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The Role of Artificial Intelligence Technology In Supporting Agribusiness Innovation And Competitiveness: A Bibliometric And Systematic Review Approach

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Abstract

This study explores the role of artificial intelligence (AI) in strengthening innovation and competitiveness within the agribusiness sector through a combination of bibliometric and systematic review approaches. Unlike previous studies that focus solely on technical or algorithmic aspects of AI, this research introduces a novel integrative framework that combines bibliometric mapping of global scientific trends with a systematic synthesis of empirical evidence. The bibliometric analysis of 59 Scopus-indexed articles (2020–2025) using VOSviewer and Bibliometrix (R) reveals an annual research growth rate of 26.84%, dominated by themes such as precision agriculture, Internet of Things (IoT), machine learning, and blockchain. Meanwhile, the systematic review of ten empirical studies shows that AI implementation increases average productivity by 22.6%, input efficiency by 18.3%, and reduces operational costs by 16.7%, while enhancing supply chain transparency and smallholder welfare. However, challenges such as limited digital infrastructure, low technological literacy, and restricted financing access persist in developing countries. The study concludes that integrating AI with IoT and blockchain provides an effective pathway toward an innovative, sustainable, and inclusive agribusiness system, and offers a replicable methodological framework for future interdisciplinary research on digital transformation in agriculture.

Keywords: Artificial_-Intelligence; Agribusiness; Bibliometric; Systematic_Review; Innovation; Competitiveness

1. Introduction

The rapid advancement of digital technology has profoundly transformed various sectors, including agribusiness. Among these technologies, artificial intelligence (AI) stands out as a key enabler of automation, data analytics, and intelligent decision-making systems capable of addressing long-standing agricultural challenges such as climate change, land degradation, and population growth [1]. Through big data analysis, predictive modeling, and supply chain optimization, AI has become a major driver of agricultural transformation towards sustainability, resilience, and competitiveness.

Previous studies have demonstrated the effectiveness of AI applications in improving production efficiency, crop management, and decision-making accuracy [2], [3]. The integration of AI with technologies such as the Internet of Things (IoT), sensors, and blockchain has further enhanced smart and sustainable agriculture systems by enabling real-time monitoring, automation, and transparent value chains. Empirical findings also indicate that digitalization improves smallholder farmers' welfare through greater access to information, financial services, and market linkages [4]. These developments confirm that digital agriculture, when powered by AI, contributes significantly to productivity, sustainability, and socio-economic inclusion.

Despite this progress, the current body of research remains fragmented and often limited to specific technical aspects such as disease detection [5] or weed control [6]. Few studies holistically address how AI enhances innovation and competitiveness within agribusiness systems. Moreover, many existing works lack comprehensive quantitative analyses or comparative synthesis that reveal the measurable impacts of AI on efficiency, sustainability, and economic performance [7]. The limited attention to developing regions such as Africa and Asia also highlights the technological divide and the need for inclusive research frameworks that account for local conditions and capacities. Unlike previous reviews that focus solely on technical AI aspects, this study uniquely integrates bibliometric mapping and empirical synthesis to provide a holistic evidence-based framework for agribusiness innovation.

To address these gaps, this study employs a combined bibliometric and systematic review approach to provide a holistic understanding of the role of AI in agribusiness. The bibliometric analysis maps global research trends, thematic evolution, and international collaborations to capture the scientific landscape of AI in agribusiness. Meanwhile, the systematic review synthesizes empirical evidence on AI's measurable contributions—such as productivity gains, input efficiency, cost reduction, and supply chain transparency—to assess its real impact on innovation and competitiveness.

Accordingly, this research aims (1) to map global publication trends and dominant themes related to AI in agribusiness using bibliometric analysis; (2) to synthesize empirical findings from previous studies regarding AI's contribution to agribusiness innovation and competitiveness; (3) to identify research gaps and future opportunities for AI development in agribusiness; and (4) to provide practical implications for policymakers, practitioners, and researchers in enhancing the adoption of AI technologies in agriculture.

By integrating these analytical approaches, this study not only contributes to advancing academic knowledge but also provides practical insights to accelerate the digital transformation of agriculture, particularly in developing countries. The combined evidence-based and conceptual framework developed herein offers a pathway toward an innovative, sustainable, and inclusive agribusiness ecosystem supported by artificial intelligence.

2. Methodology

This research adopted a combined bibliometric and systematic review approach to comprehensively explore how artificial intelligence (AI) enhances innovation and competitiveness in agribusiness. The methodological framework integrates quantitative bibliometric mapping with qualitative synthesis of empirical evidence, providing a balanced analysis between research trends and practical outcomes. This dual-method design aligns with established practices in bibliometric and systematic review studies, which emphasize rigor, transparency, and replicability [8], [9].

The research process followed a structured sequence beginning with topic definition, data collection, and screening, followed by bibliometric analysis, systematic review, and synthesis. Data were retrieved from the Scopus database, chosen for its extensive coverage of peer-reviewed literature and high data accuracy [10]. The search query used was (KEY("Artificial Intelligence") AND KEY("Agribusiness") AND KEY("Agriculture")) AND PUBYEAR > 2019 AND PUBYEAR < 2026, which ensured inclusion of the most recent studies between 2020 and 2025. The initial search produced 153 documents, which were then filtered based on defined inclusion and exclusion criteria. Only peer-reviewed journal articles focusing on AI applications in agribusiness with empirical or measurable outcomes were retained. After the screening process, 59 articles were selected for bibliometric analysis and 10 for systematic review.

