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Data value creation in agriculture: A review

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ABSTRACT

Agricultural data have great potential to improve decision-making, enhance operational efficiency, and drive innovation. Despite the growing acknowledgment of their value, there remains a gap in understanding how data value creation is perceived and implemented in agriculture. This study addresses this gap by investigating data value creation mechanisms, targets, and impacts through a structured literature review of 80 articles, including 13 core articles retrieved via targeted database searches and 67 additional articles identified through cross-reference snowballing. Key "value creation mechanisms" are categorized as transparency and access, discovery and experimentation, prediction and optimization, customization and targeting, learning and crowdsourcing, and monitoring and adaptation. The value creation mechanisms aim to enhance key "targets", namely organizational performance, business process improvement, product and service innovation, and consumer and market experience. Organization performance was the most frequently addressed value target, appearing in approximately 85% of the core articles, followed by business process improvement, highlighted in approximately 77% of the articles. Together, the mechanisms and targets create "impact", constructing the value of data. The findings reveal that all core articles (100%) emphasize the functional value of agricultural data, while 54% also explore their symbolic value, which enhances reputation and market positioning. A key takeaway is that, unlike many other assets, the value of agricultural data increases with reuse, which calls for a shift in focus from data ownership to ownership of the value derived from them. This study highlights the need for robust frameworks to fully realize the potential of agricultural data and calls for future research to further characterize and assess this value. These insights are essential for developing tools and methodologies that enhance productivity, sustainability, and profitability in agriculture.

1. Introduction

Traditionally, data usage in agriculture was rudimentary, primarily depending on farmers' observations and manual records. The advent of Information and Communication Technology (ICT) and the Internet of Things (IoT) has revolutionized this process, enabling extensive data collection and analysis (Ayaz et al., 2019; Khanna & Kaur, 2019; Kour & Arora, 2020; Sinha & Dhanalakshmi, 2022). As a result, agriculture has transitioned from a data-scarce industry to a data-abundant one, significantly improving the potential for optimized decision-making and value creation in the agri-food sector (DeLay et al., 2023; Falcão et al., 2023; Karunathilake et al., 2023; Kumar et al., 2024; Lioutas et al., 2019; Rasmussen et al., 2021; Wysel et al., 2021). By 2035, it is estimated that a typical farm will produce more than four million data points each day (Kaur & Dara, 2023). These data, when aggregated and analyzed, can reveal patterns and insights previously inaccessible (DeLay et al., 2023; Kenney et al., 2020; Lioutas et al., 2019), and sharing these data with stakeholders can lead to significant advancements in agricultural practices.

The perception of the value of data has evolved dramatically, with many now viewing data as more valuable than oil (Baarbé et al., 2019). This paradigm shift resulted in the economics of data to become recognized (DeLay et al., 2023), and has prompted powerful seed, chemical, and machinery firms to reconsider their business strategies (Hackfort, 2023; Hackfort et al., 2024; Kosior, 2020; Birner et al., 2021; Wolfert et al., 2017). Data have become central to the business models of many agribusinesses (Hackfort et al., 2024), and they are investing heavily in data-driven technologies and analytics to drive profit (Hackfort et al., 2024; Wolfert et al., 2017). As Wolfert et al. (2017) have noted, big data are expected to propel the creation of novel business models designed to extract maximum value from data.

Numerous studies have explored the enhancement of crop

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management through precision agriculture, the optimization of resource use, and the improvement of supply chain efficiencies (Falcão et al., 2023; Karunathilake et al., 2023; Papadopoulos et al., 2024; Birner et al., 2021). Despite the growing body of research, a significant gap remains in fully realizing the potential of vast amounts of agricultural data to create actionable insights and practical benefits for farmers, agribusinesses, and policymakers (Anidu & Dara, 2021). Indeed, once an object is declared valuable, it becomes necessary to express and justify what constitutes that value (Bustamante, 2023).

The motivation for this research stems from the recognition that while enormous volumes of agricultural data are being collected (Anidu & Dara, 2021; Kaur & Dara, 2023; Kenney et al., 2020), their potential to create value is not being fully exploited (Basel et al., 2023). Lioutas et al. (2019) stated the need to define how value is created from data, what it means to different agri-stakeholders, and how power dynamics affect access to this value. In many instances, data are collected and stored with the expectation of deriving future value (Hackfort et al., 2024), yet the practical application of deriving value from data remains a challenge. The current gap lies in effectively translating these data into actionable strategies that can drive significant improvements in agricultural practices (Viet et al., 2021). Therefore, the research will focus on the following objectives: (1) To identify key mechanisms and targets for value creation from agricultural data, (2) to evaluate the impact of data value creation on the agricultural sector, economy, and society, and (3) to propose future directions for research in the field of data value creation. By achieving these objectives, this research aims to provide a foundation for the development of tools and methodologies that can help farmers harness the power of data to enhance their productivity, sustainability, and profitability.

2. Methodology

2.1. Search and Selection criteria

In the present research, a structured literature review methodology as recommended by Easterby-Smith et al. (2021) is followed. The methodology involved a two-stage process: an initial database search and a subsequent cross-reference snowballing. The snowballing method begins with a foundational set of key papers, typically selected from high-impact journals in the relevant field, which serve as a starting point for identifying additional studies through tracing references and citations (Jalali & Wohlin, 2012; Webster & Watson, 2002). This method is effective for uncovering additional relevant studies in interdisciplinary areas like agricultural data value creation, where the concept is still emerging and has not yet been extensively explored in existing literature. An illustration of the literature review process, adapted from Geissdoerfer et al. (2018), is provided in Fig. 1 for clarity.

Database Search: A systematic search was conducted using a predefined search string that included keywords relevant to the value of agricultural data on April 20th, 2024 (see Table 1). The search query was carefully structured to encompass three main components: keywords related to data value, relevance to the agricultural domain, and the inclusiveness of data. The first set of keywords, including "data value creation," "value capture," "data assetization," and "data monetization," was chosen to align with the central theme of the research, how agricultural data creates value. These keywords have been extensively used in previous studies exploring the economic and operational benefits of data in various sectors (Hartmann et al., 2016; Saggi & Jain, 2018; Ylijoki & Porras, 2018; Ray, 2018; Kazantsev et al., 2023), including agriculture (Aravamuthan et al., 2024; Borrero & Mariscal, 2022; Bustamante, 2023; Hackfort et al., 2024; Klingenberg et al., 2022). The second set was selected to ensure the relevance of the search to the

Table 1
Databases and Search Strings.

