

Article

Bridging Big Data Analytics Capability and Competitive Advantage in China's Agribusiness: The Mediator of Absorptive Capacity

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Abstract: This research examines the relationship between big data analytics capability (BDAC) and competitive advantage (CA) in China's agribusiness sector, with a specific focus on the mediating role of absorptive capacity (AC). Although BDAC has been extensively studied in other industries, its role within agribusiness remains underexplored, particularly in developing economies like China. This study addresses this gap by investigating how BDAC can be utilized to enhance competitive advantage in the unique context of agribusiness. Grounded in Resource-Based Theory (RBT), a comprehensive framework is developed to elucidate the interconnections among BDAC, CA, and AC. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data collected from 287 agribusiness firms in China, the findings reveal that key resources—such as data quality, infrastructure, information systems, data governance, data-driven culture, managerial expertise, and technical proficiency—significantly influence BDAC. Moreover, BDAC is shown to positively impact CA, with AC serving as a critical mediator in this relationship. These results emphasize the strategic importance of integrating BDAC and AC to enhance the competitiveness of agribusinesses, particularly amidst rapid digital transformation. This study provides valuable contributions to the literature on BDAC, enriches the theoretical foundations of RBT in agribusiness contexts, and offers practical recommendations for digital transformation strategies in the sector.

Keywords: agribusiness; big data analytics capability; competitive advantage; absorptive capacity; China



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1. Introduction

In recent times, rapid developments in digital technologies have profoundly reshaped numerous industries, agribusiness included. Integrating big data analytics capability (BDAC) has become pivotal in enabling organizations to not only analyze large datasets but also derive actionable insights that foster innovation and efficiency. This enhancement

is achieved by providing more detailed insights into market trends, consumer behaviors, and operational efficiencies [1]. As enterprises increasingly adopt digital transformation strategies, BDAC emerges as a pivotal component in sustaining competitive advantages, particularly in dynamically changing markets [2].

Digital transformation has become essential for businesses aiming to maintain a competitive edge. By 2024, more than 50% of the worldwide economy will be impacted by or dependent on digital transformation activities, as stated by the International Data Corporation (IDC). Moreover, more than 90% of companies and institutions are expected to prioritize digital transformation as a core element of their competitive strategy [3]. These statistics underscore the profound impact that digital transformation and, by extension, BDAC can have on the future of global business and competitiveness.

Agriculture, as a cornerstone of national economies, significantly contributes to GDP and drives overall economic development. However, the agricultural sector faces unique challenges, such as the complexity of managing unstructured and diverse data sources, including weather patterns, crop performance, and market trends. This makes the integration of BDAC not only a necessity but also a challenge for agribusinesses. Despite growing recognition of BDAC's transformative potential in enhancing decision-making, operational flexibility, and organizational effectiveness, its application in the agribusiness context remains underexplored, particularly in developing economies like China.

Prior studies have highlighted BDAC's positive impact on competitive advantage in non-agricultural fields, such as manufacturing firms [4], IT businesses [5], and the small and medium enterprises (MSME) sector [6]. However, there is a significant gap in understanding its unique relevance and application in agribusiness contexts, where operational conditions differ greatly from other industries. This gap presents a compelling research opportunity to investigate how BDAC can be leveraged to augment competitive advantages in agribusinesses.

The purpose of this study is to investigate the nexus between BDAC and CA in Chinese agribusinesses. Specifically, it addresses the following research questions:

1. What resources can affect the use of BDAC in Chinese agribusinesses?
2. How does BDAC influence competitive advantage in Chinese agribusinesses?
3. What role does absorptive capacity play in moderating this relationship?

By incorporating absorptive capacity (AC), defined as an organization's aptitude to recognize, combine, and utilize external information, this study aims to provide deeper insights into the elements that affect CA [7].

To address these research questions, an elaborate BDAC model was developed, substantiated, and subsequently validated. Grounded in Resource-Based Theory (RBT), which emphasizes the strategic importance of valuable, rare, inimitable, and non-substitutable resources, this study develops a conceptual framework to examine these relationships. RBT is particularly suited for this analysis as it provides a robust theoretical foundation to understand how BDAC, as a strategic resource, contributes to competitive advantage. Unlike the Dynamic Capabilities Framework, which focuses on adaptability, RBT underscores resource acquisition and deployment, making it highly relevant to the analysis of BDAC in agribusiness.

To provide context for this research, the focus is on medium- and large-scale agribusinesses in China, which are characterized by their significant role in the agricultural value chain and their proactive adoption of digital technologies. These enterprises possess greater resource and technological integration capabilities, allowing them to adapt and innovate in response to market changes and policy adjustments. Consequently, they serve as ideal subjects for examining the application of BDAC in agriculture, particularly in light of China's rapid agricultural modernization and the increasing penetration of digital technologies.

In terms of data collection methodology, this study employs a quantitative approach, utilizing purposive sampling to gather insights from key stakeholders within these organizations. This distinctive method allows for a focused examination of BDAC in a rapidly evolving agribusiness landscape, ensuring that the data collected accurately reflects the complexities and unique challenges faced by these enterprises. By concentrating on stakeholders with relevant experience in digital transformation and big data applications, the research provides a representative and meaningful sample that enhances the validity of the findings.

This research is structured as follows: First, an overview of BDAC and its relevance to agribusiness is provided. Next, a conceptual model is developed, and hypotheses are presented. The methodology is then outlined, followed by an in-depth analysis of the data and presentation of findings. Finally, this study concludes by discussing theoretical contributions, practical implications, and potential avenues for future research.

2. Literature Review

2.1. *Big Data Analytics Capability*

In recent years, big data analytics capability (BDAC) has emerged as a crucial factor for organizations seeking to leverage large datasets for strategic advantage. BDAC encompasses the integration of technological infrastructure, data management practices, and analytical skills to transform raw data into actionable insights [8]. While existing research highlights BDAC's transformative potential, much of it focuses on general business contexts, leaving sector-specific applications underexplored. For example, existing studies on BDAC focus largely on manufacturing and IT industries, emphasizing operational efficiency and innovation [9]. However, agribusiness faces unique challenges such as unstructured data and stakeholder resistance, which remain underexplored.

In the context of agribusiness, BDAC offers unique opportunities for optimizing resource allocation, forecasting market demands, and enhancing supply chain efficiency [10,11]. Kamilaris, Kartakoullis [12] found that BDAC significantly enhances precision agriculture, enabling farmers to make data-driven decisions that improve crop yields and reduce waste. Similarly, Perçin [13] demonstrated how BDAC facilitates real-time supply chain management, reducing costs and improving market responsiveness. These findings suggest that BDAC can be a critical enabler of competitive advantage in agribusiness. However, compared to other industries, the adoption of BDAC in this sector faces unique challenges, such as limited access to digital infrastructure and resistance to change among traditional stakeholders [14]. Research by Zhao, Xie [14] identified several barriers to BDAC adoption in agribusiness, including a lack of technical expertise, insufficient infrastructure, and resistance to change among stakeholders. These barriers underscore the need for further investigation into how agribusinesses can overcome these obstacles and effectively leverage BDAC to drive competitive advantage.