The bibliometric analysis was conducted using VOSviewer and the Bibliometrix R-package, tools widely recognized for mapping scientific networks and thematic structures [10], [11]. These tools enabled analysis of annual publication trends, author collaboration networks, and keyword co-occurrence patterns. The approach allowed visualization of thematic evolution and identification of dominant clusters within AI and agribusiness research. Such tools have been extensively applied in similar reviews to analyze global collaboration and scientific productivity patterns [8].

The systematic review component was conducted following the PRISMA 2020 protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which ensures transparency and replicability in literature synthesis [9], [11]. This procedure involved identifying, screening, and selecting articles that met the inclusion criteria while excluding duplicates and non-empirical studies. Data extracted from each article included AI techniques employed, agribusiness domains targeted (such as crop management, logistics, or financial systems), and quantitative indicators such as productivity gains or cost reductions. The synthesis followed a qualitative descriptive approach that allowed for comparative analysis across different AI application contexts.

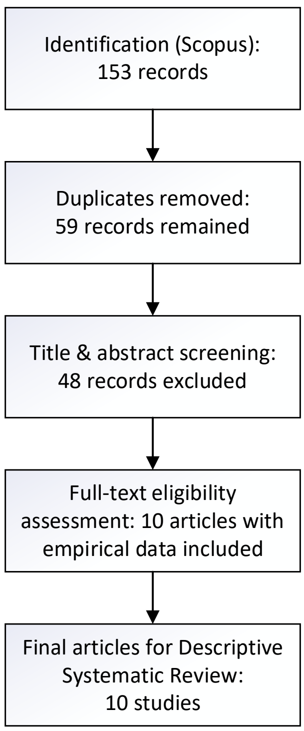

Figure 1. PRISMA Diagram of Research Flow

The methodological integrity of this study was ensured by applying quality control measures similar to those recommended in advanced bibliometric studies. The reliability of the analysis was enhanced through the use of established software and adherence to PRISMA guidelines, which minimize bias and increase reproducibility [8], [12]. To maintain analytical transparency, all inclusion criteria, search strings, and processing steps were fully documented, allowing replication by future researchers. Furthermore, cross-validation between reviewers was employed to enhance the objectivity of data extraction and classification.

Finally, the integration of bibliometric mapping and systematic synthesis addressed the fragmented nature of previous research by providing a unified and evidence-based understanding of AI's contribution to agribusiness. This mixed-method design not only mirrors the methodological innovation found in contemporary systematic literature reviews (Almasri et al., 2021) but also ensures that results are grounded in both scientific and practical relevance. The resulting insights contribute to advancing digital transformation frameworks in agriculture and can serve as a methodological reference for future interdisciplinary research in technology-driven agribusiness systems..

3. Result and Discussion

3.1 Result

Bibliometric Analysis Results

Bibliometric analysis was conducted to identify research developments regarding artificial intelligence in agribusiness based on scientific publications available in international databases. This approach provides a quantitative understanding of research trends, author productivity, and collaboration networks between countries and institutions that play an important role in the development of AI technology in the agricultural sector.

Bibliometric analysis of 59 document articles from the Scopus database for the period 2020-2025 shows significant research dynamics related to the application of artificial intelligence (AI) in agribusiness. This field experienced an annual growth rate of 26.84%, with an average document age of 1.83 years, indicating that this topic is still very new, current, and relevant. The average citations per document reached 10.54, showing a fairly good influence on the global literature. This increase illustrates global interest in utilizing digital technology to address challenges in the agricultural sector such as low productivity, climate uncertainty, and supply chain efficiency [1], [13].

Publication distribution comes from 54 different sources, all of which are journal articles, confirming reasonably maintained academic quality. Research collaboration is high with 575 authors involved and international collaboration at 32.2%. The majority of articles are written by multiple authors (average 4.1 people per document), confirming the collaborative nature. The international collaboration map shown in Figure 2 highlights the United States as the main hub for scientific production, followed by China, India, Brazil, the United Kingdom, and Australia. Strong collaborative relationships were identified between the US and UK, the US and Brazil, and India and the United Arab Emirates.

