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Artificial intelligence in agriculture: Unveiling trends in supply chain advancements

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ABSTRACT

Farmers, consumers, and intermediaries such as processors, traders, and wholesalers form essential components of the agricultural supply chain (ASC). This paper presents a bibliometric analysis of Artificial Intelligence (AI) methodologies contributing to Agriculture 4.0 based on publications retrieved from the Scopus database from the years 2000–2021. Using multiple correspondence analysis and topic dendrograms, key research trends are identified through keyword clustering. The study examines global collaboration in AI-driven agriculture and explores AI and machine learning (ML) applications across pre-production, production, and post-harvest stages. By mapping thematic developments, this research provides insights into the transformative role of AI in modernizing ASCs.

1. Introduction

Agriculture is an essential sector for the economic growth of every nation [1]; Kashyap and Shukla, 2022, [2]. The development of science and technology has driven the evolution of agricultural practices through four distinct phases, from Agriculture 1.0 to Agriculture 4.0. Initially, Agriculture 1.0 relied heavily on manual labor and simple hand tools [3]. The transition to Agriculture 2.0 introduced mechanization, with tractors reducing the need for physical labor, along with the application of herbicides and fertilizers to enhance crop protection and productivity. Agriculture 3.0, emerging in the late 20th century, marked the integration of early digital technologies, such as guiding systems, GPS, and monitoring tools, to improve precision and efficiency in farming [4]. Finally, Agriculture 4.0 represents the current era, characterized by the integration of advanced, data-driven technologies like the Internet of Things (IoT), robotics, AI, blockchain, and big data analytics, aimed at achieving more intelligent and sustainable agricultural practices [5]. The agriculture industry has a direct impact on the development of an individual's health as well as a nation's wealth; thus, it is crucial to track the journey of agricultural goods from farm to fork.

In addition to tackling the issue of sustainability, agricultural businesses have a tremendous duty to provide safe and secure food [6]. According to Costa et al. [7] and Kamble et al. [8], traceability becomes even more crucial when considering the security and trustworthiness perceived by consumers in the ASC. Agricultural economics and management scholars were the first to propose the notion of the supply chain in agriculture [9,10]. The names ASC, FSC, agricultural value chain, and food value chain are interchangeable when referring to related parts of this significant sector. Like other supply chains, the ASC includes stages such as pre-production, manufacturing, storage, processing, retail, and distribution prior to reaching the customers [11–13]. In contrast to other supply chains, ASC's complexity necessitates improved operational level coordination as it deals with perishable goods [8,14,15]. However, the study on this topic is not restricted to the disciplines of agricultural sciences and agricultural economics; it also encompasses business management disciplines such as operations management and supply chain management. Agricultural supply chain management (ASCM) examines the relationship between the supply of raw materials, manufacturing processes, logistics of goods, and distribution to retailers and consumers [16,17]. Agriculture's traditional practices and supply chain inefficiencies have significantly impacted the sector's overall performance. Lehmann et al. [18] argue that agriculture must embrace ethical and sustainable practices. Several authors have concurred that the agri-food business is being negatively impacted and unable to