Scopus	Web of Science
TITLE-ABS-KEY ("data valu*" OR "value of data" OR "value creation" OR "value capture" OR "data asseti?ation" OR "data moneti?ation" OR "data asset") AND TITLE-ABS-KEY ("agriculture" OR "farm*" OR "agri*") AND TITLE-ABS-KEY ("data" OR "agri-data") AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (PUBSTAGE, "final"))	TS=("data valu*" OR "value of data" OR "value creation" OR "value capture" OR "data asseti?ation" OR "data moneti? ation" OR "data asset") AND TS=("agriculture" OR "farm*" OR "agri*") AND TS=("data" OR "agri-data") AND PY=(2014–2024) AND LA = English
Results: 229 Articles	**Results:** 157 Articles
Combined: 386 Articles	

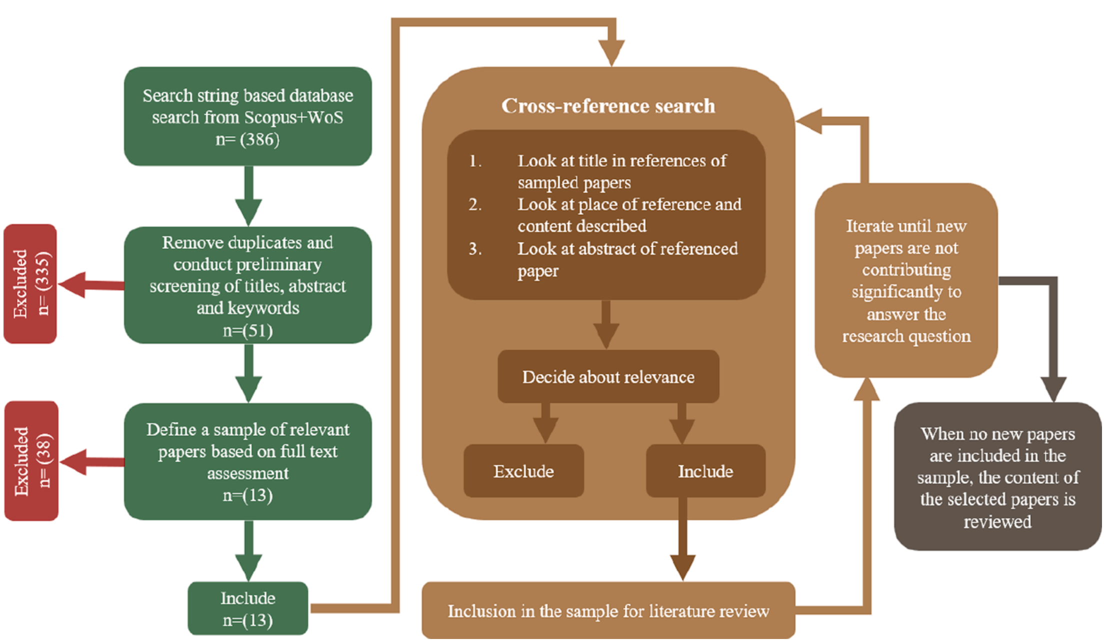

Fig. 1. Illustration of Literature Review Approach (Adapted from Geissdoerfer et al. (2018)).

agricultural domain, while the third set included terms related to the nature and specificity of the data itself, such as "data," "agri-data," and "big data," which were important for identifying studies that not only focus on value creation but also on the utilization of data in doing so. The database search was conducted on April 20th, 2024. And covered literature from 2014 onwards to capture recent developments. Research from the last decade was chosen due to significant technological advancements and the emergence of IoT, artificial intelligence (AI), and big data analytics (DeLay et al., 2023; Rozenstein et al., 2024; Yépez-Ponce et al., 2023).

After removing duplicates and conducting a preliminary screening of titles, abstracts, and keywords, 51 articles were retained. These articles were then evaluated based on the inclusion criterion of discussing the 'value of the data in agriculture'. While many articles highlighted the advantages of data-driven agriculture, they did not directly interrelate these advantages with data value and have been excluded. As a result, a full-text assessment reduced the number to 13 articles that explicitly addressed data value in agriculture. These articles will hereafter be referred to as "core articles".

Cross-reference Snowballing: Given that the context of value is not widely discussed in the current literature on agriculture, an additional cross-reference snowballing technique was employed to identify further relevant literature and provide a broader perspective (Geissdoerfer et al., 2018; Jalali & Wohlin, 2012; Webster & Watson, 2002). This process involved scanning the titles of publications referenced within the core articles and examining their contextual relevance and cited content. Abstracts of identified publications were then examined to determine their relevance to the study. This method resulted in the inclusion of 67 more articles, aiming to provide a broader perspective on data value creation.

Integration and Synthesis: The final sample of literature, comprising 80 articles (both core articles and relevant cross-references), was integrated and synthesized. This involved a comprehensive review and analysis of the selected literature, ensuring that key themes, concepts, and findings were systematically identified and compiled. The 13 core articles were assessed to set the center of discussion, while the 67 articles from cross-referencing were used to provide additional relevant information and broader context.

2.2. Conceptual framework

This research is structured by an adaptation of the strategic business value creation framework proposed by (Grover et al., 2018), specifically tailored to the agricultural context. Although initially designed for general big data analytics, this framework is highly applicable to agriculture, where data-driven insights are crucial for enhancing productivity and sustainability. The framework encompasses three primary components: Value Creation Mechanisms, Value Targets, and Impact (Fig. 2).

This conceptual framework (Grover et al., 2018) structured the literature review, ensuring a comprehensive examination of how big data analytics can drive value creation in agriculture. Section 3, the Results and Discussion, begins with an overview of the selected articles. Section 3.1 defines the general concept of value, which is further divided into subsections that examine the mechanisms, targets, and impacts of value creation. Each subsection offers an in-depth analysis of how agricultural data can be utilized for strategic advantage. Section 4 discusses the limitations, and Section 5 provides concluding remarks, identifying research gaps and suggesting future directions for data value research in agriculture.

3. Results and discussion

The analysis of agricultural data value creation is based on two distinct yet complementary sets of literature: (1) the core articles identified through the initial database search, and (2) additional articles discovered via cross-reference snowballing. The database search was conducted with a targeted query, specifically seeking articles that explicitly address the "value of agricultural data." This inclusion criterion was important to maintain focus on articles that directly engage with the concept of data value in agriculture. However, this focus also limited the number of core articles selected (13 in total), as much of the literature discusses the broader benefits of data-driven agriculture without explicitly focusing on data value. To address this limitation, cross-reference snowballing was employed, resulting in the identification of 67 additional articles. These cross-referenced articles provide broader insights by discussing related topics such as the role of data-driven technologies, decision-making processes, and innovations that contribute to understanding how data creates value in agriculture. While they may not all center explicitly on data value, they offer valuable perspectives that support value creation.

Fig. 3 illustrates the distribution of selected publications by year, showing that most core articles have been published since 2020. This reflects the growing interest in agricultural data value, likely driven by the increasing integration of digital technologies in farming practices and the growing interest in the data economy. The surge in recent years is largely attributed to advancements in data analytics technologies and the growing emphasis on the value of data in decision-making processes. On the other hand, the lower number of core articles in 2024 compared to 2023 is mostly due to the database search being completed on April 20th, 2024. The cross-referenced articles, covering a wider time span, offer valuable historical context and help trace the progression of discussions on agricultural data. They highlight how early debates and developments have shaped the present-day emphasis on the value of data in agriculture, ultimately driving the current focus on data as a key strategic asset for value creation.

3.1. The value of agricultural data

In agriculture, data encompass a wide range of inputs, from traditional observational records to sophisticated datasets generated by advanced technologies such as satellite imagery, IoT devices, unmanned aerial vehicles (UAVs), and machine learning (ML) models (Akhter & Sofi, 2022; Coble et al., 2018; Janssen et al., 2017; Birner et al., 2021; Zhang et al., 2018). These data include detailed information about weather conditions, soil properties, crop performance, pest and disease prevalence, and supply-chain dynamics (Baarbé et al., 2019), which are important for improving decision-making and optimizing resource use.