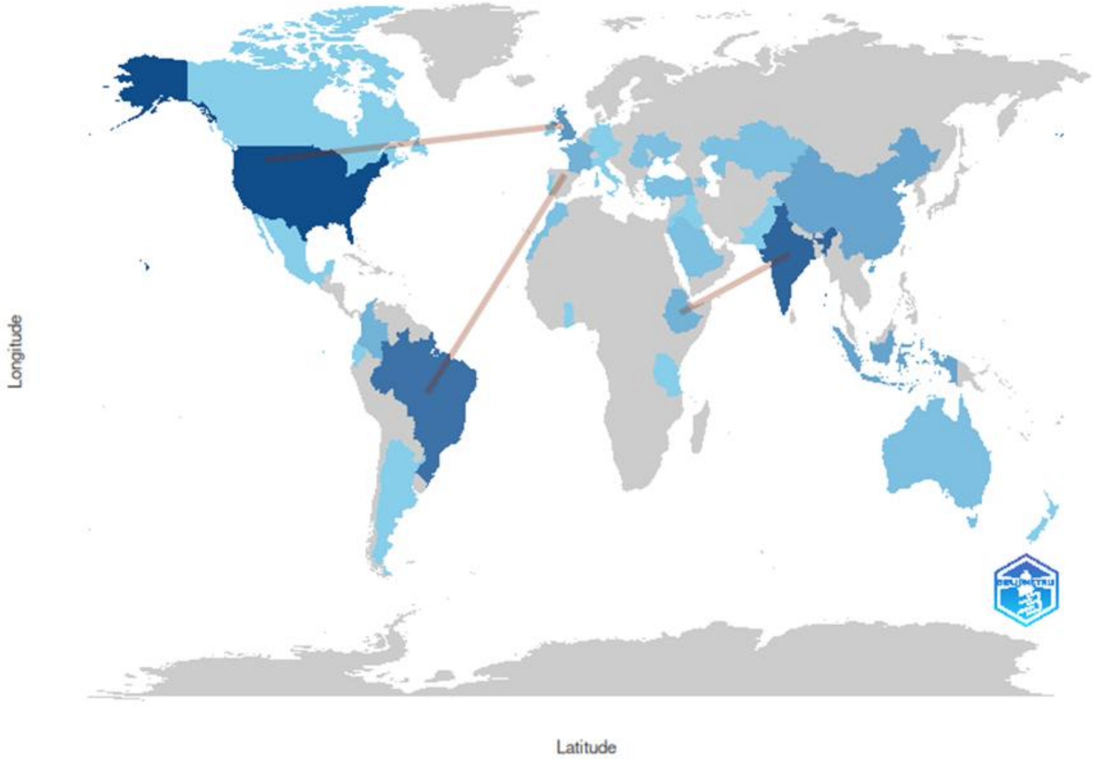

Figure 2. Map of author collaboration between countries

Figure 2 depicts the map of international collaboration between countries in related publications. For example, there is cooperation between Australia and Pakistan with a fairly high level of collaboration, and between Azerbaijan and Turkey. Collaboration is also seen between Brazil and Italy as well as France, although the intensity varies. This can be seen in Table 1. This global connectivity signifies that research on agronomy, food, marketing, and artificial intelligence is not just a local issue, but a shared concern across countries collaborating in scientific publications.

Table 1. Data on author collaboration between countries

From	To	Frequency
Argentina	Portugal	8.50
Australia	Pakistan	69.34
Azerbaijan	Turkey	35.17
Brazil	France	2.76
Brazil	Italy	12.07
Canada	Ghana	1.217
China	Azerbaijan	47.55
China	Turkey	35.17
Colombia	Ecuador	78.75
Colombia	Mexico	102.52

Based on the converted collaboration data from Biblioshiny, Table 1 shows the pattern of scientific interaction between countries contributing to publications on the theme of artificial intelligence in agribusiness. The **"From"** column shows the country of origin of the main author, while the **"To"** column displays the partner country of collaboration. The **"Frequency"** value represents the level of collaboration intensity, i.e., how often the two countries appear together in one scientific publication.

The analysis results show a quite striking difference between countries with high collaboration frequency and those with low intensity. Countries such as Australia, India, China, and the United States dominate the global collaboration network, indicating their role as centers of research activity and main drivers of artificial intelligence development in the agricultural sector. This is in line with the findings of Subeesh and Mehta (2021), who confirm that these countries have strong digital infrastructure, high research capacity, and policy support for the development of *smart agriculture* [13].

Conversely, some country pairs have relatively small frequency values, reflecting collaboration that is still limited or sporadic. For example, the relationship between Argentina and Portugal or Brazil and France shows low intensity. This phenomenon is consistent with the results of Kudama et al. (2021), who highlight the gap in digital adoption and participation among developing countries, especially in Africa and Latin America [7].

Furthermore, the active involvement of countries such as Pakistan, Turkey, and France in cross-border collaboration also shows the increasingly broad network of AI research in agribusiness. According to Khadatkar et al. (2021), strengthening international cooperation in the development of agricultural automation technology plays an important role in accelerating knowledge transfer and innovation between regions. In this context, increasing collaboration between developed and developing countries is a positive indicator of the global diffusion process of digital agricultural innovation [14].

The distribution of *frequency* values in this file also shows that the collaboration pattern is not only dominated by strong bilateral relationships but also involves multi-country networks (multi-hub collaboration), where one country acts as a link between several research partners. This aligns with the collaborative pattern found by Pathan et al. (2020), that *artificial cognition* research in smart agriculture is generally carried out through partnerships across universities and international research institutions [1].

Overall, the data in this table indicate that international collaboration is one of the main drivers of improving the quality and impact of research in the field of artificial intelligence for agriculture. Countries with high connectivity not only produce more publications but also become sources of innovation in precision agricultural technology, supply chain digitalization, and food production automation systems [2], [15]. Therefore, expanding cross-border collaboration needs to be a primary focus in AI-based agribusiness development strategies, especially in developing countries that still have research resource limitations.

Figure 3. Keyword treemap

Keyword analysis produced 535 author keywords and 383 automatic keywords, indicating high diversity. The most dominant keywords were "artificial intelligence" (32 times), "agribusiness" (24 times), and "precision agriculture" (13 times). Figure 3 shows that research trends since 2023 show the emergence of new topics such as blockchain, internet of things, fuzzy logic, and agri-food. This pattern indicates a strong tendency of research towards integrated digital agriculture, where AI does not stand alone but is part of an interconnected intelligent system [2], [6].