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function up to its potential due to inefficiencies in various phases of the ASC, including inadequate infrastructure, poor logistics, lack of traceability, and outdated management practices. These inadequacies disrupt the flow of goods, reduce transparency, and hinder the adoption of technology, ultimately affecting productivity and sustainability [19–21]. Lehmann et al. [18] recommend the use of technologies such as IoT, blockchain, ML, and AI to increase the efficiency of this field. However, the field of ASC is too complex to be managed using the strategies previously used. In addition, the exponential growth of the global population necessitates the use of the most advanced data-driven technology. Moreover, worldwide internet connectivity has boosted the quantity and diversity of data in recent years [22–24]. The use of AI and ML is strongly related to the availability of data; thus, it may be possible to create a model that may assist the ASC in resolving its issue [25–28]. In addition, such a model may aid in recognizing market demand and alert agricultural companies to regularly change their approach. According to Li and Liu [29], this transformation will provide new possibilities and trends in the supply chain industry [30,31]. The ASC is undergoing a significant transformation with the integration of AI and ML, which are reshaping production efficiency, decision-making, and resource optimization. While numerous studies have explored AI-driven innovations in agriculture, a systematic understanding of research trends, key thematic developments, and collaborative networks remains limited. This study aims to bridge this gap through a comprehensive bibliometric analysis of AI methodologies in ASC, providing an overview of how research in this domain has evolved over time. By leveraging multiple correspondence analysis and topic dendrograms, the paper uncovers distinct keyword clusters that indicate emerging research trajectories. Additionally, advanced visual tools, such as tree maps and word clouds, offer a structured view of the thematic focus areas within AI applications in agriculture. Rather than attributing research progress to nations as singular entities, this study examines patterns of international collaboration, highlighting the networks of researchers and institutions driving AI advancements in agriculture. By analyzing co-authorship and citation networks, the study provides insights into how knowledge is shared and developed globally, identifying influential contributors and research hubs.

The bibliometric analysis is based on data retrieved from the Scopus database, with search criteria encompassing key terms related to ASC and AI, including "Supply Chain," "Agriculture," "Machine Learning," "Industry 4.0," "Deep Learning," "IoT," and "Artificial Neural Networks." The search was restricted to articles and conference proceedings published in English between 2000 and 2021. The methodology involves data preprocessing, filtering, and clustering using multiple correspondence analysis, followed by visualization techniques such as thematic mapping and co-occurrence analysis to derive meaningful patterns.

This multifaceted approach distinguishes the paper from previous works, providing both a broad and granular understanding of AI's role in transforming ASCs. The present investigation addresses the following research questions (RQ):

(RQ1) what is the trend of publication, and who are the most influential researchers and authors in the last two decades?
(RQ2) what are the major research themes, keywords, and the most promising sources of publication around ASC?
(RQ3) what is the trend of research collaboration and which countries are the leading researchers in this field?

This article has been further organized into six sections. Section 2 consists of the similar studies followed by Section 3 which contains the methodology. Bibliometric analysis has been carried out in Section 4, followed by an elaborated discussion in Section 5. Eventually, Section 6 concludes the paper with some relevant implications and future perspectives of the research.

2. Review background

In recent years, there has been a notable surge in research focusing on various aspects of agriculture, particularly in the areas of circular economy within ASC, food waste quantification, and food security. Additionally, the integration of cutting-edge technologies such as the IoT, AI, and ML into the agricultural sector has garnered significant scholarly attention. For instance, Jha et al. [32] and Dokic et al. [33] explored the use of sensors and data analytics to automate agricultural operations, while Patricio and Raider [34] investigated the application of AI and computer vision in precision agriculture to enhance crop yield and quality. These studies mark the beginning of sophisticated agricultural research, emphasizing the profound influence of technological integration on the future of the industry.

Furthermore, Barbosa [13] conducted a scientometric analysis to examine the environmental implications of the ASC, identifying gaps and potential research areas. The impact of COVID-19 on environmental parameters has been studied by Casado-Aranda et al. [35] through bibliometric analysis, highlighting the role of scientific research in understanding and mitigating pandemic-related challenges. In terms of operational efficiency, blockchain technology has been examined by Niknejad et al. [36] for its role in empowering stakeholders and optimizing processes in the food and agricultural sectors. Additionally, Bouzembrak et al. [37] used IoT in a bibliometric analysis to explore the connections between nations, authors, and topics in the food industry. To further justify the necessity of this literature review and to clarify the importance of our contribution, Table 1 provides a synopsis of previous systematic literature reviews (SLRs) and bibliometric studies on the subject. Notably, Gajdic et al. [38] offered a thorough analysis of the literature on collaboration, trust, and performance in the ASC from 2003 to 2020, aiming to uncover theoretical foundations and organize the existing body of research. Armenta-Medina et al. [39], Santana et al. [40], Malanski et al. [41], and Yadav et al. [42], whose work provides valuable insights into current challenges and opportunities within the agricultural industry, proposing solutions to improve productivity, reduce waste, and foster sustainable practices.