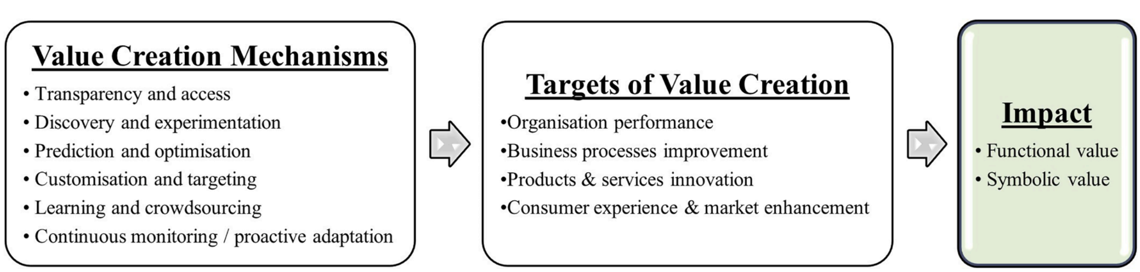

Fig. 2. Value Creation by Big Data Analytics (Adapted from Grover et al. (2018)).

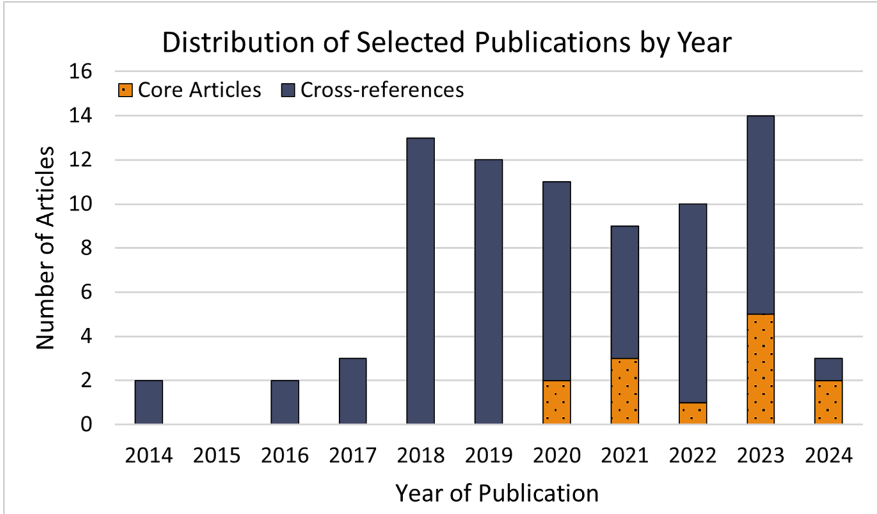

Fig. 3. Number of selected publications by year up until April 20th, 2024.

As data have emerged as a foundational resource, they now play a pivotal role in shaping modern farming practices and the agri-food supply chain (Anidu & Dara, 2021; Baarbé et al., 2019; Karunathilake et al., 2023; Birner et al., 2021). With the continuous influx of data, the primary challenge has shifted from data acquisition to effectively reusing and translating this data into meaningful insights (Basel et al., 2023), or in other words 'something beautiful and functional' as it was stated in (Carolan, 2020a). Value of agricultural data extends far beyond the collection of information; it lies in the ability to transform raw, unstructured data into actionable insights that inform key decisions, improve operational efficiency, and foster innovation (Eastwood et al., 2023; Lioutas et al., 2019; Rolandi et al., 2021; Wysel et al., 2021).

The classification of agricultural data as structured, semi-structured, or unstructured reveals much about their potential value and is essential for effective utilization of data in agribusinesses. Structured data, with an organized format, facilitate efficient storage, access, and retrieval, making them highly valuable due to their reliability (Cravero et al., 2022). Conversely, unstructured data, although potentially rich in business value, pose challenges due to the extensive processing needed to make them usable (Ray, 2018). The cost and effort involved in this transformation can reduce their utility, making unstructured data more of a potential digital asset rather than a direct data asset (Ray, 2018). Structured data's inherent value lies in their ease of management and immediate applicability, making it essential for organizations seeking effective data utilization (Cravero et al., 2022).

The value of agricultural data is closely linked to their capacity to address some of the most pressing challenges in agriculture, including optimizing resource management, enhancing yields, reducing waste, and mitigating the impacts of climate change and other external factors (Klingenberg et al., 2022; Viet et al., 2021). For instance, by integrating real-time sensor data with predictive models, farmers can make more informed decisions regarding irrigation, fertilization, and pest control, thus reducing inefficiencies and promoting sustainable practices (Coble et al., 2018; Karunathilake et al., 2023; Sonka, 2014; Sumathi et al., 2018). Yet, the value of data extends beyond these technological applications; it also encompasses the broader economic, social, and environmental implications of data-driven agriculture (Hackfort et al., 2024; Klingenberg et al., 2022; Viet et al., 2021; Wysel et al., 2021).

Unlike traditional agricultural assets that are typically constant or depreciating over time, agricultural data hold dynamic and cumulative value. As data are collected, processed, shared, and reused, their utility and therefore their value increases (Basel et al., 2023). Each additional layer of analysis or application reveals new insights (Coble et al., 2018; Karunathilake et al., 2023; Saggi & Jain, 2018), transforming data into assets whose value appreciates with use. The reusability of data, particularly when shared across different stakeholders enhances its capacity to generate value repeatedly over time (Baarbé et al., 2019).

Moreover, the concept of data value in agriculture shifts the perspective from viewing data as a mere byproduct of farming activities to understanding it as a strategic asset that can revolutionize business models. Hackfort et al. (2024) states that data assets are not necessarily to be bought or sold in markets, in a way other assets might. Instead, such assets are deemed to be valuable, and worthy of investing based on their potential to generate (future) income. Wysel et al. (2021) emphasize the critical role of data within platforms, pointing out that value is generated only when all platform components are functioning. In these platforms, data act as the input, and value is the output (Borrero & Mariscal, 2022; Kenney et al., 2020; Wysel et al., 2021). To create competitive advantage, platforms are important, and many agribusinesses have shifted their business models to develop their own platforms due to the monopolistic advantages (Hackfort et al., 2024).

Recognizing the value of data also introduces the need to understand its broader implications within the context of stakeholder dynamics. The ability of data to create value is inherently tied to the infrastructure and policies that govern its collection, access, and usage (Anidu & Dara, 2021; Baarbé et al., 2019; Ylijoki & Porras, 2018). As more stakeholders in the agricultural ecosystem adopt data-driven tools, it becomes essential to ensure that data are not only accessible but also equitable (Kaur & Dara, 2023). Smallholder farmers need to be empowered to benefit from the growing body of agricultural data (Birner et al., 2021; Sadovska et al., 2023), which often requires building capacity for data literacy, fostering data-sharing frameworks, and ensuring that data ownership and privacy rights are respected (Anidu & Dara, 2021; Baarbé et al., 2019; Jakku et al., 2019; Jiménez et al., 2019; Birner et al., 2021).