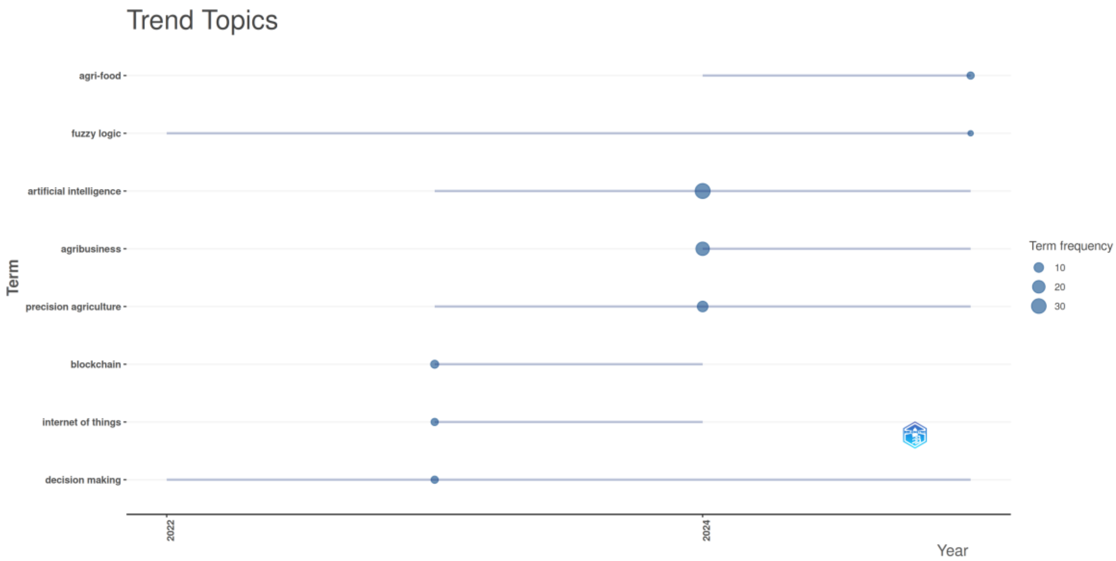

Figure 4. Plot of topic trends from keywords

Figure 4 depicts the evolution of research keywords from 2022 to 2024 based on SCOPUS data. The light blue line shows the interquartile range of keyword frequency, where the midpoint indicates the median value, while the bubble size represents the annual intensity or frequency of that keyword. The larger the bubble size, the more prominent the role of that keyword in the research landscape. From this visualization, it can be seen that some topics emerged earlier with consistent frequency, while others have only gained attention in recent years.

The term *decision making* emerged early in 2022 and remained stable throughout the observation period, signifying the importance of decision-making in the context of technology application in agriculture. The year 2023 marked the initial emergence of terms like *blockchain* and *internet of things (IoT)*, which quickly gained relevance in academic studies, especially related to supply chain transparency and integration of smart sensors in agriculture. The year 2024 was marked by a significant surge in the terms *artificial intelligence*, *agribusiness*, and *precision agriculture*, evident from the much larger bubble sizes. This indicates that the research focus is shifting strongly towards the use of smart technologies for production efficiency, supply chain management, and enhancing agribusiness competitiveness. In the same year, terms *agri-food* and *fuzzy logic* also emerged as new topics, albeit with lower frequency, indicating initial exploration of the integration of the food sector with smart technologies and the application of advanced computational approaches.

Overall, this pattern shows a convergence between cutting-edge technologies—such as AI, blockchain, and IoT—with the agribusiness and food systems. This evolution confirms that research in agriculture is no longer solely production-oriented but also focuses on transparency, sustainability, and the adoption of digital innovations. The fact that technology topics are becoming more prominent indicates rapidly growing research opportunities, especially in integrating artificial intelligence with modern agribusiness practices.