2.2. *The Outcome of BDAC: Competitive Advantage*

BDAC has emerged as a powerful resource for organizations striving to gain and sustain competitive advantage (CA) [4]. The growing volume, variety, and velocity of data have made BDAC a crucial component in strategic management.

Competitive advantage (CA) refers to the ability of an organization to outperform its competitors by creating superior value for its customers, reducing operational costs, or leveraging unique capabilities that are difficult for competitors to imitate. Porter [15] defines competitive advantage as the capacity of a firm to achieve greater profits than its rivals, either by offering products that are valued more highly by customers or by producing them at a lower cost.

Ávila [16] builds on this by emphasizing that competitive advantage arises from organizational competencies that are difficult for rivals to replicate. These competencies may include unique resources, capabilities, and processes that differentiate a company in the marketplace. In the digital age, BDAC have become a pivotal source of such competencies.

In the context of agribusiness, BDAC's role in enhancing CA is particularly significant. For example, Valencia-Cárdenas, Restrepo-Morales [17] noted that BDAC enables agribusinesses to integrate weather forecasts, market demand patterns, and resource availability into their decision-making processes. This capability is crucial for reducing operational uncertainties and maximizing efficiency. Furthermore, BDAC supports supply chain transparency, enabling firms to adapt to market changes swiftly [18,19]. Despite these benefits, the extent to which BDAC contributes to CA in agribusiness has not been fully explored, especially in terms of how firms mobilize internal resources to maximize these benefits.

2.3. Absorptive Capacity as a Mediator

Absorptive capacity (AC) is defined as a firm's ability to recognize the value of new external information, assimilate it, and apply it to achieve organizational goals [20]. This dynamic capability plays a critical role in determining the effectiveness of BDAC, as it enables firms to transform raw data into actionable insights and strategic decisions [21]. In agribusiness, where data often comes from diverse and unstructured sources, AC is especially important for ensuring that BDAC generates tangible competitive advantages.

Firms with high AC are better equipped to integrate BDAC insights into their operations, leading to improved efficiency and innovation [22]. For instance, Zahra and George [23] argued that AC facilitates the adoption of new technologies by enhancing an organization's ability to process and utilize external knowledge. In agribusiness, this could mean better integration of environmental data, market trends, and production metrics into actionable strategies. However, research on the mediating role of AC in the BDAC-CA relationship remains limited. Exploring this interaction within the context of Chinese agribusinesses can provide valuable insights into how firms can enhance their competitive positioning through improved AC.

2.4. Identifying the Research Gap

This review identifies significant gaps in understanding BDAC's application in agribusiness, particularly its role in competitive advantage and the mediating effect of absorptive capacity. Specifically:

1. Limited sector-specific research: While BDAC's impact has been extensively studied in manufacturing and IT sectors, its relevance to agribusiness remains underexplored.
2. Barriers to adoption: Challenges such as unstructured data, insufficient infrastructure, and stakeholder resistance hinder the effective application of BDAC in agribusiness.
3. Mediating role of AC: There is a lack of empirical research on how AC influences the BDAC-CA relationship, particularly in the context of agribusiness.

These gaps highlight the need for empirical investigation into how Chinese agribusinesses can effectively utilize BDAC to enhance competitive advantage while addressing sector-specific challenges. This study seeks to address these gaps by exploring the interplay between BDAC, CA, and AC in Chinese agribusinesses, contributing to both theoretical development and practical applications.

3. Theoretical Background and Hypothesis Development

3.1. Underlying Theory: Resource-Based Theory (RBT)

Resource-Based Theory (RBT) has emerged as a cornerstone of strategic management, emphasizing the critical role of unique and valuable resources in creating and sustaining

competitive advantage [24]. At its core, RBT posits that firms are unique aggregations of tangible and intangible assets, which, when synergistically harnessed, can forge a formidable competitive position [25,26]. The groundbreaking research on RBT defines resources as assets that are unique to a corporation and are distinguished by their scarcity, inability to be replicated, and lack of substitutes. These traits are crucial for organizations aiming to execute strategies that generate value and maintain a sustainable competitive edge.

A critical comparison of RBT with other theoretical frameworks, such as the Dynamic Capabilities Framework (DCF) and the Knowledge-Based View (KBV), highlights RBT's advantages in explaining competitive advantage, particularly in the context of Big Data Analytics Capability (BDAC). While all three frameworks share a focus on resources and capabilities, they differ in their emphases and scope. RBT prioritizes internal resources as key drivers of competitive advantage, offering a nuanced analysis of how specific resources create value. This makes RBT especially relevant for examining BDAC, which integrates technological infrastructure, data management practices, and analytical skills to transform raw data into actionable insights.

In contrast, DCF emphasizes adaptation processes and a firm's ability to respond to dynamic market conditions. While this perspective is valuable for understanding how organizations adapt to external changes, it may overlook the foundational aspects of resource management and development that are central to RBT. However, KBV focuses primarily on knowledge as a critical resource, often neglecting other resource categories such as physical infrastructure and organizational processes. RBT, by encompassing a broader range of assets—including physical, technological, and organizational resources—offers a more comprehensive understanding of how firms achieve and sustain competitive advantage.

In the agribusiness context, RBT provides a robust framework for examining how firms can leverage BDAC to address sector-specific challenges and opportunities. Agribusinesses operate in a highly complex environment characterized by diverse data sources, seasonal variability, and fragmented supply chains. RBT underscores the importance of internal resource mobilization, making it an ideal lens for understanding how BDAC can contribute to competitive advantage in this sector. By prioritizing the effective management of scarce and inimitable resources, RBT enables a focused analysis of how agribusinesses can deploy BDAC to improve decision-making, operational efficiency, and market responsiveness.

Furthermore, RBT's distinction between resource acquisition and capability development aligns with the dual nature of BDAC. Resource acquisition refers to obtaining the necessary infrastructure, data, and technical expertise, while capability development involves integrating these resources into organizational processes to derive actionable insights and drive strategic decisions [27]. This dual perspective is particularly relevant for agribusinesses, where both access to advanced technologies and the ability to utilize them effectively are critical for success.

In summary, RBT not only provides a theoretical foundation for this study but also aligns well with the practical realities of leveraging BDAC in Chinese agribusinesses. By integrating its emphasis on internal resources with a broader scope of assets and capabilities, RBT offers a comprehensive framework for understanding how firms can harness BDAC to achieve long-term success in competitive markets.

3.2. Research Model

Within the framework of RBT, this study proposes a comprehensive research model (see Figure 1) to investigate the relationships among BDAC, AC, and CA. The model is based on the following resource categories:

1. Tangible resources: Data quality (DQ), robust infrastructure (IN), advanced information systems (ISs).

2. Intangible resources: A data-driven culture (DDC) and strong data governance (DQ) practices.
3. Human skills and knowledge: Managerial expertise (ME) and technical proficiency (TP).