Consequently, defining how agricultural data creates value requires a comprehensive understanding of its multifaceted nature, which goes beyond immediate technical applications to encompass their long-term contributions to agricultural efficiency, sustainability, and stakeholder collaboration. Despite its vast potential and the growing body of literature on data management in agriculture, the concepts of data value and the mechanisms of value creation have only recently gained significant attention in academic discussions (Basel et al., 2023; Wysel et al., 2021). The development of robust frameworks for agricultural data valuation and value creation will be key to ensuring that the potential of agricultural data is fully realized, driving innovation and growth across the entire agri-food sector.

3.1.1. Value creation mechanisms

The mechanisms through which agricultural data create value can be broadly classified into several key areas: transparency and access, discovery and experimentation, prediction and optimization, customization and targeting, learning and crowdsourcing, and continuous monitoring and proactive adaptation (Grover et al., 2018). Each of these mechanisms plays a critical role in transforming raw data into actionable insights that drive efficiency, productivity, and sustainability in the agricultural sector.

Transparency and access are important for creating and assessing the value of data for organizations (Baarbé et al., 2019; Saggi & Jain, 2018). By ensuring data accessibility and transparency, stakeholders across the agricultural value chain can make informed decisions (Baarbé et al., 2019; Jakku et al., 2019; Tsolakis et al., 2023). Access to and utilization of agricultural data can significantly contribute to tackling global food insecurity, especially in developing countries (Baarbé et al., 2019). By generating descriptive data, and widely disseminating it across farming operations, transparency fosters trust and accountability, as data on farming practices, crop conditions, and supply chain processes can be shared openly. Similarly, blockchain technology can provide a transparent ledger of transactions and farm activities, ensuring traceability of products from farm to table (Demestichas et al., 2020; Lin et al., 2018; Salah et al., 2019). Digitalizing these supply chains can improve transparency and traceability, driving sustainable outcomes, maximizing value and enabling the monetization of data (Tsolakis et al., 2023). Furthermore, accessible data enable researchers and policymakers to develop better regulations and support systems for the agricultural sector, driving improvement in farming practices.

Agricultural data enable ***discovery and experimentation***, one of the most emphasized aspects of data analytics (Grover et al., 2018), facilitating the development of new farming techniques, crop varieties, and management practices (Baarbé et al., 2019; Eastwood et al., 2023; Karunathilake et al., 2023). Agronomic and crop data are utilized to enhance current products and services, increase the profitability of established business models, and introduce new data-driven services to the market (Hackfort et al., 2024; Janssen et al., 2017; Karunathilake et al., 2023). The value of data primarily lies in their re-use (Basel et al., 2023), so agri-stakeholders should be encouraged to share data, facilitating discovery and experimentation and thus capturing further value. Many farmers prefer sharing data with universities, research institutes, or cooperatives, as these institutions are perceived to have fewer incentives to misuse the data (Turland & Slade, 2020; Zhang et al., 2021). However, the value creation from research experimentation often faces challenges due to a gap in trust and communication between farmers and researchers, driven by concerns over data ownership, privacy, and misuse (Wiseman et al., 2019; Zhang et al., 2021). This disconnect presents a significant socio-economic barrier to maximizing the potential benefits of big data in agriculture (Wiseman et al., 2019; Yépez-Ponce et al., 2023; Zhang et al., 2021).

Prediction and optimization are at the heart of utilizing agricultural data for better decision-making (Lioutas et al., 2019; Sumathi et al., 2018). The value of predictive analytics in agriculture lies in forecasting future events, identifying optimal strategies, and enabling farmers to make informed decisions by predicting weather patterns, pest outbreaks, and crop yields using historical and real-time data (Coble et al., 2018; Birner et al., 2021; Sumathi et al., 2018; Wolfert et al., 2017). ML algorithms process data streams to determine the best times for planting, watering, and harvesting (Coble et al., 2018; Karunathilake et al., 2023; Wolfert et al., 2017; Carolan, 2020a; Sumathi et al., 2018). Prediction models can help develop early warning systems and proactive disaster management strategies, reducing the impacts of natural disasters, pest outbreaks, and other agricultural threats (Wang et al., 2022). This allows farmers and policymakers to take timely action to mitigate the effects of these events, leading to cost savings, environmental benefits, and improved resilience of agricultural systems through the efficient allocation of resources and optimized production processes.

The use of data enables the ***customization and targeting*** of services and products to meet specific conditions and needs, thereby improving customer-related outcomes (Grover et al., 2018; Saggi & Jain, 2018). This mechanism focuses on tailoring agricultural solutions to the unique characteristics of individual farms, consumer preferences, or even local market demands (Baarbé et al., 2019; Bronson & Knezevic, 2016; Wolfert et al., 2017). For example, data collected from farmers' production practices or consumer behavior allows agribusinesses to deliver highly customized product recommendations or services, ranging from personalized seed or feed suggestions to targeted advisory services that address specific challenges faced by individual farms (Bronson & Knezevic, 2016; Wolfert et al., 2017). Additionally, in the marketing domain, consumer data enables businesses to create personalized product offerings and targeted marketing campaigns, ensuring that the right products reach the right customers (Latino et al., 2018; Shah & Murthi, 2021). This targeted approach helps in better aligning agricultural output with market needs, increasing profitability while simultaneously fostering customer loyalty by providing more relevant and personalized solutions (Shyu et al., 2023). Such mechanisms, when effectively implemented, can enhance customer retention and strengthen long-term business relationships.

Learning and crowdsourcing are mechanisms that leverage collective knowledge and experiences to enhance agricultural practices. Farmers and researchers can share data and insights through online platforms and communities, fostering collaborative problem-solving and innovation (Coble et al., 2018; Janssen et al., 2017; Kaur & Dara, 2023). Crowdsourced data, collected from numerous farms, provide a rich dataset for analyzing trends and developing best practices (Janssen et al., 2017). A single farm's data are usually insufficient for making meaningful decisions; they need to be combined with data from other farms to be truly effective (Anidu & Dara, 2021; Jakku et al., 2019). The value of these data significantly increases when they are pooled and processed to provide actionable recommendations (Wolfert et al., 2017). Aggregating farm data across many operations generates positive network externalities, benefiting the broader agricultural community (DeLay et al., 2023). Additionally, farm data are valuable to third parties, such as banks and insurance companies, for risk assessment and financial planning (Kenney et al., 2020). Improving data sharing and encouraging cooperation between valuable data holders and solution developers is important for maximizing the public advantages of various data types (Gasco-Hernandez et al., 2018). Integrating farm data with the entire food chain enhances their benefits, leading to increased productivity, improved profitability, better record-keeping, informed policymaking, real-time information, supply chain optimization, quality control, and greater international collaboration and learning (Anidu & Dara, 2021; Jakku et al., 2019). Continuous learning is supported by ML algorithms that evolve with new data, refining models and predictions over time (Coble et al., 2018; Sumathi et al., 2018). ML algorithms offer a novel method for predicting weather, optimizing irrigation based on soil moisture, enhancing crop yields, efficiently using pesticides and fertilizers, and reducing unnecessary harvesting costs (Sumathi et al., 2018). This collective intelligence approach accelerates the adoption of effective farming practices and technologies, leading to overall sectoral improvement. However, the competitive nature among agri-stakeholders should not be neglected in the case of crowdsourcing. Stakeholders need to cooperate to create higher value, even as they continue to compete with each other (Lioutas et al., 2019).

