucidate the mechanisms by which agribusinesses can achieve sustained competitive advantages in a challenging and dynamic environment.

1.2.1 Big data analytics and Data-driven innovation in agribusiness

As the amount of data, known as big data, continues to grow, new tools and techniques are being developed to effectively collect, handle, and analyse it. The vast magnitude and intricate nature of big data exceed the capacities of conventional databases and systems, rendering the extraction of meaningful insights challenging (Judijanto, 2023). The emergence of BDA has resulted from the integration of two crucial components: big data and business analytics (Wang et al., 2018). The key to extracting relevant insights from large datasets is in the efficient application of analytics (Sun & Huo, 2019). Big data is crucial for the operational workflows of several “Born Digital” enterprises such as Amazon, Google, eBay, Twitter, and Facebook. Their ability to utilize data has provided them with a significant competitive edge (Otchere et al., 2021). Through the utilization and examination of these vast data collections, firms may get a more comprehensive comprehension of the market, enhance operational effectiveness, and establish a competitive edge (Belaud et al., 2019). Utilizing resilient analytical methods on large datasets may greatly improve organizational effectiveness and revolutionize managerial procedures within an evidence-based decision-making culture (Korherr & Kanbach, 2023). Moreover, implementing BDA enables companies to quickly attain financial and operational

efficiency improvements by making decisions based on data (Fosso Wamba et al., 2024). Companies who embraced BDA at an early stage have surpassed their rivals and achieved a significant advantage in the market. BDA plays a crucial role and offers substantial contributions across several sectors of the business (Awan et al., 2021). During the adoption phase, it is crucial to smoothly integrate BDA into current systems and business processes. BDA activities need continuous and robust backing from senior management and other pertinent stakeholders, in contrast to conventional projects (Aamer et al., 2020). Furthermore, the effectiveness of analytics depends on the data and the methodologies employed for storing, processing, and evaluating it. Facilitating the production of valuable information may need cooperation across different departments or partner companies in order to achieve a smooth and continuous workflow.

BDA encompasses the gathering, manipulation, and examination of substantial amounts of data from many origins throughout the agricultural supply chain. The availability of agricultural data facilitated by big data analytics, facilitates predictive modelling for agribusiness (Soares et al., 2023). By analysing historical data on weather conditions, pest outbreaks, trends in markets and agricultural performance, predictive models can forecast yields, assess risks and support decision-making processes. These insights enable farmers and agribusinesses to proactively address challenges and optimize their operations (Lohit & Mujahid, 2022). By utilizing data analytics and data-driven technologies, businesses can achieve greater transparency,

traceability, and efficiency in the movement of agricultural products. Additionally, data-driven market intelligence helps businesses understand consumer preferences, market trends, and demand patterns, allowing them to customize their goods and plans accordingly (Sadiku et al., 2020).

Utilizing data analytics, sensors, and satellite imagery (Delgado et al., 2019), farmers can obtain information on soil quality, weather conditions, and crop health. This allows them to make data-driven decisions about the precise use of fertilizers, pesticides, and water, resulting in optimized resource usage and higher yields (Javaid et al., 2023). For example, the Internet of Things (IoT) has transformed agribusiness by linking various sensors, devices, and machinery on farms. This connectivity facilitates the collection and analysis of real-time data on environmental conditions, crop development, and livestock health. Through IoT and data analytics, farmers can automate tasks, monitor farm operations remotely, and enhance efficiency (Ladasi et al., 2019).

The data-driven revolution and the application of digital technologies are profoundly changing agriculture. These innovative technologies are pushing the conventional agricultural supply chain towards a digital environment that is heavily reliant on data. Consequently, it is crucial for organizations to attain a high degree of supply chain visibility, ensuring that essential information is readily accessible to decision-makers for crafting sustainable supply chain strategies (Kamble et al., 2020; Kero & Endebu, 2023). The rapid progress in information and communication

technology (ICT), such as artificial intelligence, blockchain, cloud computing, and the internet of things, has resulted in a large amount of data. This data not only helps agricultural organizations make informed decisions, reduce risks, and improve operational processes, but also encourages innovation based on data (Ochuba et al., 2024).