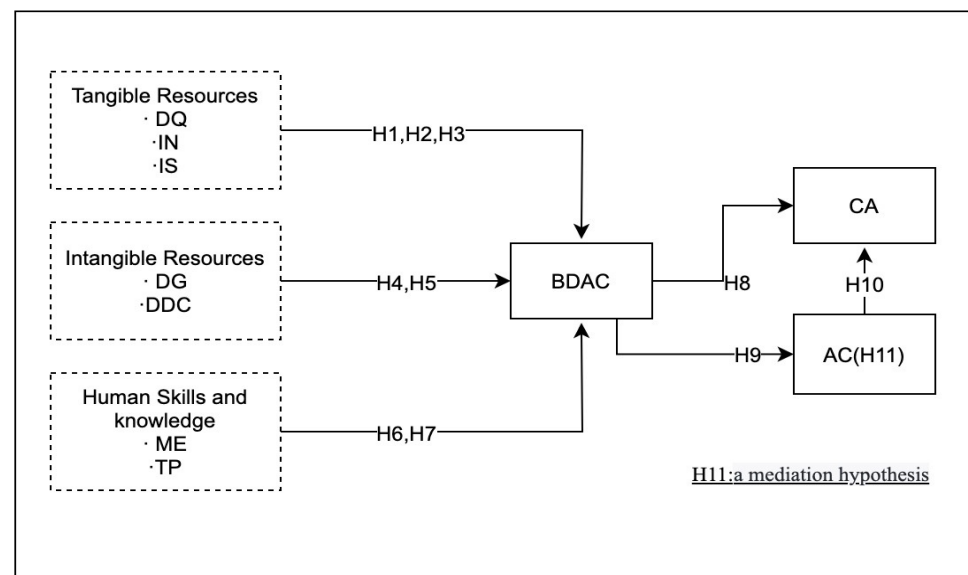


Figure 1. Research model. Note: DQ = data quality; IN = infrastructure; IS = information systems; DDC = data-driven culture; DG = data governance; ME = managerial expertise; TP = technical proficiency; BDAC = big data analytics capability; AC = absorptive capacity; CA = competitive advantage.

Aligned with Barney's (1991) perspectives and the forward-looking insights of Alkhatib and Valeri [28], BDAC is recognized as a pivotal capability for firms seeking to secure and sustain a competitive advantage. It meets the VRIN criteria—valuable, rare, inimitable, and non-substitutable—establishing BDAC as a powerful tool for navigating the complexities of the contemporary business environment. By strategically leveraging data, BDAC enhances decision-making, improves operational efficiency, and fosters ongoing innovation within agribusiness. Furthermore, absorptive capacity is identified as a dynamic capability that complements RBT by facilitating the integration and utilization of external knowledge, thereby transforming BDAC into actionable strategies. This interplay underscores the mediating role of absorptive capacity, optimizing the potential of BDAC in achieving competitive advantage. Each hypothesis in this research is explicitly linked to RBT, illustrating how superior resource utilization through BDAC and the enhancement of capabilities via absorptive capacity collectively contribute to improved firm performance. By integrating these constructs within a cohesive conceptual framework, this study bridges the gap between theory and practice, elucidating the mechanisms through which BDAC and absorptive capacity drive competitive advantage in the increasingly data-driven global marketplace.

3.3. Hypothesis Development

3.3.1. Linking the Resources and BDAC

Building upon the principles of RBT, this study seeks to clarify the essential resources that facilitate the development of BDAC within organizations. According to Mikalef, Pappas [29], these resources can be classified into three primary categories: tangible resources, which include items like data quality, infrastructure, and information systems; intangible resources, which include items like data governance and a data-driven culture;

as well as human skills and knowledge, which include both technical proficiency and managerial expertise.

Data Quality

Data quality is an essential technical characteristic of data that indicates its appropriateness for consumer use [30]. The establishment of BDAC is inherently connected to the quality of data, recognizing its utmost significance [31]. Moreover, data quality is sometimes defined as a “technical property” of data [32], indicating the degree to which data are suitable for utilization by data consumers. Accurate and reliable data are crucial for improving BDAC; however, inaccurate and unreliable data might cause a series of incorrect interpretations, ultimately leading to a decrease in BDAC [33]. This study conducts a critical evaluation of the function of data quality as a crucial resource in the development of BDAC, based on previous research. Thus, the subsequent hypothesis is put forward:

H1: *Data quality has a positive influence on BDAC.*

Infrastructure

Infrastructure is paramount for enabling organizations to efficiently manage, process, and extract insights from vast data volumes [34]. The infrastructure must be capable of storing substantial amounts of data, ensuring rapid and secure data transmission, and supporting effective data analysis. This is especially crucial when handling extensive and heterogeneous datasets, which are characterized by their size, diversity, and dynamic nature. These datasets frequently contain both structured data, which includes numerical and categorical information, and unstructured data. Each type of data has distinct difficulties in processing and interpretation. Tayefi, Ngo [35] highlight the necessity of specialized infrastructure to unlock valuable insights from unstructured data. Despite its rapid growth and widespread presence, unstructured data are frequently underutilized due to the complexities involved in its processing and analysis [36]. Specialized infrastructure solutions may encompass advanced data storage systems, high-performance computing resources, sophisticated analytics software, and machine learning algorithms designed to handle the intricacies of unstructured data. As a result, the following hypothesis is proposed by this empirical investigation:

H2: *Infrastructure has a positive influence on BDAC.*

Information Systems

Information systems (ISs) encompass a diverse array of technologies and strategies aimed at managing and leveraging information within organizational contexts [37]. These systems serve as pivotal tools for gathering, storing, analyzing, and distributing data, forming the backbone of organizational data infrastructure. They facilitate seamless data handling and advanced analytical processes, enabling them to extract useful insights and make sound choices based on data [38,39]. Through the integration of these functions, ISs offer a comprehensive view of organizational operations and performance, thereby enhancing decision-making capabilities. The fusion of big data technologies with traditional IS has significantly expanded their potential, enabling real-time data analysis and more precise predictive modeling. This has resulted in the formation of the hypothesis that is given below.

H3: *Information systems have a positive influence on BDAC.*

Data Governance

Data governance encompasses the holistic administration of data inside an organization, including ensuring its availability, usefulness, integrity, and security [40]. Effective data governance is critical for ensuring high-quality data and proper management practices, which are essential for leveraging big data analytics [41]. Mikalef, Boura [42] emphasize that data governance frameworks are essential for ensuring data quality and consistency, which are foundational for effective big data analytics. Their study highlights that organizations with strong data governance practices are better equipped to utilize their data assets efficiently, leading to enhanced BDAC. Therefore, these insights lead to the formulation of the following hypothesis.

H4: *Data governance has a positive influence on BDAC.*

Data-Driven Culture

The assertion that a robust data-driven culture within organizations enhances the perception of data as an indispensable asset is well supported. This cultural framework significantly boosts the usage of data in decision-making processes. Chatterjee, Chaudhuri [43] note that organizations committed to data-driven practices are likely to develop superior BDAC by creating an environment where data are not only systematically analyzed but also seamlessly integrated into strategic decision-making. However, not all investments in big data yield success. Lucivero [44] argues that failures often occur when the cultural aspects of big data initiatives are overlooked. By embedding big data analytics into their operational ethos, organizations can derive actionable insights from extensive datasets, thereby enhancing decisions related to cloud computing strategies and resource management, as discussed by Storm and Borgman [45]. Moving away from reliance on intuition, it is expected that senior executives will better position their businesses for success by embracing a culture that places a priority on making decisions based on evidence. This has resulted in the formation of the hypothesis that is presented below.