Continuous monitoring and proactive adaptation are essential for maintaining the health and productivity of agricultural systems. Advances in technology, particularly through the IoT devices and various sensors, enable real-time monitoring of important parameters like soil moisture, nutrient levels, and crop health (Kour & Arora, 2020; Sinha & Dhanalakshmi, 2022). These sensors, often wireless, can collect data from remote locations without the need for traditional infrastructure (Yépez-Ponce et al., 2023). This continuous flow of data allows for early detection of issues such as disease outbreaks or water stress, enabling farmers to take immediate corrective action (Ayaz et al., 2019; Khanal et al., 2020; Virnodkar et al., 2020). Similarly, sensors and monitoring technologies collect data on animal health and welfare, enabling farmers to make informed decisions about feed and waste management, thereby enhancing efficiency and productivity in livestock operations (Karunathilake et al., 2023). Governments also contribute by collecting and using data on national statistics, weather, subsidies, taxes, and environmental performance to enhance monitoring at a broader level (Janssen et al., 2017). As more data are collected, IoT systems allow for constant monitoring and automated alerts for irregularities, improving the ability to prevent future problems (Grover et al., 2018). By utilizing more data, farming decisions become increasingly precise, allowing for proactive adaptation as algorithms continuously advance through learning (Kamilaris & Prenafeta-Boldú, 2018). However, managing such large datasets also presents challenges. Traditional algorithms may not be equipped to handle the computational demands of modern agriculture, leading to potential inefficiencies in data processing (Cravero et al., 2022). Overcoming these challenges is critical to fully harnessing the power of data-driven farming strategies.

3.1.2. *Value targets*

The mechanisms through which agricultural data create value are intrinsically linked to specific value targets, enhancing organizational performance, improving business processes, fostering products and services innovation, and boosting consumer experience and market engagement (Grover et al., 2018). Defining specific targets for value creation is essential to ensure that agricultural data drive actionable outcomes and significant improvements in farming practices. Table 2 presents an overview of the core articles analyzed in this study, highlighting the specific value targets identified in each article. Organization performance and business process improvement were the two most frequently addressed value targets, appearing in approximately 85 % and 77 % of the core articles, respectively.

Table 2
Value targets of data utilization from the core articles.

Core Articles from database search	VALUE TARGETS			
	Organization Performance	Business Processes Improvement	Products & Services Innovation	Consumer Experience & Market Enhancement
Hackfort et al., 2024	X	X	X	X
Aravamuthan et al., 2024	X	X	X	
Gebresenbet et al., 2023	X	X		X
Hackfort, 2023	X		X	
Basel et al., 2023	X		X	
DeLay et al., 2023	X	X		X
Klug & Prinz, 2023		X		X
Klingenberg et al., 2022	X	X	X	X
Viet et al., 2021	X	X		X
Kieti et al., 2021			X	X
Wysel et al., 2021	X	X	X	X
Fote et al., 2020	X	X		
Carolan, 2020a	X	X	X	

3.1.2.1. *Organizational Performance.*

Agribusinesses are using data to improve business performance and create value. In an industry characterized by tight margins and unpredictable variables such as weather and market prices, data enable more informed operational optimization (Basel et al., 2023; Wysel et al., 2021). The value creation potential of big data depends on the ability to use the information it generates to make strategic or operational decisions (Viet et al., 2021). By adopting new technologies and management techniques, agribusinesses can increase the value of their underlying agricultural assets through more effective observation, measurement, and analysis (Wysel et al., 2021).

Agribusinesses primarily use data analytics to enhance profitability. For agricultural producers, this value stems from cost reductions and profit increases, which enhance efficiency (Aravamuthan et al., 2024; Klingenberg et al., 2022). Data facilitate precise monitoring and forecasting of crop yields, market prices, and resource utilization (Baarbé et al., 2019; Karunathilake et al., 2023; Sumathi et al., 2018). By examining historical data and present trends, agribusinesses can make well-informed choices about which crops to plant, the optimal harvest times, and product pricing strategies (Baarbé et al., 2019; Coble et al., 2018; Karunathilake et al., 2023). Predicting market demands and adjusting production helps agribusinesses avoid financial losses from overproduction or underproduction (Coble et al., 2018; Wolfert et al., 2017). Precision management further boosts operating profits by either increasing total production or cutting input costs (DeLay et al., 2023). The productivity, resilience, competitiveness, and environmental performance of crop, horticulture, and livestock farming can be significantly enhanced by employing cost-effective and reliable new hardware and software, data analysis, smart sensor applications, and optimized precision farming practices (Gebresenbet et al., 2023). For farmers, the benefit of farm data lies in the profitability difference between site-specific management using farm data and uniform management without it (DeLay et al., 2023). The argument holds true not only for precision management but also for general data utilization. The on-farm value of data for farmers consistently lies in the increased profitability it provides compared to not utilizing it.

Improving crop management practices is another important goal for agribusinesses using data. Farmers can gain more value from these new solutions by achieving greater efficiencies (Klingenberg et al., 2022). As the accumulation of data for a given field increases over time, it allows for more accurate predictions of the field's true characteristics (DeLay et al., 2023). By analyzing data on soil health, weather patterns, and pest activity, agribusinesses can make precise agronomic decisions (Hackfort et al., 2024). This includes optimizing irrigation schedules, applying fertilizers and pesticides more effectively, and selecting the best crop varieties for specific conditions. Data-driven agronomy introduces a more scientific approach to farming, reducing guesswork and increasing the reliability of crop performance. The added value can be increased by applying novel AI and ML approaches that provide practical support to farmers' decision-making processes (Gebresenbet et al., 2023). For example, disease diagnosis in agriculture often relies on pattern recognition, but diagnoses are typically made when it is too late. By training a model, pattern recognition can be advanced to the point where diseases can be diagnosed before they are visible to the naked eye (Carolan, 2020a). Another example is John Deere's See & Spray technology, which uses a ML algorithm to identify weeds, enabling site-specific herbicide spot spraying instead of broadcast spraying (Hackfort et al., 2024). These advances are transforming farm management from simply managing fields to addressing each crop individually (Klingenberg et al., 2022). Assessing the value of data requires an understanding of the connections within the data, the insights derived from it, and the implications for supply chain decisions (Viet et al., 2021). The goal of integrating data into agribusiness operations is to improve decision making at all levels of the organization. According to Fote et al. (2020), a novel data processing architecture for a knowledge-based management system has been proposed. This architecture aims to streamline decision support and monitoring activities, help farmers and stakeholders use data more effectively, and maintain a long-term perspective on the knowledge it contains (Fote et al., 2020).

3.1.2.2. Business Processes Improvement. Agribusinesses are increasingly recognizing how transformative data can be in enhancing their business operations. Ray (2018) highlights that much of the focus on the importance of data revolves around business analytics and intelligence. Smart farming generates data that provide foresight into future results through predictive models, facilitate immediate operational decisions, and revolutionize business processes for rapid, innovative actions and transformative business models (Wolfert et al., 2017; Wysel et al., 2021).