During the past decade, data-driven innovation has now entered a golden age as digital technologies become increasingly pervasive across various sectors (Babu et al., 2024). The advent and maturation of BDA, has significantly enhanced the capacity of companies to collect, process, and analyse an unprecedented volume and variety of data. This extensive data capability provides a robust foundation for innovation within organizations, profoundly influencing the management and trajectory of innovation processes (Siew & Farouk, 2023). The proliferation of BDA empowered companies to collect vast amounts and varieties of data, sparking meaningful directions for innovation within organizations and significantly impacting innovation management practices. In agricultural enterprises specifically, the influx of smart technology and equipment has led to a massive increase in data. These technologies, ranging from precision agriculture sensors to automated machinery, collect data on various aspects of farming operations such as soil conditions, crop vitality, meteorological conditions, and equipment efficiency. This wealth of data, coupled with advances in computing power and storage capabilities, has created opportunities for agricultural organizations to leverage BDA effectively.

Despite the significant advancements in big data research both within academic circles and practical applications, the potential of BDA to bolster the competitive advantage of agricultural enterprises has not been fully realized. In recent years, the competitive edge of agribusinesses has notably diminished due to stagnation in innovation, value creation, and productivity enhancements. Specifically, there is a conspicuous paucity of knowledge regarding the effective utilization of BDA to fortify the competitive standing of agricultural firms. Additionally, numerous companies recognize big data as a pivotal resource that catalyses innovation, which, in turn, contributes to competitive superiority. Consequently, the nature of the relationship between DDI facilitated by BDA and CA warrants deeper investigation.

1.3 China in Context

Agricultural development plays a crucial role in the overall growth of the Chinese economy. In 2014, the World Bank Group introduced a classification system based on the significance of agriculture to a nation's Gross Domestic Product (GDP) and employment. This system indicates that when the agricultural sector's contribution to GDP falls below 10%, it enters a phase of modernization, transformation, and development. Data from 2019 to 2023 reveal that the contribution of the primary sector to GDP has stabilized at around 7%, suggesting that China's agriculture is in a critical modernization transition period (Golubev, 2021).

Modern agriculture is characterized by its foundation in advanced industry, research, and technology, having emerged during the era of capitalist industrialization, and evolving significantly after the Second World War. It encompasses the concept of smart agriculture, which aligns with Industry 4.0 and the post-industrial era(Guo & Lyu, 2024). This model of agriculture is distinguished from previous agricultural industrialization, representing a shift towards practices that are automated, personalized, ecological, and precision-focused, with an emphasis on integrating a smart economy alongside the health industry.



Figure 1.1 The proportion of the three industries in GDP from 2019 to 2023

In 2018, the Opinions of the CPC Central Committee and The State Council on Implementing the Rural Revitalization Strategy clearly put forward the idea of “accelerating the transformation from a large agricultural country to a strong agricultural country”. This transformation is contingent on improving the quality, competitiveness, and performance of agricultural practices (Dai et al., 2024).

Table 1.1 Comparison of agricultural added value per labour between China and major agricultural powers

Country	Agriculture, forestry, and fishing, value added per worker		Relative Gap			
			Multiple of 1 in China		Relative gap coefficient (%)	
	2015(Year)	2023(Year)	2015(Year)	2023(Year)	2015(Year)	2023Year)
China	4325.71	7,713.73	1.00	1.00	0.00	0.00
USA	86890.29	100061.65	20.09	12.97	-95.02	-92.30
Australia	102737.1	126,821.32	23.75	16.45	-95.79	-93.92
France	53430.63	47,432.93	12.35	6.15	-91.90	-83.74
Germany	40699.79	57,378.26	9.41	7.44	-89.37	-86.56
Japan	19752.32	22,596.12	4.57	2.93	-78.10	-65.85
Upper middle income	4834.84	7,077.47	1.12	1.09	-10.53	-8.99
World	3479.15	4011.96	0.80	0.52	24.33	47.48
High income	36229.73	27,591.58	8.38	3.58	-88.06	-72.80

Note: Relative gap coefficient = (China ÷ other economies) ×100 - 100.