H5: *Data-driven culture has a positive influence on BDAC.*

Managerial Expertise

The efficient utilization of big data within organizations is dependent upon the presence of managerial knowledge as a crucial component. This expertise encompasses not only technical proficiency but also strategic vision and leadership capabilities, which are essential for creating an environment that supports and leverages big data analytics. Managers who possess extensive experience and knowledge in data analytics are better prepared to develop and execute strategic initiatives that enhance BDAC. Their capacity to synchronize large-scale data efforts with organizational objectives and stimulate innovation through data-informed decision-making greatly enhances the overall success and competitive edge of the business. Therefore, possessing management expertise in data analytics is crucial for optimizing the potential and value obtained from big data efforts. As noted by Akhtar, Frynas [46], experienced managers can align big data initiatives with organizational goals, ensuring that data analytics projects are focused on areas with the highest potential for impact. Effective managers allocate resources more efficiently to support BDAC. They understand the importance of investing in advanced analytics tools, recruiting skilled data scientists, and fostering a data-centric culture. According to Akter, Wamba [47], managerial expertise enables better planning and carrying out of big data initiatives, optimizing both human and technological resources to enhance BDAC. This has resulted in the formation of the hypothesis that is given below.

H6: *Managerial expertise has a positive influence on BDAC.*

Technical Proficiency

Technical proficiency encompasses the skills and knowledge required to effectively utilize big data technologies, tools, and methodologies, which are crucial for enhancing BDAC within organizations. Technically proficient employees are better equipped to handle complex data analytics tasks, from data extraction and transformation to sophisticated analysis. According to Ciampi, Demi [18], organizations that invest in developing the technical skills of their workforce see significant improvements in their BDAC, as these skills enable employees to leverage advanced analytics tools effectively. Technical proficiency ensures that employees can make the best use of big data tools and technologies. Schoenherr [48] highlights that those proficient users can maximize the capabilities of data analytics software, leading to more accurate and insightful data analysis. This, in turn, enhances the organization's overall BDAC. This has resulted in the formation of the hypothesis that is given below.

H7: *Technical proficiency has a positive influence on BDAC.*

3.3.2. Linking BDAC and Competitive Advantage

Leveraging BDAC enables organizations to adopt data-driven decision-making processes, which in turn enhances operational efficiency [49]. By effectively utilizing these abilities, firms can uncover valuable patterns and trends, optimize their operations, and maintain a competitive edge. Consequently, the strategic application of BDAC is instrumental in transforming data into actionable insights, thereby fostering improved performance and innovation within the organization. Furthermore, BDAC provides deep insights into customer preferences, enabling personalized offerings [50]. This capability also drives innovation in product development [51], allowing organizations to create products that better meet market demands. Additionally, BDAC empowers organizations to respond promptly to market changes [52], thereby strengthening their competitive advantage. Ultimately, the strategic implementation of BDAC facilitates sustained growth and success in a digital world. Hence, this gives rise to the formulation of the following hypothesis.

H8: *BDAC positively affects competitive advantage.*

3.3.3. Linking BDAC and Absorptive Capacity

Recent research indicates that BDAC greatly boosts an organization's absorptive capacity by improving the processes of data acquisition, assimilation, transformation, and application. Arshad, Kun Yu [53] demonstrated that organizations with advanced BDAC are more adept at identifying valuable external information, combining it with their current expertise, and using it to enhance operational processes and strategic decision-making. The ability to effectively manage and analyze big data facilitates the continuous updating of an organization's knowledge base, thereby bolstering its absorptive capacity. Additionally, Khan and Tao [54] emphasized that BDAC equips organizations to effectively adjust to dynamic market conditions and technological progress. This ongoing update and integration of new knowledge significantly contribute to an organization's capability to effectively absorb and leverage external information. Furthermore, big data analytics serves as crucial for improving organizational learning and fostering innovation. Lozada, Arias-Pérez [55] noted that BDAC not only improves data processing capabilities but also fosters a culture of continuous learning and innovation. By providing deeper insights into market trends and customer behaviors, BDAC enables organizations to develop new

competencies and refine existing ones, thereby augmenting their overall absorptive capacity. Consequently, these insights lead to the formulation of the following hypothesis.

H9: *BDAC positively affects absorptive capacity.*

3.3.4. The Mediating Effect: Absorptive Capacity

Rooted in the theoretical framework of the resource-based view (RBV), which postulates that a sustained competitive advantage is derived from the possession of resources and competencies that are unique, valuable, and difficult to replicate. As a dynamic capability, absorptive capacity amplifies a firm's capacity to translate data analytics into actionable strategic insights and initiatives [56]. Recent research, exemplified by the study by Lozada, Arias-Pérez [55], elucidates that organizations with heightened absorptive capacity exhibit a superior ability to leverage big data analytics to refine their innovation processes and bolster their overall competitive standing. Furthermore, findings from studies such as that by Patrucco, Marzi [22] underscore that firms endowed with superior absorptive capacity are more adept at translating insights derived from big data analytics into strategic actions that augment their market positioning. These empirical insights underscore the essential function of absorptive capacity in magnifying the impact of BDAC on competitive advantage. Consequently, based on these scholarly insights, it is plausible to formulate the following hypothesis:

H10: *Absorptive capacity positively affects competitive advantage.*

H11: *Absorptive capacity positively mediates the relationship between BDAC and CA.*

4. Method

4.1. Sample Selection

The population for this research consists of agribusinesses located in China, focusing on those that utilize data-driven technologies such as artificial intelligence (AI), big data, machine learning, and the Internet of Things (IoT). This focus is particularly relevant given that over 98% of agricultural entities in China are small-scale family operations, which typically lack the capacity to adopt such technologies. Therefore, this study specifically targets medium- and large-scale agricultural firms.

A total of 500 agricultural firms were selected through the China Agricultural Enterprise Alliance, with a geographical distribution highlighting the eastern region (56.20%), followed by the western (15.20%), central (14.40%), and northeastern regions (14.20%). Notably, Shandong, Heilongjiang, and Anhui provinces accounted for 46.40% of the firms, with 161, 43, and 28 companies, respectively.

Once the population was identified, purposive sampling was employed to select respondents based on specific criteria essential for this study. Participants were required to meet the following conditions:

1. The company must actively use big data analytics to analyze supplier and customer behaviors, plan inventory, and calculate market demand.
2. The business must be engaged in agribusiness sectors, including farming, agri-food processing, agricultural machinery manufacturing, agricultural trading, agricultural services, pesticide and fertilizer supply, or agricultural research and development.
3. The selection criteria were included in the cover letter of the questionnaire, with filter questions positioned in the demographic section to ensure respondents met the necessary attributes.

To determine the minimum sample size, G*Power version 3.1 software was utilized, calculating a required sample size of 102 for a multiple regression analysis with 7 predictors, using an alpha level of 0.05 and a power of 0.80.

4.2. Measurements

This study used an adapted version of an established questionnaire specifically designed to align with its objectives in the context of China's agribusiness sector. The measurement items were carefully selected and modified to reflect the unique characteristics and challenges of this industry, thereby enhancing their relevance compared to the existing literature.