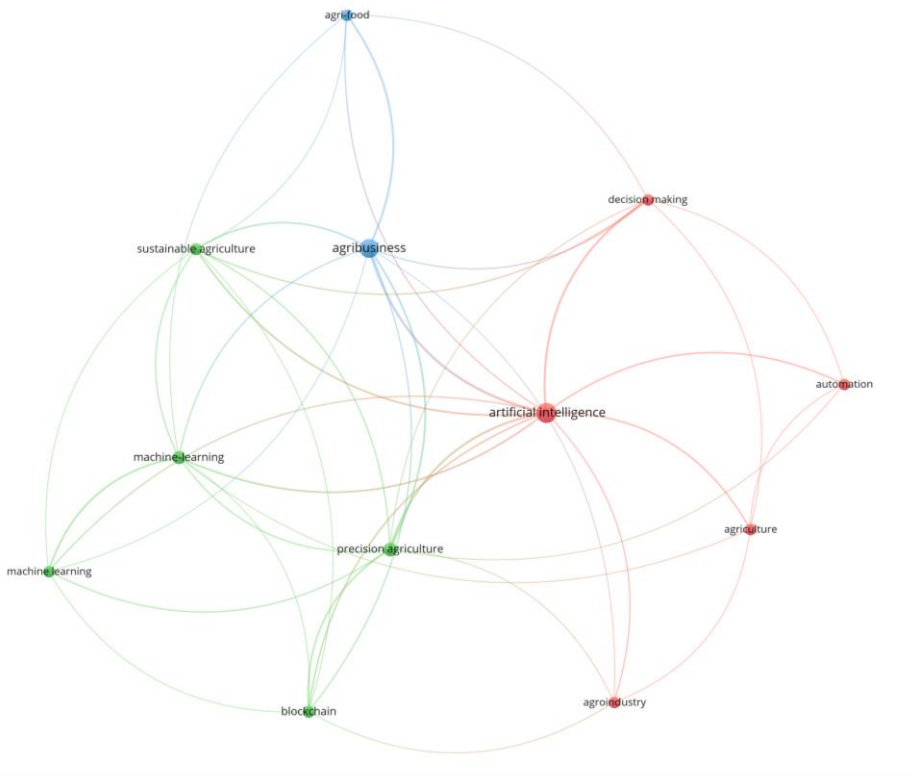

Figure 5. Keyword network map

Figure 5 shows three main clusters: (1) Agribusiness, closely connected to agri-food and decision making, (2) Artificial Intelligence, connected to automation, agriculture, and agriindustry, and (3) Sustainability, connected to machine learning and blockchain. Thematically, the most dominant research clusters are related to precision agriculture, plant disease detection, smart farming, and blockchain-based supply chain. These themes indicate a shift in research focus from the algorithm development stage towards the implementation of intelligent systems at the field level [5], [15]. For example, research by Pathan et al. (2020) emphasizes the importance of integrating artificial cognition to improve decision-making accuracy in smart agriculture, while Xu et al. (2020) show how blockchain plays a role in the transparency of the agri-food value chain.

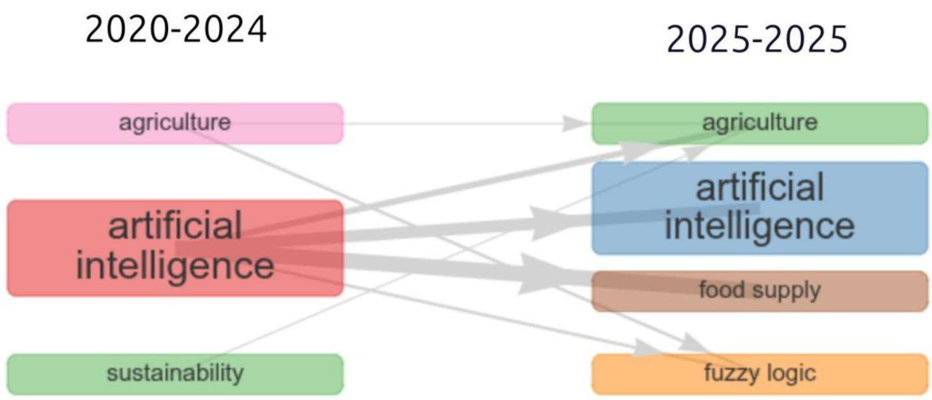

Figure 6. Thematic evolution

Thematic evolution presents technical parameters related to the analysis of thematic evolution. The analysis was performed on descriptor keywords (DE) with a maximum of 250 themes considered, a minimum frequency of 5 times, and a visualization size of 0.3. From this, it can be understood that the research is directed at seeing how themes develop over time, specifically up to the year 2024. Thematic evolution allows researchers to see how an initial topic develops into a more complex field of research.

Interpretation of the plot of research topic evolution from the period 2020-2024 to 2025 shows that *Artificial Intelligence* (AI) is a very important and sustainable topic. From the initial period to the most recent period, AI has consistently been at the center of research attention. This indicates that artificial intelligence is not just a temporary trend but has developed into a field of research that is continuously expanded and applied in various contexts, including agronomy, food, and marketing. Topics such as *smart agriculture*, *precision farming*, *IoT-based agriculture*, and *machine learning for sustainability* have become increasingly prominent in the last five years. This is in line with the research results of [3], who confirm that the integration of AI with IoT technology and big data analytics can create smart agricultural systems oriented towards resource efficiency, waste reduction, and yield optimization [3].

On the other hand, the topic *Agriculture* also remains present throughout the period, although it appears that the main research focus has shifted more towards AI. This signifies that although agricultural aspects still form the basis of discussion, their integration with modern technologies has directed academic attention more towards digital innovations rather than conventional practices.

The theme *Sustainability*, which was quite prominent in the 2020-2024 period, appears to have a reduced role in the most recent period. This topic is no longer a central focus of discussion in 2025, although it was previously relevant in the context of sustainable agricultural development and food security. This shift may occur because sustainability issues are now integrated into broader themes such as artificial intelligence or smart agribusiness.

Thematic evolution shows a shift from general topics like "agriculture" and "sustainability" towards more specific topics like "food supply" and "fuzzy logic" in 2025. The strategic map groups AI and agribusiness as motor themes (central and developing), blockchain and agroindustry as niche themes (specific and less connected), and food production and alternative agriculture in basic themes. Furthermore, the results of co-word analysis show that sustainability issues become a common thread in many recent studies. AI is utilized to address resource limitations, minimize environmental risks, and enhance the resilience of agribusiness systems to climate disruptions. This approach is also in line with the idea of [16], who emphasize the need to integrate social, economic, and environmental indicators in every technology-based agricultural innovation [16].