Agribusinesses leverage data to enhance operational efficiency and minimize inefficiencies. Despite common concerns about algorithms replacing farmers' knowledge, data is anticipated to transform the way farm businesses operate (Carolan, 2017; Wolfert et al., 2017) and enhance the farmers' work routines (Carolan, 2020b). By gathering and analyzing data from sources such as machinery, labor, and supply chain activities, they can pinpoint bottlenecks and areas needing improvement (Karunathilake et al., 2023). AI plays a crucial role in providing accurate predictions and recommendations in scientific contexts (Fote et al., 2020; Smith, 2018). Continuous real-time data monitoring, combined with historical data and newly developed models, aids in making optimal decisions during critical situations by offering timely, high-resolution, and up-to-date information (DeLay et al., 2023; Gebresenbet et al., 2023; Smith, 2018; Wolfert et al., 2017). For instance, data analytics-driven predictive maintenance can substantially decrease machinery downtime by detecting potential issues before failures occur (Fordal et al., 2023). This proactive approach to maintenance improves equipment efficiency and lifespan, enabling better management of the complexities and constraints within the livestock industry and beyond (Rojo-Gimeno et al., 2019). Fote et al. (2020) developed a novel data analytic architecture focused on precision livestock farming to enhance livestock production, animal welfare, and farming processes, where the decision support system interprets data analysis outcomes and expert system insights, transforming them into human-readable information delivered to end-users. Furthermore, the web application can clean data for subsequent analysis, generate interactive graphics for exploratory and expository visualization, and export high-quality figures for documents, reports, and presentations using interactive views (Aravamuthan et al., 2024).

In labor management, agribusinesses strive to optimize workforce deployment by utilizing data to analyze productivity and time utilization. Farmers leverage data developed by these systems to either reduce their personal costs for achieving similar outcomes or to attain better outcomes for the same cost (Wysel et al., 2021). According to (Carolan, 2020a), a farmer who previously cultivated arable crops mentioned that he has saved hundreds of hours by not having to manually count plants and noting that he earns tens of thousands of dollars more each growing season because he is now able to grow the best possible crops (Carolan, 2020a).

While existing literature has mainly concentrated on leveraging big data to enhance processes within individual firms, evaluating the value of data and big data necessitates understanding the connections within the data, the insights derived from them, and their impact on supply chain decisions (Viet et al., 2021). In supply chain management, agribusinesses utilize data analytics to enhance visibility and control. According to Klingenberg et al. (2022), production processes benefit from predictive maintenance, simulation, remote monitoring, and connectivity, leading to greater efficiency both in supplier companies and on farms. Data also aid in better inventory management by forecasting demand and adjusting supply accordingly, which helps in minimizing overproduction and stockouts. Consumers are increasingly demanding detailed information about the origin and production processes of their food (Latino et al., 2022; Menon & Jain, 2021; Shahid et al., 2020). Efficient supply chain management boosts customer satisfaction and cuts operational costs. Producers expect to gain additional revenue by communicating the true costs incurred, thereby providing a stronger basis for negotiation through increased transparency (DeLay et al., 2023; Klug & Prinz, 2023).

The machinery sector is benefiting from the technology embedded in its products, which simplifies data collection and improves operational efficiency (Klingenberg et al., 2022). The efficient flow of information has numerous benefits, including improved animal and crop productivity, competitiveness, and the adoption of best agricultural practices, all of which can contribute positively to the future of agriculture (Gebresenbet et al., 2023). Similarly, reducing the costs associated with optimizing farming systems through smart agriculture technologies increases the value of farming operations by improving data access and application across the farm (Wysel et al., 2021). In addition, agronomic and crop data are being used to improve existing products and services, increase the profitability of existing business models, and bring new data-driven services to market (Hackfort et al., 2024).

3.1.2.3. Products & Services Innovation. Data play a crucial role in research and development within the agribusiness sector (Fielke et al., 2019) and it is important to assess the impact of data on end users and on advancing scientific research and development (Basel et al., 2023). By examining decades of field and experiment data, it is possible to develop new farming methods, crop varieties, probability models and products (Carolan, 2020a). For instance, Earth observation via satellites has been providing continuous time-series data since the 1980s, offering a valuable source for monitoring and analyzing agricultural trends across diverse locations. The expansion of detailed satellite data has driven a growing demand for satellite-based data analysis and applications, enhancing the precision of agricultural practices (Janssen et al., 2017).

Data-driven research and development result in innovations that boost productivity, enhance resilience, and increase profitability. Consequently, data-based opportunities provide farms with operational models that differ significantly from those of previous generations (Wysel et al., 2021). Introducing new, solution-oriented products and ensuring these products and services are available for the first time is critical to staying ahead of the competition (Kieti et al., 2021).

The creation of new features, products, or services is a significant aspect of value generation through novelty (Kieti et al., 2021). Additionally, novelty can result in innovative solutions to existing issues or the identification and resolution of new problems (Kieti et al., 2021). According to numerous interviewees in the study by Klingenberg et al. (2022), data are fundamental in the development of new products and services, as well as in generating new revenue streams. The benefits derived from adopting new technologies or management practices enhance the value of agricultural assets by enabling more personalized effective observations, measurements, or analyses (Aravamuthan et al., 2024; Wysel et al., 2021). By integrating farm data, such as seed varieties, fertilizer use, and soil quality, technology and service providers can enhance the development of data-driven products and services, significantly boosting their value (Hackfort, 2023). Data-driven innovations like predictive maintenance and precision seed placement exemplify this value creation in agriculture, as they transform raw data into tailored solutions that improve operational efficiency, deepen customer relationships, and introduce new business models (Hackfort et al., 2024).

3.1.2.4. Consumer Experience & Market Enhancement. Agribusinesses are increasingly leveraging data to enhance consumer experience and market engagement, focusing on key value targets that drive customer satisfaction, market growth, and brand reputation. One of their primary goals is to gain a precise understanding of consumer preferences and behaviors with a diversity of needs, beliefs, and interests (Kieti et al., 2021). By analyzing data, they can tailor their products and marketing strategies to align with consumer demands (Hackfort et al., 2024). This deep understanding enhances customer satisfaction and strengthens connections with consumers. Data-driven insights also help agribusinesses identify and capitalize on new market opportunities by enabling informed decisions on product development, keeping them ahead of competitors and responsive to market changes.

Today's consumers place increasing importance on understanding where their food comes from and how it is produced (Latino et al., 2022; Menon & Jain, 2021; Shahid et al., 2020). This demand for transparency is driven by the need to verify the authenticity of sustainability claims, which helps boosting credibility (Klug & Prinz, 2023). Data-driven traceability systems enable agribusinesses to provide comprehensive details about sourcing, production processes, and sustainability practices (Demestichas et al., 2020; Lin et al., 2018; Salah et al., 2019). Retailers benefit from transparency systems by better communicating added values and offering consumers improved product comparability (Klug & Prinz, 2023). This transparency meets consumer demand for ethically produced and environmentally sustainable products, fostering trust and loyalty. Moreover, transparency benefits not only consumers and retailers but also producers, who anticipate additional revenue through accurate cost transmission and improved negotiation foundations (Klug & Prinz, 2023). In precision livestock production, continuous measurement of environmental variables, along with animal health, welfare, reproduction, and productivity, plays a vital role in enhancing transparency, traceability, and monitoring throughout food supply chains, thereby adding value for both producers and consumers (Gebresenbet et al., 2023).