In the context of ML's relevance to agriculture, Martinho et al. [43] conducted a literature review to investigate the connection between ML and food security in the framework of Agriculture 4.0. Their study underscores the potential benefits of ML in addressing food security challenges through a systematic review and bibliometric evaluation. Similarly, Sadraei et al. [44] performed a bibliometric and thematic analysis of 163 articles on food waste in production processes, employing a circular economy framework to explore potential solutions to the issue. Santeramo [45] also provided a comprehensive review of circular and green economy literature, with a focus on agri-food systems and supply chains. Further expanding the discussion on ML, Jin and Xu [46–53] have made notable contributions through their application of neural networks and other ML models across various industries. Their work includes forecasting prices of key energy commodities like crude oil, heating oil, and natural gas [46], and applying neural networks to predict wholesale prices of green grams in the agricultural sector [47]. They extended their research into environmental economics by predicting carbon emission allowance prices using neural networks [48]. Additionally, they employed Gaussian process regression to forecast the wholesale prices of yellow corn [49], demonstrating the applicability of ML in agricultural commodities.

In the industrial domain, Jin and Xu [50] applied ML to forecast regional steel price indices, while their study on contemporaneous causality among steel price indices [53] advanced understanding of price dynamics in the steel industry. Their further work on pre-owned housing price indices [51] and regional steel prices for east China [52] showcases the versatility of ML in various market predictions.

Recent research has increasingly focused on the application of AI and ML across various sectors, highlighting their transformative potential in improving efficiency, forecasting, and decision-making. Studies have

Table 1
List of similar studies by different authors.

Author(s) & Year	Sector/Focus	Key Contribution
Jha et al. [32]	Agriculture	Explores the use of sensors and data analytics to automate agricultural operations.
Dokic et al. [33]	Agriculture	Focuses on sensor integration and data analytics in automating processes within agriculture.
Patricio & Raider [34]	Precision Agriculture	Studies AI and computer vision in precision agriculture for enhancing crop yield and quality.
Barbosa [13]	Environmental Science	Conducts a scientometric analysis of environmental impacts within the ASC.
Casado-Aranda et al. [35]	Environmental Science	Uses bibliometric analysis to investigate the impact of COVID-19 on environmental parameters.
Niknejad et al. [36]	Blockchain in Agriculture	Investigates the use of blockchain technology to empower stakeholders and optimize operations in the food and agricultural sectors.
Bouzembrak et al. [37]	IoT in Agriculture	Utilizes bibliometric analysis to investigate IoT adoption and thematic correlations in the food industry.
Gajdic et al. [38]	ASC	Provides a comprehensive analysis of collaboration, trust, and performance in the ASC between 2003 and 2020.
Armenta-Medina et al. [39]	Agriculture	Explores key challenges and opportunities in agriculture, focusing on technology integration.
Santana et al. [40]	Agriculture	Focuses on enhancing productivity and sustainable practices in agriculture.
Malanski et al. [41]	Agriculture	Discusses minimizing waste and promoting sustainable practices in agriculture.
Yadav et al. [42]	Agriculture	Proposes solutions to key challenges faced by the agriculture sector, including waste minimization and productivity enhancement.
Martinho et al. [43]	Food Security	Examines the relationship between ML and food security through systematic reviews and bibliometric evaluation.
Sadraei et al. [44]	Circular Economy in Agriculture	Analyzes scholarly articles on food waste using circular economy frameworks, providing insights into the current state of research and the potential to address waste.
Santeramo [45]	Circular Economy in Agri-Food Systems	Reviews circular and green economy concepts, focusing on agri-food systems and their associated supply chains.
Jin & Xu [46]	Energy	Utilizes neural networks to forecast prices of energy commodities.
Jin & Xu [47]	Agriculture	Applies neural networks to forecast green gram prices, demonstrating ML's role in agricultural pricing.
Jin & Xu [48]	Environmental Economics	It uses neural networks to predict carbon emission allowance prices, contributing to environmental market insights.
Jin & Xu [49]	Agriculture	Employs Gaussian process regression to forecast yellow corn prices, showcasing ML in agricultural commodities.
Jin & Xu [50]	Industrial Markets	Leverages ML to predict steel price indices for northeast China, demonstrating the utility of predictive models in industrial markets.
Jin & Xu [51]	Real Estate	Uses Gaussian process regression to forecast pre-owned housing price indices, applying ML to real estate forecasting.
Jin & Xu [52]	Industrial Markets	Applies ML in predicting regional steel price indices for east China, extending ML's applicability in industrial market analysis.
Jin & Xu [53]	Industrial Markets	Investigates price dynamics in steel markets using ML, advancing the understanding of steel product price correlations.