Data quality was assessed using four items sourced from Purwanto, Zuiderwijk [32], which were tailored to capture the specific data challenges faced by agribusinesses, such as variability in data sources and the impact of environmental factors on data integrity. Infrastructure evaluation incorporated two items from Gupta and George [57], focusing on the technological capabilities that are particularly critical in the agribusiness context, where robust infrastructure is essential for managing agricultural data. Information systems were measured with three items derived from Gupta and George [57] and Riggins and Wamba [58], emphasizing the integration of information systems in agricultural operations, which is often overlooked in traditional studies.

The presence of a data-driven culture was evaluated using four items from Karaboga, Zehir [59], reflecting the cultural shift necessary for agribusinesses to leverage big data effectively. Data governance was assessed through four items derived from Mikalef, Krogstie [60], specifically addressing the regulatory and compliance aspects that are vital in the agribusiness sector. Managerial expertise was measured using two items selected from AlNuaimi, Khan [61], while technical proficiency was evaluated with two items from Ciampi, Demi [18], both of which were adapted to emphasize the unique skill sets required in agribusiness environments.

The measurement of BDAC was conducted using five items derived from Raguseo and Vitari [62], focusing on the specific analytical capabilities that drive competitive advantage in agribusiness.

Competitive advantage was assessed using a scale developed by Navarro-García, Ledesma-Chaves [63], which includes three dimensions: cost leadership (four items), product differentiation (four items), and service leadership (three items). Cost leadership refers to how efficiently a company uses resources in production and marketing, impacting both the cost and perceived value of its products in international markets. Product differentiation highlights the unique qualities, design, and features that set a product apart from competitors. Service leadership focuses on service-related aspects such as delivery speed, reliability, and after-sales support. This multidimensional approach offers a comprehensive understanding of competitive advantage in the agribusiness sector.

Absorptive capacity was measured using eight questions derived from Hernández-Perlines, Moreno-García [64], assessing both potential and realized absorptive capabilities. Potential absorptive capacity helps a firm identify and acquire knowledge, while realized absorptive capacity allows the firm to apply that knowledge effectively for innovation and strategic advantage. Both are crucial for organizations to remain competitive and adapt to rapidly changing markets.

The questionnaire predominantly employed a 5-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree, consistent with standard research methodologies. However, the scale for the dependent variable related to competitive advantage was extended to a 7-point scale, from 1 = much worse than most to 7 = much better than most, allowing for a more granular assessment of competitive positioning.

4.3. Data Collection

Data were collected through an online questionnaire survey, which effectively reached geographically dispersed participants in agribusiness, offering rapid distribution and convenience for respondents to complete the survey at their own pace. The questionnaire was pre-tested and expertly reviewed and revised by a panel of three big data scholars and two industry experts, whose feedback led to further refinement of the questionnaire. A pilot study was conducted with 15 agribusiness owners or managers to evaluate the clarity and consistency of the constructs. Given the primary use of Chinese in China, a skilled translator ensured the questionnaire's accuracy, which was then reviewed by two additional experts to maintain cultural and contextual relevance. Out of the 500 firms contacted, a total of 287 valid questionnaires were received, yielding a satisfactory response rate. The demographic and personal characteristics of the participants are detailed in Table 1.

Table 1. Demographic information.

Characteristic	Frequency	Percentage (%)
Gender		
Male	177	61.67%
Female	110	38.33%
Age		
Below 24	5	1.74%
25–35	65	22.65%
36–45	186	64.81%
46–55	20	6.97%
More than 55	11	3.83%
Education Level		
Ph.D.	6	2.09%
Master	87	30.31%
Undergraduate degree	130	45.30%
Diploma	61	21.25%
High school and below	3	1.05%
Position		
Top management	25	8.71%
Middle management	206	63.07%
Other staff	56	28.22%
Stage of BDA usage		
Early start-up (1–3 years)	142	49.48%
Young (3–5 years)	85	29.62%
Established (more than 5 years)	60	20.91%
Type of agribusiness		
Farming	23	8.01%
Food processing	41	14.29%
Machinery manufacturing	30	10.45%
Agricultural trading	76	26.48%
Inputs (pesticide and fertilizer suppliers)	23	8.01%
Agricultural services	59	20.56%
Agricultural research and development	35	12.20%

5. Results

5.1. Statistical Analysis

Partial Least Squares Structural Equation Modelling (PLS-SEM) is a robust statistical tool particularly effective for examining intricate multivariate interactions between latent (unseen) and observable variables. This method is preferred in research aimed at prediction or in cases where theoretical underpinnings are not yet solid, facilitating an exploratory

analysis of relationships. Unlike covariance-based SEM (CB-SEM), which is more confirmatory, PLS-SEM is ideal for complex models like the one in this study, which includes numerous variables and does not adhere to multivariate normality. PLS-SEM excels in managing non-normally distributed data and aims to optimize the explained variance of latent endogenous constructs.

Resource-Based Theory (RBT) underscores that firms can gain and sustain a competitive advantage through unique, valuable, and non-substitutable resources. In line with this theory, the model in this study focuses on the importance of resources such as data quality, infrastructure, information systems, and managerial expertise, which are crucial for enhancing BDAC. The decision to use PLS-SEM is grounded in the complexity of the research model, which examines the interplay of various resources (predictors) and their effects on organizational outcomes, such as competitive advantage (CA) and absorptive capacity (AC).

Given that all constructs in the model are made up of multiple items and are defined as reflective rather than formative, PLS-SEM is deemed appropriate for delineating and comprehending the dynamics within this complex research setup. In applying SEM-PLS, it is crucial to validate two main components: (1) the measurement model and (2) the correlations and hypotheses using the structural model, as noted by Ramayah, Cheah [65].

5.2. Full Collinearity Testing

To address potential common method bias, a comprehensive examination of the data collection process was undertaken. Full collinearity was evaluated using the variance inflation factor (VIF), with thresholds commonly set at 5, as per Hair Jr., Hult [66], or 3.3, according to Diamantopoulos and Siguaw [67]. All of the variables are regressed on a common variable in order to carry out this technique, which requires doing a regression analysis. An indication that there is no considerable bias originating from a single data source is provided by VIF values that are less than 5.

All variables in this study had VIF values < 3.3, as shown in Table 2. Therefore, it may be inferred that there is no notable problem of multicollinearity among the variables in this research. This finding implies that the assumptions underpinning the regression analysis, particularly concerning the independence of predictor variables, are satisfactorily met.

Table 2. Full collinearity testing (VIF value).

AC	BDAC	CA	DDC	DG	DQ	IN	IS	ME	TP
1.242	1.879	1.191	1.329	1.188	1.148	1.15	1.292	1.262	1.176

5.3. Measurement Model

Prior to examining the results of the structural model, this study first evaluated the accuracy of the measurement model, in accordance with the recommendations established by Ramayah, Cheah [65]. The examination centered on determining the validity and reliability of the measurement items. Since the present study utilizes a reflective-formative framework, the evaluation procedure is separated into the following two stages: first, evaluating the reflecting components and second, assessing the formative constructions.

5.3.1. Evaluating Reflective Constructs

The assessment of reflective constructs entailed the examination of loadings, average variance extracted (AVE), and composite reliability (CR). Based on Hair Jr., Hult [66], it is anticipated that loadings should be above a minimum threshold of 0.5, the average variance extracted (AVE) should be no less than 0.5, and the composite reliability (CR) should be 0.7 or higher.