Data also play a critical role in enhancing the reputation of agribusinesses. For instance, a landowner with two decades of georeferenced yield data from high-yielding farmland can use this information to attract potential buyers or renters, leveraging the accumulated data to establish a positive reputation (DeLay et al., 2023). Demonstrating effective use of data can differentiate agribusiness in a competitive landscape, contributing to increased market share and sustainable success.

Furthermore, agribusinesses that use data to drive their operations often seek rapid expansion of their customer base to establish market leadership (Klingenberg et al., 2022). In this context, a common strategy for value creation is customer lock-in, where companies encourage repeated use of their platforms and cultivate long-term relationships (Kieti et al., 2021). While lock-in can strengthen customer loyalty and create sustained value for companies, it is important to balance this strategy by ensuring that customers also see ongoing benefits, keeping the relationship mutually beneficial.

3.1.3. Impact

The value creation mechanisms and targets collectively influence the utilization of data, generating impact through two primary lenses: functional value and symbolic value. These processes generate functional value by optimizing resource allocation, improving decision-making, and increasing efficiency and productivity. Simultaneously, they provide symbolic value by enhancing the organization's reputation for innovation and sustainability, fostering consumer trust, and attracting investment. Thus, the strategic use of data not only delivers operational benefits but also bolsters market position and stakeholder confidence,

Table 3 provides an overview of the value impact categorization from the core articles, illustrating how each study addressed the functional and symbolic value generated through the strategic use of agricultural data. The findings reveal that all core articles (100 %) emphasize the functional value, which will likely remain the primary perspective on data value. For agri-stakeholders, especially farmers, the value of data is fundamentally tied to the profit gained from utilizing them. Additionally, 54 % of the core articles explore the symbolic value of data, indicating that symbolic aspects should also be acknowledged when constructing the overall value, as data play an important role in enhancing reputation, trust, and market positioning.

Table 3
Impact categorization from the core articles.

Core Articles from Database Search	IMPACT Functional Value	Symbolic Value
Hackfort et al., 2024	Economic Benefits, Data Assetization	Market Positioning, Reputation
Aravamuthan et al., 2024	Decision-support	
Gebresenbet et al., 2023	Decision-support, Productivity, Innovation, Transparency, Traceability, and Monitoring	
Hackfort, 2023	Assetization, Predictive Maintenance, Control over Technological Development	Market Influence, Technological Leadership, Reputation for Innovation
Basel et al., 2023	Decision-support, Research and Development, Data accessibility	
DeLay et al., 2023	Economic Value of Data Insights, Precision Management & Profitability, Productivity	Reputation Enhancement, Market Signal, Trust and Transparency
Klug & Prinz, 2023	Data Monetization & Economic Benefits, Transparency, Operational Insights	Trust in Sustainability, Reputation, Credibility & Consumer Confidence, Negotiation Power
Klingenberg et al., 2022	Efficiency & Productivity, Data-Driven Operations, Product Quality	Reputation, Market Influence, Power Dynamics, Leadership through Innovation
Viet et al., 2021	Strategic and Operational Decision-making	
Kieti et al., 2021	Enhanced Service Efficiency by platforms	Digital Inclusivity, Early Adopter Advantage
Wysel et al., 2021	Economic Benefits, Productivity and Efficiency, Decision-support	Attraction of High-Performing Stakeholders, Network Value Enhancement
Fote et al., 2020	Decision-support, Operational Monitoring, Knowledge Discovery/ Generation,	
Carolan, 2020a	Data Reliability, Operational Accuracy, Actionable Insights	

3.1.3.1. Functional value. Functional value encompasses both tangible and intangible benefits derived from transforming data assets into actionable insights that improve organizational performance (Grover et al., 2018). Ray, (2018) advocates for the recognition of data as a financial asset, like other corporate assets. In the agricultural sector, the integration of big data has become critical to corporate business models, as highlighted by the companies themselves (Bronson, 2022; Hackfort et al., 2024). On its own, raw data have low value (Fote et al., 2020). However, when used effectively, data becomes a powerful asset that drives functional value and provides numerous benefits (Eastwood et al., 2023).

The significance of data is also evident in their capacity to predict and manage risks, such as pest outbreaks and severe weather conditions, which are vital for maintaining yield stability and promoting sustainability (Gebresenbet et al., 2023). Furthermore, the economic value of data grows over time, as continuous data collection enhances the quality and reliability of insights, thereby improving long-term decision-making processes (Anidu & Dara, 2021; Basel et al., 2023; Fote et al., 2020; Klug & Prinz, 2023). Additionally, the interoperability and precision of data, along with advanced storage and computational capabilities, increase their value, allowing for more efficient and effective utilization of data technologies (Gebresenbet et al., 2023).

Agribusinesses have developed advanced strategies to collect, process, and utilize large amounts of data (a process called assetization) to extract economic value and gain competitive advantage (Basel et al., 2023; Hackfort et al., 2024; Klingenberg et al., 2022; Carolan, 2020a; Klug and Prinz, 2023). There is an increasing recognition that greater data possession equates to increased power (Kaur & Dara, 2023; Klingenberg et al., 2022; Lioutas et al., 2019). Lioutas et al. (2019) highlight that power imbalances stem not from unequal access to big data, but from the value extracted from them, placing value at the core of power dynamics.

Service providers in agriculture exemplify how data-driven services like predictive maintenance enhance product offerings and create significant market advantages, reinforcing the control of valuable data and further deepening power imbalances within the sector (Hackfort, 2023). However, there is limited understanding of how value is generated as a new service ecology within agriculture (Wysel et al., 2021). Value creation occurs through the exchange of information and services between different parties, with economic value largely captured through fee structures (Bonina et al., 2021; Bustamante, 2023; Dushnitsky et al., 2022). Service and technology providers, recognizing the high value of agricultural data, employ various lock-in strategies to control it. These strategies often exclude farmers, who only have access to less valuable individual data sets (Hackfort, 2023). Additionally, a weak value proposition causes technologies to be driven by supply rather than the needs of end-users (Eastwood et al., 2023; Ingram et al., 2022). The current legal framework, characterized by inadequate regulation and a lack of enforceable protections for farmers (Wiseman et al., 2019), supports the data-assault goals of large corporations. This environment allows corporations to prioritize access to datasets and profit from farm-level data, often at the expense of farmers (Hackfort, 2023; Hackfort et al., 2024; Lioutas et al., 2019).

There is a significant gap between how large agribusinesses and smallholders' access and use data (Fleming et al., 2018; Hackfort, 2021; Jakku et al., 2019; Kaur & Dara, 2023). Large companies have the resources to invest in sophisticated analytics and management systems, enabling them to derive significant value from their data. In contrast, smallholder farmers face challenges such as limited access to technology, data literacy, and financial constraints that hinder their ability to fully leverage data (Jiménez et al., 2019; Kshetri, 2014). This disparity has raised concerns about whether big data will benefit all organizations and society, or primarily a few large companies (Kaur & Dara, 2023; Kempenaar et al., 2016). Some argue that data only benefit those with the means and expertise to collect and use it (Kshetri, 2014), suggesting that digitization may lead to further corporate consolidation (Rotz et al., 2019). This critique is particularly relevant to platform development, where "winner-takes-all" strategies appear to be consolidating power within the food system (Bustamante, 2023; Klerkx & Rose, 2020). Despite these challenges, addressing these disparities offers an opportunity to advance data equity in agriculture. Improving access to data technologies and promoting data literacy can help ensure that the functional value of agricultural data benefits all stakeholders, driving productivity, sustainability, and resilience across the sector.