explored how these technologies are used for predictive modeling, from commodity pricing in agriculture to energy and industrial markets. Such advancements demonstrate the adaptability and precision of AI and ML in addressing complex challenges, fostering innovation, and enabling more sustainable practices. Building on this foundation, the study presents a comprehensive bibliometric analysis of AI's contributions to Agriculture 4.0. By identifying key research trends, clustering thematic areas, and examining international collaborations, this study enhances the understanding of AI's transformative role across different stages of the ASC, offering insights that can inform future research and practical applications.

3. Methodology

A literature review is essentially an approach that assists in the comprehension of any scientific field via the examination of various scientific publications [54–56]. One such technique is the systematic literature review (SLR) method, which is generally used for management research, whereas bibliometric analysis, as defined by Raghuram et al. [57], is an interdisciplinary science that integrates mathematics and statistics and aids in the quantitative analysis of scholarly literature. This technique is usually referred to as science mapping since it analyses bibliometric information by mapping the structure and development of any scientific topic. In addition, it covers the relationship between various authors and sources, as well as international collaborations.

The strength of bibliometric analysis lies in its ability to objectively and systematically identify various features within the literature [58]. It facilitates the examination of relationships between keywords, citation patterns (including authors, sources, and countries), and overall research trends. This approach provides insights into the distribution patterns of existing literature, the current state of scientific inquiry within a field, and the evolution of research domains over time. The results are often represented through visualizations akin to geographic maps, aiding in knowledge structuring and comprehension [59–61]. Bibliometric analysis employs multiple quantitative methods, including co-citation analysis, co-occurrence analysis, citation network analysis, and performance evaluation, each offering distinct insights into research trends. Science mapping, as described by Boyack and Klavans [62], integrates visualization and classification techniques to systematically represent the intellectual structure of a research field. This methodological approach provides a transparent, replicable, and structured assessment of scholarly work, allowing researchers to analyze citation networks, collaboration patterns, and keyword trends. The two primary applications of bibliometric analysis are performance analysis—which evaluates the impact and productivity of publications, authors, and journals—and science mapping, which visualizes the structure and dynamics of a research area [63–65]. In general, bibliometric analysis follows a structured five-step process, as shown in Fig. 1 [66]. The first step, *Design of Study*, involves defining research questions, selecting relevant keywords, and choosing an appropriate database to ensure comprehensive data collection. Establishing a clear research objective is essential to selecting the most suitable bibliometric approach for addressing the study's goals. The second step, *Collection of Data*, entails gathering relevant documents from the selected database. This process includes data loading and conversion to ensure compatibility with