As illustrated in Table 3, all items exhibit loadings above the 0.5 minimum value, indicating satisfactory indicator reliability. Additionally, all constructs possess CR values exceeding 0.7, which demonstrates strong internal consistency reliability, and the AVE values, which are over 0.5, suggest that the constructs explain more than half of the variation of their indicators.

Table 3. Reflective scale accuracy analyses.

Reflective Constructs	Item	Loadings	CR	AVE
BDAC	BDAC1	0.793	0.893	0.625
	BDAC2	0.802		
	BDAC3	0.835		
	BDAC4	0.784		
	BDAC5	0.734		
DDC	DDC1	0.855	0.907	0.709
	DDC2	0.872		
	DDC3	0.809		
	DDC4	0.830		
DG	DG1	0.808	0.908	0.713
	DG2	0.884		
	DG3	0.887		
	DG4	0.795		
DQ	DQ1	0.890	0.912	0.723
	DQ2	0.842		
	DQ3	0.851		
	DQ4	0.817		
IN	IN1	0.880	0.884	0.793
	IN2	0.900		
IS	IS1	0.861	0.891	0.732
	IS2	0.830		
	IS3	0.876		
ME	ME1	0.917	0.871	0.772
	ME2	0.839		
TP	TP1	0.900	0.882	0.789
	TP2	0.876		

Discriminant validity was evaluated in the next phase using the HTMT criteria. The HTMT values have to be less than 0.85, with a more forgiving top limit of 0.90. Based on Table 4, the HTMT values remained below the threshold of 0.9, indicating that the participants were capable of differentiating between the nine constructions. The results of these validity tests cumulatively demonstrate that the assessment items possess validity and reliability.

Table 4. HTMT results.

	BDAC	DDC	DG	DQ	IN	IS	ME	TP
1.BDAC								
2.DDC	0.528							
3.DG	0.372	0.251						
4.DQ	0.384	0.196	0.188					
5.IN	0.381	0.152	0.137	0.124				
6.IS	0.497	0.34	0.242	0.198	0.291			
7.ME	0.462	0.321	0.347	0.226	0.07	0.356		
8.TP	0.398	0.295	0.232	0.239	0.061	0.214	0.359	

5.3.2. Evaluating Formative Constructs: Absorptive Capacity (AC) and Competitive Advantage (CA)

This study employed formative measurements to represent the notions of absorptive capacity (AC) and competitive advantage (CA). It is crucial to assess the importance and applicability of the formative indicators at this point. When evaluating the contribution of each signal, outer weight is an important criterion for formative constructs. The dependent variable is the latent variable scores, while the independent variables are the formative indicators. The outer weights, derived by bootstrapping, are accompanied by t-values to assess the statistical significance of each indicator's weight, demonstrating its relative relevance [65].

If the outside weight of an indicator is not statistically significant but its outer loading is large (>0.50), the indicator is considered to be absolutely vital, albeit not comparatively important, and is usually kept. Nevertheless, when an indicator displays a weight that is not statistically significant and an outer loading below 0.50, researchers must carefully examine whether to keep or discard the indicator by assessing its theoretical significance and possible redundancy with other indicators in the same construct.

To examine the convergent validity of the formative measures, redundancy analysis is employed, as recommended by Chin [68]. Table 5 shows that the formative constructs of AC and CA have path coefficients of 0.772 and 0.762, respectively, which are both higher than the criterion of 0.7. These findings suggest that the constructs tested in a formative manner have adequate convergent validity.

Table 5. Formative scale accuracy analyses.

Formative Constructs	Indicator	CR	AVE	Outer Weight	Sig	Outer Loadings	VIF
AC	PAC	0.772	0.634	0.776	$p < 0.01$	0.905	1.092
	RAC			0.444	0.001	0.670	1.092
	Cost			0.617	$p < 0.01$	0.853	1.204
CA	Product	0.762	0.521	0.372	0.009	0.653	1.139
	Service			0.361	0.032	0.640	1.132

Additionally, the presence of multicollinearity among the indicators is evaluated. All indicators for the formative constructions satisfy the VIF criterion, with values consistently below the threshold of 3.3. This indicates that there is no significant collinearity among any of the formative components, which means that it does not provide an issue for estimating the PLS path model. Ultimately, the importance and applicability of the external weights of the formative constructs are analyzed, and the findings demonstrate that all formative indicators are statistically significant.

5.4. Analysis and Presentation of Structural Model Results

This research utilizes a systematic way to examine and report the findings of our structural equation model (SEM), which includes beta coefficients (β), standard errors, t-values, and p-values. In order to guarantee robustness and reliability, a resampling bootstrapping approach was employed, with a sample size of 10,000. In addition, Hahn and Ang [69] expressed criticism towards the only use of p-values for assessing the significance of hypotheses. They argued for a more complete method that incorporates p-values, confidence intervals, and effect sizes (f^2). The hypotheses in this study were assessed using the criteria listed in Table 6.

Table 6. Hypothesis testing.

Hypothesis	Relationship	Std. Beta	Std. Dev.	t-Value	p-Value	PCI LL	PCI UL	f ²
H1	DQ→BDAC	0.17	0.045	3.747	$p < 0.01$	0.095	0.243	0.047
H2	IN→BDAC	0.185	0.046	4.047	$p < 0.01$	0.108	0.258	0.058
H3	IS→BDAC	0.185	0.052	3.531	$p < 0.01$	0.097	0.27	0.05
H4	DG→BDAC	0.127	0.048	2.625	0.004	0.045	0.205	0.025
H5	DDC→BDAC	0.259	0.051	5.05	$p < 0.01$	0.177	0.346	0.101
H6	ME→BDAC	0.142	0.052	2.716	0.003	0.056	0.227	0.029
H7	TP→BDAC	0.120	0.05	2.408	0.008	0.04	0.205	0.023
H8	BDAC→CA	0.144	0.072	1.997	0.023	0.014	0.253	0.022
H9	BDAC→AC	0.294	0.068	4.306	$p < 0.01$	0.17	0.398	0.095
H10	AC→CA	0.298	0.06	4.997	$p < 0.01$	0.176	0.38	0.094
H11	BDAC→AC→CA	0.088	0.026	3.317	$p < 0.01$	0.046	0.131	—

Initially, we examined the factors that influence BDAC and determined that the coefficient of determination (R^2) is 0.441. This suggests that the seven predictors account for 44.41% of the variation in BDAC. The variables that have a significant positive relationship with BDAC are as follows: data quality (DQ) with a beta coefficient (β) of 0.17 and a p -value of less than 0.01, infrastructure (IN) with a β of 0.185 and a p -value of less than 0.01, information systems (ISs) with a β of 0.185 and a p -value of less than 0.01, data governance (DG) with a β of 0.127 and a p -value of less than 0.01, data-driven culture (DDC) with a β of 0.185 and a p -value of less than 0.01, managerial expertise (ME) with a β of 0.142 and a p -value of 0.003, and technical proficiency (TP) with a β of 0.12 and a p -value of 0.008. These data provide evidence in favor of hypotheses H1 to H7. This aligns with RBT, where these are seen as critical resources that contribute to a firm's capability to process and utilize data effectively.