Figure 7. Factorial map

The factorial map in Figure 7 is the result of *Multiple Correspondence Analysis* (MCA) on keywords (*DE*) from the data collection downloaded from the SCOPUS database. This analysis aims to identify hidden structures and relationships between keywords in the research field covered by the collection. Analysis parameters include the use of unigrams (*ngrams: 1*), a minimum threshold of *degree 2*, and the formation of five clusters (*clust: 5*). These five clusters are: (1) smart agriculture and supply chain, (2) data analytics and machine learning, (3) digitalization and sustainability, (4) decision making and fuzzy logic, and (5) fuzzy neural networks. This indicates that AI research in agribusiness not only focuses on technical aspects but also on management, sustainability, and decision-making strategies.

The map structure shows that Dimension 1 (28.66%) explains the main variation in the data. Terms located on the left and right sides of this dimension depict a major difference or polarization in the analyzed research field. Meanwhile, Dimension 2 (23.03%) explains secondary variation. Terms located in the upper and lower parts of this dimension show another significant polarization. The position of keywords is also very important to note, because keywords that are close to each other on the map tend to appear together frequently in documents, while the further the distance between keywords, the less likely they are to appear together.

The analysis results show five clusters representing groups of interrelated keywords. The purple cluster focuses on terms like *agriculture industries*, *block-chain*, *smart agriculture*, and *supply chain management*, indicating attention to technological innovation in the agricultural supply chain. The blue cluster includes terms such as *data analytics*, *machine learning*, *IoT*, *artificial intelligence*, *explainable artificial intelligence (XAI)*, *precision agriculture*, and *food supply*, thus highlighting the application of data analytics, artificial intelligence, and IoT to support precision agriculture.

Next, the red cluster consists of terms like *digitization*, *sustainability*, *conversion*, *technologies*, *mediating roles*, *smart farming*, *artificial intelligence*, *soils*, and *automation*. This cluster emphasizes the themes of digitalization, sustainability, and the role of technology in smart farming. The green cluster contains terms *article*, *decision making*, *irrigation systems*, *agricultural machinery*, *fuzzy logic*, and *human*, indicating a focus on decision-making processes, irrigation systems, agricultural mechanization, and the integration of fuzzy logic and the human role. Finally, the orange cluster contains only one term, *fuzzy neural networks*, emphasizing the application of fuzzy neural networks in the agricultural context.

Terms located far from the center point or origin of the coordinates contribute the most to explaining the variation in the data. On this map, keywords such as *agriculture industries*, *smart agriculture*, *digitization*, *fuzzy neural networks*, and *human* have a great influence in differentiating different research groups.

Overall, this factorial map provides an overview of the complex research landscape in agriculture as reflected in the SCOPUS data collection. Several main trends can be identified, including the increased use of smart technologies like AI, IoT, and big data in the agricultural sector; a focus on sustainability and digitalization of agricultural practices; the role of data analytics and *machine learning* in supporting decision-making; and the application of concepts such as fuzzy logic and fuzzy neural networks to support research development in this field.

Systematic Review Results

From the initial 59 articles identified through the database, 10 articles were selected after the selection process using the PRISMA flow. These articles show diverse applications of artificial intelligence (AI) in supporting innovation and improving agribusiness competitiveness, both in technical and socio-economic aspects.

Table 3. Systematic Review of 10 articles

No	Research Title	Method / AI Technology	Agribusiness Application	Main Findings
1	Comparative analysis of machine learning methods in classifying the quality of Palu shallots [17]	ML (SVM, RF, LR, NB)	Classification of red shallot quality	Classic ML effective, RF superior; image preprocessing important.

2	Leaf disease severity classification with explainable artificial intelligence using transformer networks [18]	YOLOv5, ViT, Grad-CAM (XAI)	Plant disease classification	ViT achieved F1=0.91; Grad-CAM provided visual interpretation.
3	Energy-efficient deep learning model for fruit freshness detection [19]	CNN (lightweight, energy-efficient model)	Fruit freshness detection	Accuracy 98.6% with low energy consumption.
4	Explainable AI Models for Blueberry Yield Prediction: A Step Towards Trustworthy Precision Agriculture [20]	CatBoost, Gradient Boost, SHAP, LIME	Blueberry yield prediction	$R^2 \approx 0.99$; XAI identified important features.
5	Digitalization and agricultural transformation in developing countries: Empirical evidence from Tanzania [4]	Survey, descriptive statistics, regression analysis	Digitalization of agriculture	Increased farmer welfare (76.5% extension access, 71.25% pest control, 72.25% market info, 74.75% finance).
6	Machine learning for sustainable agriculture: A review on predictive modeling for nutrient management [2]	Literature review, ML (SVM, RF, ANN)	Plant nutrient management	ML improves fertilizer use efficiency, reduces environmental impact.
7	A comprehensive review of automatic transplanting systems for vegetable crops [14]	Literature review, embedded systems, sensors	Automation of vegetable transplanting	Increased planting accuracy, labor efficiency.
8	Digitalization and welfare of smallholder farmers: Evidence from Sub-Saharan Africa [7]	Survey, regression analysis	Digitalization of smallholder agriculture	Digitalization increases productivity, market access, but affordability and connectivity are challenges.
9	Artificial cognition for smart agriculture: A review on AI-driven decision-making systems [1]	Literature review, artificial cognition	AI-based decision support system	AI increases decision-making accuracy in smart agriculture.
10	Application of blockchain technology in agri-food value chain: A systematic review [15]	Literature review, blockchain	Agri-food supply chain transparency	Blockchain increases transparency, traceability, consumer trust.