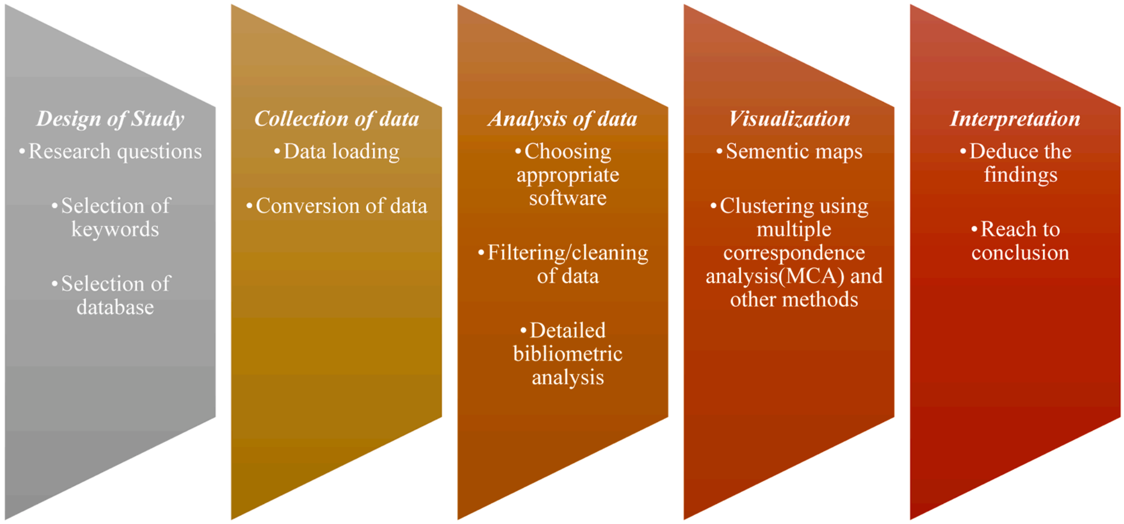

Fig. 1. Different stages of bibliometric analysis [66].