Hypothesis H8 examines the influence of BDAC on CA, with a standardized beta coefficient of 0.144, a t -value of 1.997, and a p -value of 0.023, suggesting a modest level of significance. The bias-corrected confidence interval (BCI) spans from 0.014 to 0.253, providing evidence of a positive correlation between BDAC and CA. This result suggests that BDAC serves as a valuable resource that enhances CA, in line with RBT's assertion that a firm's internal capabilities directly affect its competitive position. Similarly, Hypothesis H9 shows that BDAC positively impacts absorptive capacity (AC), with a significant coefficient ($\beta = 0.294$, $p < 0.01$). This supports the idea that BDAC, as a dynamic capability, is fundamental to improving a firm's absorptive capacity, which in turn contributes to its overall competitive advantage (H10, $\beta = 0.298$, $p < 0.01$).

The mediation analysis (H11) further highlights that absorptive capacity mediates the relationship between BDAC and CA. This is consistent with RBT, which suggests that firms can achieve a competitive advantage through the effective utilization of their internal capabilities, such as AC.

This research presented PLS-predict, a method that makes use of a holdout sample-based approach to generate predictions at the individual level, particularly for items or constructs. This was performed in response to the recommendation made by Shmueli, Sarstedt [70]. PLS-predict methodology was employed in tandem with a 10-fold process to evaluate the statistical significance of the produced predictions. If all item differences (PLS-LM) are below a specific threshold, there is a significant amount of predictive ability. However, if the variances between all items were more than this threshold, it was not possible to validate the predictive significance. When most of the variations between items are below the threshold, we notice a moderate degree of predictive ability. However, a minority of cases suggest a poor level of predictive ability. According to the findings in Table 7, the errors identified in the PLS model were consistently smaller than the errors

indicated in the LM model. The data suggest that the model of this study has strong predictive powers.

Table 7. PLS-predict.

Item	Q ² Predict	PLS-RMSE	LM-RMSE	PLS-LM_RMSE
PAC	0.027	0.990	1.010	−0.02
RAC	0.018	0.994	1.026	−0.032
BDAC1	0.231	0.816	0.841	−0.025
BDAC2	0.300	0.806	0.840	−0.034
BDAC3	0.282	0.826	0.854	−0.028
BDAC4	0.227	0.841	0.873	−0.032
BDAC5	0.213	0.853	0.89	−0.037
Cost	0.032	0.987	1.034	−0.047
Product	0.001	0.998	1.052	−0.054
Service	0.016	0.996	1.046	−0.050

6. Discussion of Results

This study investigated the nexus between BDAC and CA of agribusinesses in China, specifically focusing on the role of absorptive capacity (AC) as a mediator. The discussion below synthesizes the implications of the hypotheses and offers a deeper understanding of how various organizational resources influence BDAC and its impact on CA within the framework of Resource-Based Theory (RBT).

The research’s findings provide valuable information on the resources of BDAC and their important implications for competitive advantage and absorptive capacity in the agriculture industry. Notably, the analysis revealed compelling insights into the foundational elements that contribute to the development and enhancement of BDAC, reinforcing the principles of RBT, which posits that unique and valuable resources are essential for achieving sustained competitive advantage.

6.1. Tangible Resources (Data Quality, Robust Infrastructure, Advanced Information Systems)

Data quality has been identified as a major resource that influences the efficacy of BDAC activities. High-quality data ensures that analytical outcomes are reliable and actionable, which is critical for agribusinesses relying on data-driven decision-making. This finding aligns with RBT, as high-quality data can be viewed as a valuable and rare resource that enhances an organization’s analytical capabilities. De Rijck [71] and Zhao, Xie [14] have similarly emphasized the importance of data quality in enhancing BDAC. Consistent with these findings, our study reaffirms that data quality is foundational for the effective implementation of BDAC.

This study found that infrastructure is a key resource in determining BDAC. It emphasizes the need of having strong technical infrastructure to effectively handle the activities of gathering, storing, and analyzing data for vast amounts of agricultural information. Robust infrastructure enables the seamless processing and analysis of data, which is essential for timely and accurate insights. This finding aligns with the research by Ciampi, Demi [18], which highlighted the critical effect of infrastructure in supporting BDAC across various industries. By extending this understanding specifically to the agribusiness sector, our study highlights infrastructure as a pivotal resource that supports the firm’s ability to leverage data analytics for competitive advantage, consistent with RBT’s emphasis on the importance of resource management.

Furthermore, the role of information systems was underscored, emphasizing the necessity of integrated and scalable systems for harnessing the full potential of BDAC in agribusiness operations. The overall analytical skills of an organization are improved by

integrated information systems because they make it easier for data to flow and be analyzed throughout the whole organization. When it comes to maximizing the usefulness of big data analytics, this conclusion is in line with the findings of Pathak, Krishnaswamy [72], which emphasize the significance of interconnected information systems.

6.2. Intangible Resources (Data-Driven Culture and Data Governance)

The results also emphasized effective data governance, ensuring that data practices are consistent, secure, and compliant with relevant regulations. This is in line with Mikalef, Boura [42], who pointed out that robust data governance is vital for ensuring data integrity and trustworthiness in big data initiatives.

Moreover, the promotion of a data-driven culture inside agricultural firms was seen as a crucial element in growing BDAC. This highlights the need of developing a mentality that appreciates decisions based on data and inventiveness. This aligns with the findings of Sjusdal and Lunde [73], who noted that fostering a data-driven culture is vital for the success of big data initiatives across different sectors.

6.3. Human Skills and Knowledge (Managerial Expertise and Technical Proficiency)

The present study elucidated the pivotal role of managerial expertise in driving BDAC initiatives, emphasizing the importance of leadership support, strategic vision, and domain knowledge in guiding the implementation and utilization of big data analytics technologies within agribusinesses. This finding is corroborated by the research of Singh, Dadhich [74], who highlighted the critical role of managerial expertise in successful BDAC implementation.

Moreover, technical proficiency emerged as a critical enabler of BDAC, highlighting the necessity of skilled personnel and adequate training programs to effectively leverage data analytics tools and techniques. This supports the conclusions of Hongyun, Sohu [75], who emphasized the importance of technical proficiency and training in leveraging big data analytics.

6.4. Absorptive Capacity

Furthermore, absorptive capacity was identified as a key mediating mechanism through which BDAC enhances CA. This finding underscores the importance of building organizational capabilities to effectively leverage big data analytics technologies and translate them into sustainable competitive advantages in the dynamic agribusiness landscape. Previous articles have clarified the positive role of BDAC on CA [4,76], and there are also articles describing the knowledge transformation role of AC in BDAC [23], although Rehman, Razaq [77] and Azhdary Moghadam, Akbari [78] have confirmed the important mediating role of absorptive capacity between different capabilities, but there are very few involving the agricultural field. This study demonstrated that BDAC not only directly contributes to enhancing competitive advantage but also exerts a positive influence on absorptive capacity within agribusiness organizations.