3.1.3.2. Symbolic Value. Symbolic value, on the other hand, refers to the benefits that enhance an organization's reputation, perceived innovation, and market impact (Grover et al., 2018). Although much of the research has emphasized the functional value of information technologies (see Table 3), symbolic value provides a clear indication to stakeholders of an organization's advanced capabilities. A key challenge is that the industry's understanding of value is often confined to measurable metrics, primarily because many organizations prioritize economic performance as the dominant indicator of success (Bustamante, 2023; Cagliano et al., 2016).

The integration of big data analytics in agriculture demonstrates a commitment to innovation and sustainability, which can attract investment, foster partnerships, and increase consumer trust (Fote et al., 2020; Klug & Prinz, 2023). This helps companies enhance their market credibility and expand their customer base as they work to establish themselves as industry leaders (Klingenberg et al., 2022). In addition, producers are motivated by the potential for increased demand and an improved reputation through transparency systems, which build trust in the legitimacy of their sustainability efforts while empowering consumers to support and shape sustainable agricultural practices (Klug & Prinz, 2023). Furthermore, the use of advanced technologies like blockchain and AI is important for enhancing data accuracy and reliability in agricultural operations, which further strengthens transparency and market credibility. These tools play a significant role in improving stakeholder negotiations and building trust throughout the value chain (Fote et al., 2020; Klug & Prinz, 2023). For instance, landowners with extensive yield data can leverage this information to attract potential buyers or renters by offering a reliable overview of the land's productivity (DeLay et al., 2023). This highlights how strategic use of data not only boosts transparency but also adds value to market transactions.

Another element of symbolic value is the herd behavior that organizations exhibit as they adopt new technologies to maintain competitiveness and comply with industry standards (Grover et al., 2018). This tendency is influenced by observations of earlier adoptions and the uncertainty surrounding new technologies. Farmers and other supply chain actors are hesitant to change their practices unless they are certain of the motivations for such changes (Carolan, 2017; Eastwood et al., 2023; Klerkx et al., 2019; Shepherd et al., 2020). However, beyond uncertainty, barriers to technology adoption are also shaped by the digital divide. This divide includes obstacles such as unequal access to technology and the skills needed to leverage it effectively (Janc et al., 2019; Klerkx et al., 2019; Wysel et al., 2021).

Data assets, which are difficult to reproduce or replace without the original source, foster monopolies and oligopolies that disadvantage new entrants while strengthening the position of early adopters (Hackfort et al., 2024). For early adopters, gaining access to new products and services first can provide a significant competitive advantage, as it allows them to dominate the market and establish themselves as leaders (Kieti et al., 2021). Additionally, the self-organization of stakeholders and the co-creation of value contribute to the development of strong networks, where high-performing actors attract others with similar capabilities. This positive cycle of value creation is facilitated through effective value allocation, data development, and stakeholder coordination (Wysel et al., 2021).

4. Limitations

While this study provides valuable insights into data value creation in agriculture, several limitations should be acknowledged. The literature review was confined to English-language publications from the last decade, potentially excluding earlier or non-English works that could offer relevant insights. Articles not specific to agriculture were also excluded, even if they provided useful insights, which is a limitation given that the value of data is a relatively new and evolving topic in agricultural research. Additionally, the inclusion criteria applied during the database search, which required articles to explicitly reference “value of data,” were somewhat restrictive. As a result, numerous studies that indirectly addressed data value but did not explicitly label it as such were excluded. We acknowledge that this represents a limitation, as potentially relevant and insightful articles may have been overlooked due to this criterion. Furthermore, the focus on peer-reviewed articles may have excluded practical perspectives found in grey literature or industry reports. These limitations highlight the need for future research to broaden the scope and consider more diverse sources and emerging technologies in real-time applications.

5. Conclusion

The findings from this literature review shed light on the perception of data value in the agriculture domain. The evolution from rudimentary data usage to sophisticated data analytics has significantly shifted the paradigm, positioning data as critical value enabler for informed decision making and innovation. The advancement of the state of the art is evident in the growing recognition of data as a strategic asset. Therefore, the study assessed how to systematically characterize data value creation in agriculture domain. A growing body of research in data-driven agriculture underscores the increasing awareness of data’s importance, sparking key discussions on issues like data ownership and governance. The review findings suggest that the true significance lies in the value generated from data, rather than simply in their ownership. Therefore, the focus should shift towards understanding who benefits from the value created by data and how that value is fairly distributed among the various stakeholders involved.

A key takeaway from this study is the multifaceted value of agricultural data. The findings underscore the strategic importance of data as an asset that can lead to achieving competitive advantage and operational excellence within the agricultural sector. Furthermore, the growing interest in the value of data is evident, as companies seek to enhance their services, research institutions aim to innovate new solutions, and farmers become increasingly aware of the ’assets’ they are producing. Farmers are becoming more aware of digital technologies, and are now searching for new ways to own, measure, and exploit the value of their data. This brings up the crucial question of what constitutes the actual value of this asset. Valuation, the process of determining the worth of an asset based on its functional and symbolic qualities, becomes central to this discussion (Bustamante, 2023). The literature on data-driven agriculture lacks robust frameworks for valuation processes, specifically in how values are assessed, developed, maintained, and made evident (Borrero & Mariscal, 2022). Valuation of agricultural data requires more research, due to the multifaceted and site-specific characteristics. There is also a need for clarification on how to continuously value the data since they do not lose but instead might increase their value by re-use of them.

Another critical research direction revolves around the fact that the value of data is not a one-size-fits-all concept. The interpretation of data’s value can differ significantly depending on the stakeholder involved, such as small farmers, agribusinesses, policymakers, or technology providers. For some stakeholders, data value may be tied to operational efficiency and productivity, while for others, it might be linked to market positioning or long-term sustainability goals. This variation in perspectives makes it essential to consider the context in which data are used and the specific goals of each group. For instance, data value creation must be contextualized to the value targets of different stakeholders, such as small farmers. This is crucial for arriving at more meaningful definitions of data value and, in turn, crafting data value creation pathways that are relevant to the diverse actors in the agriculture domain.

In conclusion, the study underscores the importance of data as an asset, and provides data value creation by assessing the mechanisms, targets, and impacts of it. To further develop this research field, more empirical studies are needed that build upon existing theories and frameworks to identify and characterize data value creation in agriculture. These studies are crucial for understanding how data can be effectively transformed into valuable assets, ensuring that the agricultural sector can fully capitalize on the benefits of data-driven technologies. By thoroughly examining these aspects, researchers can provide actionable insights that help stakeholders optimize their data strategies, leading to greater efficiency, productivity, and sustainability in agriculture.

CRediT authorship contribution statement

Havva Uyar: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ioannis Karvelas:** Writing – review & editing, Project administration, Conceptualization. **Stamatia Rizou:** Writing – review & editing, Supervision, Conceptualization. **Spyros Fountas:** Writing – review & editing, Supervision.

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Data availability

Data will be made available on request.

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