Source: Calculated from the World Bank's World Development Indicators Database

Unit: US dollars (constant 2015 US\$)

Countries like the United States, Australia, France, Germany, and Japan exemplify successful agricultural modernization and are often regarded as agricultural powerhouses (Kyung-Sup, 2022). Their agricultural competitiveness manifests through enhanced productivity and operational efficiencies. The direct embodiment of strong agricultural power is strong agricultural competitiveness. International development experiences demonstrate that while countries possess varying resource endowments for agricultural development, there exists a universal pursuit of enhanced agricultural competitiveness throughout the modernization process (Long, 2021). Whether it is North America's capital-intensive agricultural modernization or East Asia's labour-intensive approach, agricultural competitiveness is ultimately expressed through comparative advantages across key indicators such as added value, unit yield levels, and production costs (Salimova et al., 2020).

The strength of agricultural competitiveness is a crucial determinant of agricultural development levels and a key aspect that China must address in its goal of becoming an agricultural power. Specifically, the indicators of agricultural added value per labour force reveal significant imbalances in China's agricultural labour input and output structure, with productivity notably trailing behind that of major agricultural nations (Bashir et al., 2019). Though from 2015 to 2023, the gap in agricultural added value per labour force compared to leading agricultural powers has been gradually narrowing, it remains substantial, as shown in Table 1.1. Therefore,

improving competitiveness is still the primary task for China's agricultural development (Sansika et al., 2023).

Currently, China is advancing toward the objectives of constructing a modern socialist nation while setting forth the second centenary goal. However, major changes in domestic and international landscapes are posing new challenges to the agricultural industry's competitiveness. As agricultural production goals evolve, the industry finds itself constrained by existing operational models, unlike the industrial and construction sectors, which have undergone multiple rounds of modernization and upgrades (Białowas & Budzyńska, 2022). This necessitates the exploration of new development pathways to enhance agricultural competitiveness.

The main challenges in China's agriculture have transitioned from addressing shortages in quantity to grappling with structural issues—prominently involving low quality, efficiency, and competitiveness. China's agricultural sector is often described as large yet not robust; expansive yet not exemplary, hampered by foundational weaknesses and insufficient resilience against natural and market fluctuations (Skydan et al., 2024).

Amid these challenges, the rapid development of China's digital economy presents promising opportunities. The continual evolution of business models across various sectors through innovative digital technologies is influencing agricultural practices and driving modernization (Nipers et al., 2018). The Chinese government has underscored the importance of agricultural informatization and digital

transformation, as reflected in the Central Committee's No. 1 documents focused on "agriculture, rural areas, and farmers" (Melembe et al., 2021). Keywords such as "smart agriculture," "big data," and "digitalization" are increasingly prioritized, indicating a commitment to enhancing agricultural practices.

The integration of digital technologies into agricultural processes is reshaping production landscapes and enabling significant improvements. Increased digitalization facilitates precise agricultural practices that reduce costs and enhance operational efficiency. For instance, leveraging IoT technology enables farmers to implement automated irrigation systems calibrated to real-time data on environmental conditions, enhancing crop yields while minimizing labour costs (Kapoor & Kaur, 2022).

Additionally, the incorporation of digital technologies offers enhanced traceability and quality assurance for agricultural products. This technology allows secure documentation of production, processing, and transport phases, which boosts consumer trust through transparency and guarantees product safety. For example, agricultural cooperatives using blockchain can provide consumers with access to the production process and quality test reports via mobile applications (Elfira et al., 2022).

Furthermore, the integration of agricultural practices with digital technologies fosters a transformation from traditional methods to modernized approaches. This shift is key in elevating the added value and competitiveness of agricultural products. Agricultural enterprises employing BDA and artificial intelligence technologies can

better anticipate market demand for products and optimize crop planting strategies, thereby improving economic benefits and market positions (Singh et al., 2024).

Lastly, integrating digital solutions within the agricultural industry can bolster rural economies by enabling farmers to utilize e-commerce platforms for direct sales, bypassing traditional supply chains. This approach allows for increased product pricing and enhances farmers' income (Mahmood et al., 2019).