6.5. Competitive Advantage

The results of this study further emphasize the significant relationship between BDAC and competitive advantage (CA), highlighting BDAC as a pivotal capability in the agribusiness sector. Specifically, BDAC enhances CA by enabling firms to utilize data-driven insights for decision-making, operational optimization, and strategic differentiation. This finding aligns with the Resource-Based Theory (RBT), which posits that unique organizational resources, such as advanced analytics capabilities, are crucial for achieving sustained competitive advantage.

Recent studies underscore the critical role of BDAC in fostering CA across industries, particularly in environments characterized by high competition and rapid technological

change. For instance, Gupta, Khan [79] argue that firms leveraging BDAC to integrate market and technological data can achieve superior market positioning through innovation and enhanced customer value. Similarly, Dubey, Bryde [80] highlight that BDAC fosters organizational agility and resilience, enabling firms to adapt to dynamic market conditions, a capability especially relevant in the volatile agribusiness landscape.

The findings also extend prior studies by demonstrating that BDAC not only contributes directly to CA but also facilitates the development of complementary capabilities, such as absorptive capacity (AC), that further enhance the firm's strategic positioning. Pathak, Krishnaswamy [72] elaborate on this dual pathway, emphasizing that BDAC-driven insights promote a culture of continuous improvement and innovation, which are critical for maintaining a competitive edge.

Moreover, this study reaffirms that the competitive advantage derived from BDAC is contingent on the alignment of analytics capabilities with organizational strategy and goals. This conclusion is consistent with Chong, Abdul Rasid [4], with resource orchestration to maximize its impact on CA. Specifically, they argue that firms with robust data governance and a data-driven culture are better positioned to translate BDAC into tangible performance outcomes.

In summary, BDAC's influence on CA is multi-faceted, encompassing both direct contributions through enhanced decision-making and indirect effects via the development of dynamic capabilities such as AC. These findings contribute to the ongoing discourse on the strategic importance of big data analytics and provide a nuanced understanding of how agribusinesses can leverage BDAC to achieve sustained competitive advantage.

7. Conclusions

This research provides several important implications for both theory and practice, contributing to a deeper understanding of the relationship between Big Data Analytics Capability (BDAC) and Competitive Advantage (CA) in agribusinesses. In addition, it offers a foundation for future research that can further explore and refine these concepts. The implications are discussed from three key perspectives: theoretical implications, practical implications, and limitations and future research.

7.1. Theoretical Implications

This study contributes significantly to the field of Resource-Based Theory (RBT) by offering new insights into how BDAC acts as a unique and valuable organizational resource that drives competitive advantage in the agribusiness sector. Although RBT has been widely applied in various industries, its application to the agribusiness sector has been limited. By grounding the findings in RBT, this research not only confirms that BDAC contributes to a sustainable competitive advantage but also advances the understanding of how BDAC, through components such as data quality, infrastructure, and managerial expertise, aligns with RBT's emphasis on valuable, rare, inimitable, and non-substitutable (VRIN) resources.

Moreover, this study introduces absorptive capacity (AC) as a mediating role between BDAC and competitive advantage, highlighting the role of an organization's ability to acquire, assimilate, and apply knowledge in leveraging data analytics for strategic advantage. This integration of absorptive capacity into the RBT framework underscores the interplay between static resources and dynamic capabilities, emphasizing how BDAC transcends being merely a technological asset to act as a transformative driver of competitive outcomes. This provides a deeper understanding of how organizational resources (e.g., BDAC) work in tandem with dynamic capabilities (e.g., absorptive capacity) to influence competitive outcomes.

Furthermore, the findings extend the study by Zahra and George [81] by applying their theoretical constructs on dynamic capabilities to the agribusiness context. While previous studies largely focused on high-tech or service industries, this research situates these constructs within a traditionally underexplored sector, providing empirical evidence of their applicability in agricultural settings. The research also contributes to the big data analytics literature by providing empirical evidence on its influence in a specific industry, suggesting that BDAC is a critical capability for agribusinesses seeking to gain a competitive edge. This fills a significant gap in the literature, as much of the prior research on big data analytics has focused on sectors such as manufacturing and finance, leaving the agribusiness domain relatively underexplored.

7.2. Practical Implications

The findings of this study offer several important practical implications for agribusinesses seeking to leverage BDAC to achieve a competitive advantage. First, organizations should prioritize high-quality data and invest in the necessary infrastructure to collect, store, and analyze large volumes of agricultural data efficiently. A robust technical infrastructure enables timely and accurate decision-making, ensuring that data-driven insights are actionable. In addition, integrated information systems are essential for optimizing the flow and analysis of data across different functions, helping organizations unlock the full potential of BDAC.

Furthermore, fostering a data-driven culture is crucial for the success of BDAC initiatives. Agribusinesses should promote a mindset that values data-based decision-making at all levels of the organization, encouraging innovation and collaboration. Equally important is the development of strong data governance practices to ensure data integrity, security, and compliance, which are vital for building trust in data analytics.

Additionally, agribusinesses should invest in managerial expertise and technical proficiency within their workforce. Effective leadership is essential for driving BDAC initiatives, providing strategic direction, and ensuring alignment with organizational goals. At the same time, building the technical skills of employees through training programs is critical for successfully implementing and utilizing data analytics tools.

Finally, this study highlights the importance of absorptive capacity as a mediator in leveraging BDAC for competitive advantage. Agribusinesses should focus on building organizational capabilities to absorb and apply new knowledge, which will enable them to adapt to changing market conditions and technological advancements, ultimately strengthening their strategic position in a competitive landscape.

7.3. Limitations and Future Research

It is possible that the generalizability of the findings of this study is restricted due to certain limitations related to the investigation. To begin, conducting longitudinal studies would give a more in-depth knowledge of the long-term effects that BDAC has on the performance of organizations and the competitive advantage they have within the agricultural sector. Furthermore, conducting comparison assessments across other sectors and locations might provide additional insight into the contextual elements that impact the connection between BDAC, absorptive capacity, and competitive advantage. Qualitative research approaches can enhance quantitative studies by exploring the fundamental causes and organizational dynamics that influence the implementation and outcomes of BDAC.

7.4. Summary and Final Remarks

This study investigates the relationship between Big Data Analytics Capability (BDAC) and Competitive Advantage (CA) in Chinese agribusinesses, with a focus on absorptive capacity (AC) as a mediator. The findings highlight the critical role of both tangible resources

(e.g., data quality and infrastructure) and intangible resources (e.g., data-driven culture and data governance) in building BDAC. Additionally, human skills such as managerial expertise and technical proficiency are identified as essential for leveraging BDAC effectively to gain a competitive edge. This study also confirms the mediating role of absorptive capacity in enhancing the impact of BDAC on CA, demonstrating that organizations with stronger absorptive capacity are better positioned to transform insights derived from big data into strategic actions. However, this study is limited by its cross-sectional nature, which restricts causal inferences. Future research could benefit from longitudinal studies to explore the long-term effects of BDAC on performance and competitive advantage in the agricultural sector. Comparative studies across different sectors and regions could provide additional insights into the contextual factors that influence the BDAC-CA relationship. Moreover, qualitative approaches could enrich our understanding of the organizational dynamics and challenges involved in the implementation of BDAC. Overall, this research advances the application of Resource-Based Theory (RBT) in the context of agribusinesses and offers practical guidance for organizations seeking to harness big data analytics for sustained competitive success.

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