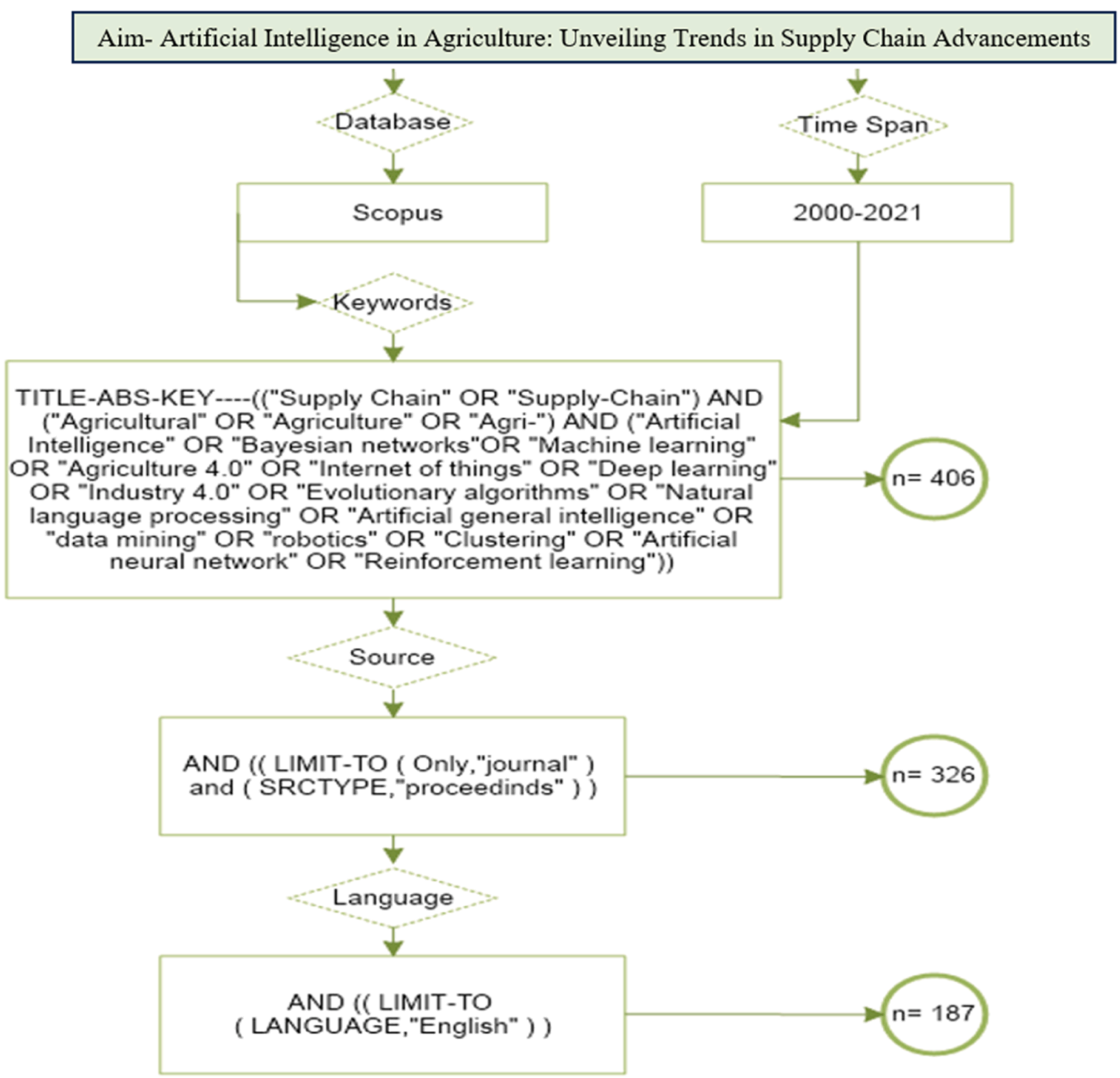

Fig. 2. Screening methodology.

bibliometric analysis tools. At this stage, it is crucial to refine the dataset by filtering out irrelevant or duplicate documents to maintain data integrity. The third step, *Analysis of Data*, focuses on data processing and detailed bibliometric examination. This involves selecting appropriate software, cleaning the dataset, and conducting a thorough bibliometric analysis. Filtering and preprocessing play a critical role in eliminating redundant entries, ensuring the accuracy of citation analysis, co-authorship networks, and research trends. As noted by White and McCain [67] and McCain [68], early bibliometric studies often relied on multidimensional scaling techniques for data analysis; however, these methods have largely been replaced by network analysis visualization, offering more precise correlations between documents, authors, keywords, and journals [69]. The fourth step, *Visualization*, translates processed data into meaningful representations. Using techniques such as semantic mapping and clustering through multiple correspondence analysis (MCA) and other advanced methods, researchers can identify relationships between keywords, authors, and publications. These visualizations create a network map of the research field, enabling the identification of emerging trends and collaborations. The last step, *Interpretation,* involves deducing key findings from the bibliometric analysis and drawing conclusions. The insights gained from the semantic maps and clustering results provide a comprehensive understanding of emerging trends, research gaps, and influential contributions in the domain. By integrating these findings, researchers can offer valuable implications for future studies and policy directions.

This research seeks to investigate the use of open-source software and Bibliometrix, an R package for bibliometric analysis, in bibliometric analysis. The methodology used a combination of keywords related to the ASC and AI, including "Supply Chain" or "Supply-Chain", "Agricultural" or "Agriculture" or "Agri", and "AI" or "Bayesian networks" or "ML" or "Agriculture 4.0″ or "IoT" or "Deep learning" or "Industry 4.0″ or "Evolutionary algorithms" or "Natural language processing" or "Artificial general intelligence" or "data mining" or "robotics" or "Clustering" or "Artificial neural network" or "Reinforcement learning". The search was limited to papers published between the years 2000 and 2021 and written in English, and the results were restricted to articles and proceedings published in journals. Furthermore, the search was limited to abstracts, titles, and keywords only. The detailed information about the inputs to the bibliometric analysis is mentioned in Fig.2.