In conclusion, the amalgamation of the agricultural sector with digital technologies holds immense potential for revitalizing China's agricultural industry. By harnessing digital solutions, the sector can enhance production efficiency, ensure product quality, facilitate industry transformation, stimulate rural economic development, and substantially increase farmers' incomes. These advancements are critical for achieving sustainable agricultural development and strengthening the overall competitiveness of the agricultural sector in China.

The Chinese government's "Plan to Advance Agricultural and Rural Modernization during the 14th Five-Year Plan Period (2021-2025)" emphasizes the necessity of enhancing quality, efficiency, and competitive advantage in agriculture while fostering international competitiveness in agribusiness (Volyk et al., 2023). Harnessing the full potential of BDA will be integral to this effort, enabling stakeholders to draw valuable insights from vast datasets, discover new opportunities, optimize operations, and catalyse continuous growth through data-driven innovation

(DDI) (Oloukoï, 2021). Therefore, whether DDI caused by BDA can also affect CA is worth studying together.

1.4 Problem Statement

In today's agribusiness landscape, the rapid development of data-driven technologies presents agricultural enterprises with significant opportunities alongside substantial challenges. The Chinese agricultural sector is undergoing a transformation characterized by increased digitization and modernization. As BDA becomes progressively integrated into agricultural enterprises, organizations are better positioned to harmonize digital and intelligent technologies, thereby enhancing operational efficiency and bolstering market competitiveness.

Despite the recognized potential of BDA to augment CA, current research has not sufficiently elucidated the specific relationship between BDA and CA within agricultural businesses, particularly concerning the mediating role of DDI. While existing literature largely focuses on how technology adoption and innovation can enhance a company's competitive standing, there remains a noticeable gap regarding the specific influences of BDA on agricultural competitive advantage, especially through the mediating role of DDI.

BDA offers the capability to conduct extensive data analysis, aiding firms in uncovering new market patterns, customer behaviours, and opportunities for operational optimization. However, in the agricultural industry, the journey of translating BDA into tangible competitive advantages remains inadequately explored

(Kumar et al., 2024). This lack of comprehensive understanding renders agricultural enterprises uncertain about effectively applying BDA to achieve sustained competitive advantages.

In addition to the challenges associated with BDA utilization, the literature has yet to sufficiently address the drivers of BDA adoption in the agricultural sector. Numerous firms acknowledge the potential of BDA, yet many face impediments such as resource constraints, talent shortages, and market uncertainties, which significantly hinder broader application (Almheiri et al., 2025). Moreover, factors such as customer orientation, risk management, and market uncertainty play critical roles in influencing BDA adoption and should be considered when examining the drivers of BDA in the agricultural context. Given the rapid growth of the big data market and the acceleration of agricultural digital transformation, it has become imperative to study what factors can effectively utilize BDA (Perçin, 2023).

This study incorporates additional variables beyond the original technology-organization-environment framework to provide a more comprehensive understanding of the driving factors behind BDA. Customer orientation is considered an essential organizational variable, defined as the process of identifying target customers and understanding their needs, which enables organizations to meet those needs effectively and gain a competitive advantage (S. Narver & S. Slater, 1990). Recent research by Camilleri (2020) and Taylor and Broløs (2024) highlights the significance of customer-centric approaches in leveraging data for product innovations.

Risk management is another crucial organizational variable, particularly relevant in agricultural supply chains that face constant change and disruptions. Odimarha et al. (2024) emphasize the importance of effective risk management in mitigating uncertainties associated with technological advancements and market dynamics. By enhancing risk diagnosis and management practices, organizations can better navigate complexities and optimize the balance between innovation and risk.

Market uncertainty is examined as a significant environmental variable impacting innovation. Recent studies by Komolafe et al. (2024) underscore the challenges posed by dynamic market conditions, emphasizing the need for firms to anticipate and respond to shifts in consumer demand and competitive forces. This uncertainty, characterized by ambiguity regarding consumer preferences and market size, highlights the importance of agile business models to succeed in volatile markets. These updated references provide contemporary insights into the organizational and environmental variables influencing the adoption and effectiveness of BDA, contributing to a more nuanced understanding of its driving factors.