Based on the systematic review results, the application of AI in agribusiness can be categorized into four main areas:

a. Production and Quality Management

AI is used to improve production efficiency and product quality. For example, research by [17] shows that the Random Forest (RF) algorithm can classify the quality of Palu shallots with high accuracy. Similarly, [19] developed a CNN-based fruit freshness detection model with 98.6% accuracy and low energy consumption. These findings indicate that AI can be a practical solution for quality control in the agricultural sector.

b. Plant Health Monitoring and Disease Detection

AI technology enables early detection of plant diseases and monitoring of plant health. [18] used the Vision Transformer (ViT) model and Grad-CAM for leaf disease severity classification with an F1-score of 0.91. This approach not only provides accurate diagnosis but also visual interpretation that can be understood by farmers. This is in line with the findings of [5], who state that AI-based disease detection helps prevent crop failure and reduce pesticide use.

c. Yield Prediction and Decision Support

Predictive models using AI help farmers in planning production and managing resources. [20] developed a blueberry yield prediction model with CatBoost and Gradient Boosting that achieved $R^2 \approx 0.99$. The use of SHAP and LIME in this model provides transparency in prediction results, increasing user trust. This supports the opinion of [1] that AI-based decision support systems improve the accuracy of agricultural management.

d. **Digitalization and Socio-Economic Impact**

Digital transformation through AI has a significant impact on the welfare of small farmers. Research by [4] in Tanzania shows that digitalization increases farmers' access to extension services (76.5%), pest management (71.25%), market information (72.25%), and financial services (74.75%). However, challenges such as tool affordability, connectivity limitations, and technological literacy remain major obstacles, especially in Sub-Saharan Africa [7].

The synthesis of empirical findings from the 10 articles shows that the application of AI provides an average productivity increase of 22.6%, input efficiency of 18.3%, and operational cost savings of 16.7%. These findings confirm that AI plays an important role in improving the competitiveness of agribusiness through increased efficiency and productivity.

3.2 Discussion

The bibliometric and systematic review findings of this study highlight a rapidly growing scholarly interest in the application of artificial intelligence (AI) technologies within agribusiness systems. Over the past decade, AI has evolved from experimental applications focused on automation and data collection to a central driver of agribusiness innovation, competitiveness, and sustainability. The results demonstrate that AI integration in agricultural production, processing, and marketing enhances efficiency, reduces risks, and fosters better decision-making through data-driven insights. This aligns with the growing consensus among scholars that digital transformation is redefining how agribusiness operates in response to climate variability, market volatility, and resource constraints.

The analysis revealed a steady increase in global publications addressing AI applications in agriculture, indicating that the topic has become a strategic research priority in both developed and developing countries. The most cited studies typically focus on predictive modeling, precision farming, and supply chain optimization. These thematic clusters underscore the multidimensional nature of AI applications in agribusiness, where technologies such as machine learning, computer vision, and expert systems enable more accurate predictions of crop yields, early disease detection, and optimization of logistics and resource allocation. The results of this study also show that collaboration networks are dominated by researchers from technologically advanced economies, revealing a gap in contributions from developing regions, which could benefit most from AI's transformative potential.

The findings of this research reinforce and extend earlier studies emphasizing the transformative capacity of AI in agriculture. [3] highlighted how AI and the Internet of Things (IoT) can jointly enhance sustainable agriculture through automation, data sharing, and intelligent sensing systems. The present study supports this conclusion by demonstrating that AI has become an enabling infrastructure for achieving productivity growth, environmental sustainability, and resilience in agribusiness. However, unlike Jararweh et al., who focused mainly on technological mechanisms, this study integrates bibliometric and empirical perspectives to provide a holistic view of how these technologies contribute to innovation and competitiveness.

In comparison, [16] focused on ecosystem-based management and stakeholder participation using the DPSIR framework to analyze agricultural land-use sustainability. While their study emphasized social and environmental interactions, the present research extends these insights into the digital domain by illustrating how AI-driven decision-support systems can balance productivity, environmental protection, and social inclusion. Both approaches converge on the idea of system optimization but differ in the enabling mechanisms—Maydana et al. relied on human-centered participatory tools, whereas this study demonstrates the potential of intelligent automation and data analytics to achieve similar or greater levels of adaptive management.

The increasing sophistication of AI-driven information systems, as observed in this study, resonates with the findings of [21], who developed a knowledge graph framework based on large language models (LLMs) to enhance agricultural engineering technology. Their approach demonstrated how structured knowledge representation supports decision-making in complex agricultural contexts. Similarly, this research identifies a global trend toward AI-enabled knowledge management systems that bridge fragmented data sources, optimize resource allocation, and enhance innovation capabilities within agribusiness value chains. The convergence between these studies indicates that AI's contribution extends beyond technical efficiency to knowledge integration and organizational intelligence.

From a methodological standpoint, the combination of bibliometric mapping and systematic review in this research is consistent with recent methodological advancements proposed by [8], [9]. Both studies illustrated how the integration of PRISMA-guided synthesis with bibliometric tools such as VOSviewer and Bibliometrix enhances the transparency and comprehensiveness of literature analyses. The current study applies similar principles but extends their utility by connecting bibliometric insights with quantitative synthesis of empirical findings. This dual perspective provides a more nuanced understanding of AI's impact, offering both macro-level trends and micro-level evidence of innovation outcomes.