4. Bibliometric analysis

The results of bibliometric analysis start with in-depth bibliometric data that include various authors, publications, and nations that have shown considerable interest in this topic. Following that, a few criteria are examined to provide answers to the research questions mentioned in the introductory section. These criteria include (1) the number of yearly scientific publications, (2) the type of research paper, (3) the sources of publication, (4) the growth of the source over time, (5) the number of research papers written by each author, (6) the use of keywords, (7) the topic dendrogram, (8) the citation of the research paper, (9) country-based publication, and (10) international collaboration. The first RQ has been answered using the following criteria: quantity of research paper, research paper type, sources of publication, and annual scientific publications. Similar characteristics, such as the author's chosen keywords and the subject dendrogram, were utilized to respond to the second RQ. The third RQ has been addressed using the remaining variables.

4.1. Annual distribution of publications

The yearly distribution of papers over the last two decades is illustrated in Fig. 3. The use of IoT, robotics (including drones), and AI in smart agriculture led to a noticeable increase in publications between 2014 and 2018, with a rise from 8–10 articles per year during this period. This growth accelerated significantly after 2018, reaching 40–50 articles annually, reflecting a sharp and sustained increase in research activity in this field [70–83].

The dataset for this study comprises 187 publications retrieved from the Scopus database, including 147 scientific articles, 35 review papers, three conference papers, and two editorials or brief surveys (see Table 2). The search covered literature published between 2000 and 2021, using a combination of AI and ASC-related keywords (as detailed in the methodology section). In the early 2000s, research on AI applications in agriculture was limited, but a significant rise in publications in recent years indicates growing scholarly interest in the field. The