Furthermore, while BDA has proven effective in enhancing competitiveness across various industries, the crucial role of DDI—essentially the process of converting big data into a driving force for innovation—remains underexplored within the context of agriculture (Dahiya et al., 2021). DDI enables agricultural firms to leverage big data insights to develop new products, optimize existing offerings, and innovate business models (Côte-Real et al., 2019). Nevertheless, empirical research

regarding how BDA influences CA through DDI in the agricultural sector is still nascent, lacking systematic exploration.

Given this context, this study aims to fill this gap by focusing on the interrelationship between BDA and agricultural CA, emphasizing the mediating role of DDI. By analysing the technological, organizational, and environmental drivers of BDA adoption in agricultural enterprises, this research seeks to uncover how BDA can elevate market competitiveness, thereby providing sustainable CA for agribusinesses. Additionally, this study will propose a new theoretical framework accompanied by empirical evidence that assists agricultural enterprises in navigating existing challenges and maximizing the potential of BDA to facilitate their digital transformation (Sazu & Jahan, 2022).

In summary, the integration of agricultural practices with data-driven technologies, particularly BDA, serves as a pivotal determinant of success in modernizing China's agricultural sector. Gaining a deeper understanding of these dynamics, particularly the role of DDI in enhancing CA, will not only benefit individual enterprises but also contribute to the broader goal of achieving sustainable agricultural development and innovation in China.

1.5 Research Questions

This thesis aims to explore the following main question: How does big data analytics (BDA) contribute to the competitive advantage (CA) of Chinese

agribusinesses through the mediating role of data-driven innovation (DDI)? To address this, the following sub-questions are posed:

1. What are the technological, organizational, and environmental (TOE) factors that drive BDA in Chinese agribusinesses?
2. What is the impact of BDA on data-driven innovation (DDI)?
3. What is the effect of BDA on the competitive advantage (CA) of agribusinesses?
4. Does DDI mediate the relationship between BDA and CA in agribusinesses?

1.6 Research Objectives

To achieve a comprehensive understanding, this study focuses on the following research objectives:

1. To examine the impact of technological, organizational, and environmental (TOE) factors on BDA in Chinese agribusinesses.
2. To assess the impact of BDA on DDI in agribusinesses.
3. To evaluate how BDA contributes to the CA of agribusinesses.
4. To analyse whether DDI mediates the relationship between BDA and CA in agribusinesses.

1.7 Scope of Study

This research is centred on a macro-level analysis, examining the relationship between BDA and CA in China's agribusiness sector with the mediating role of DDI.

The primary aim is to answer the question, “How does BDA contribute to the competitive advantage of Chinese agribusinesses, with DDI acting as a mediator?”

The focus of this study is on medium- and large-scale agribusinesses in China that are engaged in adopting and implementing data-driven technologies. While small-scale family farms dominate China’s agricultural landscape, this study specifically targets enterprises that are more likely to integrate advanced technologies such as artificial intelligence (AI), big data, machine learning, the Internet of Things (IoT), and other digital tools into their operations to drive operational improvements and enhance their market competitiveness.

The study population consists of the top 500 agricultural enterprises in China, as identified and ranked by the China Agricultural Enterprise Alliance (CAEA) in 2023. These firms are recognized for their industry influence, innovation, and competitiveness, with operating revenues exceeding 1 billion yuan. These enterprises are better positioned to adopt and utilize data-driven technologies, making them the ideal focus for understanding how digital transformation influences China’s agricultural sector.

This research specifically examines medium- and large-scale agribusinesses, as these enterprises possess the necessary infrastructure and resources to incorporate technological advancements and digital tools, which can significantly enhance operational efficiency, supply chain management, and overall competitiveness within the agricultural industry.

The scope of this study is confined to the 500 agribusinesses identified by CAEA. The data collected will primarily focus on the adoption and impact of data-driven technologies within these firms. The study does not extend to small-scale family farms, which make up the majority of agricultural operators in China, but rather focuses on those enterprises capable of undergoing digital transformation.

In conclusion, this study aims to explore the role of data-driven technologies in medium- and large-scale agribusinesses across various regions of China, investigating their impact on operational improvements, supply chain management, and market competitiveness within the agricultural sector.