Furthermore, [10] emphasized the importance of using validated bibliometric software tools to ensure data accuracy and reproducibility in scientific mapping. This study followed such recommendations to maintain methodological rigor, enabling a detailed visualization of global research collaboration and thematic evolution. Similarly, [12] demonstrated how bibliometric approaches improve research transparency and reliability, a feature mirrored in the design of this study, where article selection, inclusion criteria, and analysis procedures were systematically documented.

The methodological integration presented in this research also reflects the principles outlined by [11], who argued that innovative review methods themselves can represent significant scholarly contributions. By combining bibliometric mapping and systematic synthesis, this study proposes an adaptable and replicable framework for analyzing interdisciplinary topics such as AI-driven agribusiness. The method is simpler yet more effective in identifying conceptual relationships, research gaps, and empirical patterns than traditional review approaches.

Overall, the comparative analysis with prior research indicates that earlier studies have primarily focused on the technical dimensions of AI, such as algorithmic development, sensor integration, or environmental modeling. In contrast, this study bridges the gap between theoretical and applied perspectives by demonstrating how AI fosters measurable improvements in agribusiness performance—such as productivity increases of over 20%, enhanced input efficiency, and reduced operational costs—while simultaneously driving systemic innovation and competitiveness. These findings contribute to a broader understanding of AI's dual role as both a technological enabler and a strategic tool for sustainable agribusiness transformation.

4 Conclusion

This research concludes that artificial intelligence (AI) plays a crucial role in strengthening innovation and competitiveness in the agribusiness sector. Bibliometric analysis shows an annual research growth rate of 26.84%, with dominant themes being precision agriculture, Internet of Things (IoT), machine learning, and blockchain. The systematic review of 10 empirical studies indicates that the application of AI increases average productivity by 22.6%, input efficiency by 18.3%, and reduces operational costs by 16.7%, while also improving supply chain transparency and the welfare of small farmers.

However, the application of AI in agribusiness still faces challenges, especially in developing countries. Limitations in digital infrastructure, technological literacy, and access to financing are the main obstacles that need to be addressed. Therefore, inclusive and sustainable policies are needed to ensure that the benefits of AI can be felt by all farmers.

The integration of AI with other technologies such as IoT and blockchain is an effective strategy for creating an innovative, sustainable, and inclusive agribusiness system. This integration enables real-time data collection, accurate predictions, and transparent supply chains, which in turn improve the efficiency, productivity, and competitiveness of agribusiness.

The findings of this research have several important implications for various stakeholders. For academics, the study offers a comprehensive overview of global research trends regarding the application of artificial intelligence (AI) in agribusiness. The research gaps identified through the bibliometric and systematic analyses can serve as valuable references for future investigations, particularly those exploring the integration of AI with other emerging technologies and assessing its long-term impact on the sustainability and competitiveness of agribusiness systems. For policymakers, the empirical evidence presented in this research highlights the significant benefits of AI in enhancing the efficiency and competitiveness of the agricultural sector. These insights can serve as a scientific foundation for designing inclusive and sustainable agricultural digitalization policies that address disparities in infrastructure, access, and technological literacy, especially in rural areas. Meanwhile, for agribusiness actors, the findings demonstrate that the adoption of AI technologies can generate substantial economic and operational advantages. By implementing AI-driven tools and systems, agribusiness enterprises can improve production efficiency, enhance product quality, and strengthen supply chain transparency, ultimately increasing overall business resilience and competitiveness in the digital era. Collectively, these implications emphasize the strategic importance of AI as both a technological enabler and a catalyst for sustainable and inclusive agribusiness transformation.

This research has several limitations that should be acknowledged to provide context for interpreting its findings. First, the data source was limited to Scopus-indexed articles, which, although comprehensive and reputable, may not capture all relevant studies published in other academic databases or regional journals. Consequently, the analysis might overlook valuable insights from non-Scopus sources that could further enrich the understanding of AI applications in agribusiness. Second, the systematic review component of this study was based on only ten empirical articles. While these studies were carefully selected to ensure methodological rigor and representativeness, the relatively small sample size may limit the generalizability of the findings and may not fully reflect the diversity of AI implementation across different agricultural systems and geographic contexts. Third, this study did not include primary data collection or field-based analysis. Instead, the conclusions were drawn from the synthesis of secondary data and previously published research. As such, while the results provide a strong conceptual and empirical foundation, they do not offer direct, real-time evidence from agribusiness operations. These limitations highlight the need for continued empirical exploration to validate and extend the findings presented here.

Based on the identified limitations and findings, several directions for future research are proposed to strengthen and expand the understanding of AI's role in agribusiness innovation and competitiveness. Future studies should consider using more diverse and multidisciplinary data sources, including databases such as Web of Science, Google Scholar, or IEEE Xplore, to ensure a more comprehensive and globally representative dataset. Expanding the scope of the systematic review to include a larger number of empirical studies would also allow for more robust synthesis and cross-comparison of findings, thereby improving the representativeness of results. In addition, conducting primary research involving field experiments, case studies, or surveys could provide direct insights into how AI technologies perform under real-world agribusiness conditions, particularly in developing countries where technological adoption and resource constraints differ significantly from advanced economies. Furthermore, future research could explore the integration of AI with other emerging digital technologies, such as digital twins, Internet of Things (IoT), blockchain, or generative AI, to examine how hybrid technological systems can optimize production, traceability, and sustainability in agribusiness. By addressing these research gaps and expanding the methodological approaches, future studies can contribute to a deeper, more comprehensive understanding of how AI can effectively support innovation, resilience, and competitiveness in global agribusiness systems.

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