1.8 Significance of the Study

This study aims to contribute both theoretically and practically by integrating diverse perspectives on the link between Big Data Analytics (BDA) and competitive advantage (CA) in the agribusiness sector, with Data-Driven Innovation (DDI) acting as a mediator. The importance of this study can be summarized from two key perspectives.

1.8.1 Theoretical Significance

This study makes significant theoretical contributions to the fields of BDA, DDI, and CA, particularly in the context of Chinese agribusinesses. The theoretical significance of this research lies in its ability to integrate and extend existing knowledge on these topics, providing new insights into their interplay and impact.

Firstly, the study is pioneering in developing and testing an integrated model that explores the relationships between BDA, DDI, and CA in the agribusiness sector. While prior research has explored these factors in isolation, this study provides a more comprehensive understanding by examining how these elements interact and influence one another. This integrative approach allows for a deeper analysis of the dynamics at play, moving beyond isolated examinations of individual components.

Secondly, this study enhances the theoretical framework by incorporating additional variables, such as customer orientation, risk management, and market uncertainty, alongside the traditional TOE (technology-organization-environment) framework. These supplementary factors enrich the explanation of how BDA influences competitive advantage, offering a more nuanced understanding of the contextual drivers of BDA adoption in agribusinesses. This contribution is valuable because it addresses the complexities of the agribusiness sector and emphasizes the role of data analytics in navigating uncertain and dynamic market environments.

Thirdly, the research fills a gap in existing literature by examining how BDA can lead to competitive advantage through the iterative process of DDI. Drawing on Resource-Based View (RBV) theory, this study demonstrates the pathway from BDA to innovation, suggesting that the value of big data lies not only in its analysis but also in how it drives innovation. By positioning DDI as a mediator, the study highlights that achieving a competitive edge requires more than just analysing data—it involves

applying insights from data analytics to innovate in product offerings, cost structures, and services.

Finally, this study contributes to the broader theoretical understanding of digital transformation in industries, particularly the agricultural sector. By focusing on Chinese agribusinesses, it provides a case study that illustrates the impact of digital technology and data-driven approaches on industry competitiveness, offering valuable insights that can be applied to other emerging economies.

1.8.2 Practical Significance

The practical significance of this research lies in its to inform strategic decision-making and operational practices within the Chinese agribusiness sector. By elucidating the drivers of BDA adoption and its influence on DDI and CA, this study offers actionable insights for agricultural enterprises seeking to leverage digital technologies for sustainable growth and competitiveness.

Firstly, by identifying the technological, organizational, and environmental drivers of BDA adoption, this research equips BDA users and developers with a comprehensive understanding of the factors shaping their organizations' approach to big data analytics. This knowledge can inform resource allocation and investment strategies, enabling firms to prioritize initiatives that are aligned with their strategic goals and market realities.

Secondly, the examination of the relationship between BDA and DDI sheds light on the mechanisms through which data-driven insights translate into tangible

innovation outcomes. Understanding this relationship empowers agribusinesses to optimize their data utilization processes, fostering a culture of innovation that drives product development, process optimization, and market responsiveness. The findings guide agribusiness managers in developing data-driven strategies, enhancing data processing capabilities, fostering an innovation culture, and improving overall competitiveness and sustainability.

Thirdly, the investigation into the impact of BDA on agribusiness CA, mediated by DDI, offers a holistic perspective on the value proposition of data-driven strategies. Policymakers can support the adoption of BDA and DDI by investing in technological infrastructure, fostering talent development, and establishing regulatory frameworks. This includes financial support for data centres, R&D incentives, and the creation of industry standards for data security and privacy. By promoting a robust agricultural data ecosystem, policymakers can enhance production efficiency, market competitiveness, and sustainable development, providing a solid foundation for the digital transformation of the agricultural sector.

In summary, the results of this research provide practical recommendations for agribusiness executives dealing with the intricacies of the digital economy. By utilizing Big Data Analytics (BDA) to foster innovation and boost competitive edge, Chinese agribusinesses can strategically position themselves for sustained success in a progressively data-centric environment.