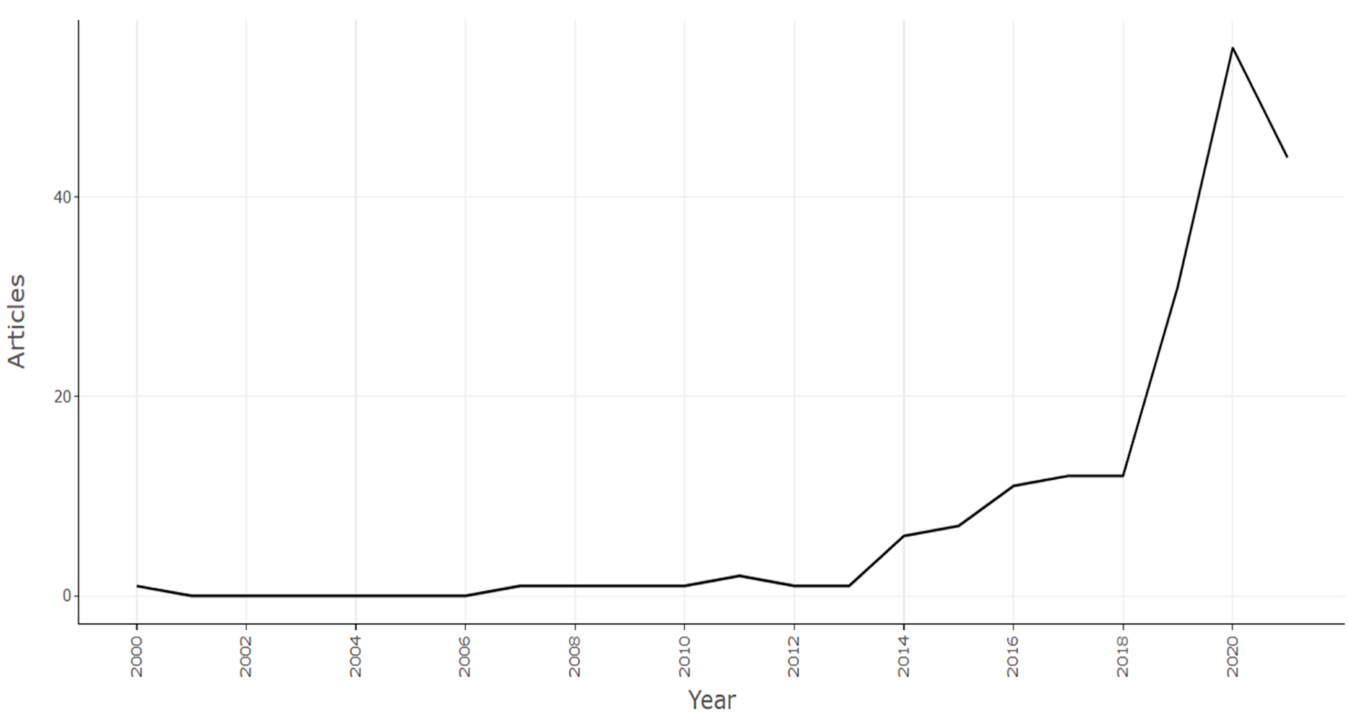

Fig. 3. Annual distribution of publications over last two decades.

Table 2
Main Information about the papers extracted from the scopus database.

Aspects	Output
KEY INFORMATION	
Sources (Journals, Books, etc.)	128
Research Papers	187
Average publication (yearly)	2.4
Average citations (per publication)	19.24
Average citations (per year per publication)	5.343
References	11,940
TYPES OF RESEARCH PAPERS	
Article	147
Conference paper	3
Editorial	1
Review	35
Short survey	1
KEYWORDS	
Keywords Plus (ID)	1484
Author's Keywords (DE)	665
AUTHORS	
Authors	619
Author Appearances	693
Author (single-authored research paper)	14
Authors (multi-authored research paper)	605
COLLABORATION OF AUTHORS	
Single-authored research paper	14
research paper per Author	0.302
Authors per research paper	3.31
Co-Authors per research paper	3.71
Collaboration Index	3.5

retrieved publications are dispersed across 128 different sources, reflecting a diverse research landscape. Regarding keyword analysis, Keywords Plus (ID)—which consists of words or phrases appearing frequently in article titles but not necessarily assigned as keywords by authors [84,85] is approximately eight times greater than the number of research papers. This suggests that commonly discussed themes in AI-driven agricultural research extend beyond explicitly assigned keywords, highlighting the evolving nature of terminology in the field. The authorship trends indicate that, on average, each author contributes to 0.302 publications, while the average number of authors per publication is 3.31. The proportion of single-authored papers is below 2 %, underscoring the dominance of collaborative research in this domain. The collaboration index, which measures the ratio of total authors to total multi-authored publications (Elango and Rajendran, 2012), stands at 3.71, reinforcing the prevalence of multi-author contributions in AI-driven agricultural studies.

Early in the twenty-first century, only a limited number of publications explored the intersection of agriculture with AI, IoT, or ML. Using the keywords "agriculture," "artificial intelligence," "Internet of Things," and "machine learning," a bibliometric analysis reveals that, as shown in Fig. 4, there was a sharp increase in publications over the past three years, indicating a growing research focus in this domain. A cluster of specialized journals has emerged, with Computers and Electronics in Agriculture, IEEE Access, and the Journal of Cleaner Production among the most prolific contributors. The top ten journals publishing in this field are presented in Fig. 5. Despite this growing interest, the highest number of publications by a single journal is nine, followed by six, five, and three, which reinforces the observation that this topic remains relatively underexplored. Figs. 4 and 5 provide quantitative insights into journal contributions, while Fig. 6 focuses on qualitative attributes, highlighting the articles with the highest H-index values. Considering the hypothesis proposed by Bradford in 1934 [86], cited by [87–89], which states that the majority of research on a specific topic is concentrated in a limited number of core journals, the remaining journals tend to either touch upon the topic peripherally or maintain a broader editorial scope. Based on Bradford's theory, the core journals in this field are identified in Fig. 7.

Computers and Electronics in Agriculture, IEEE, and Biosystems Engineering are, in nearly every way, the premier publications in the area that address agriculture and advanced technologies like AI, ML, and IoT under one roof. This section partly addresses the first RQ, with the remainder covered in the next section.

4.2. Authorship evaluation

This study contains a total of 619 authors, making it a highly

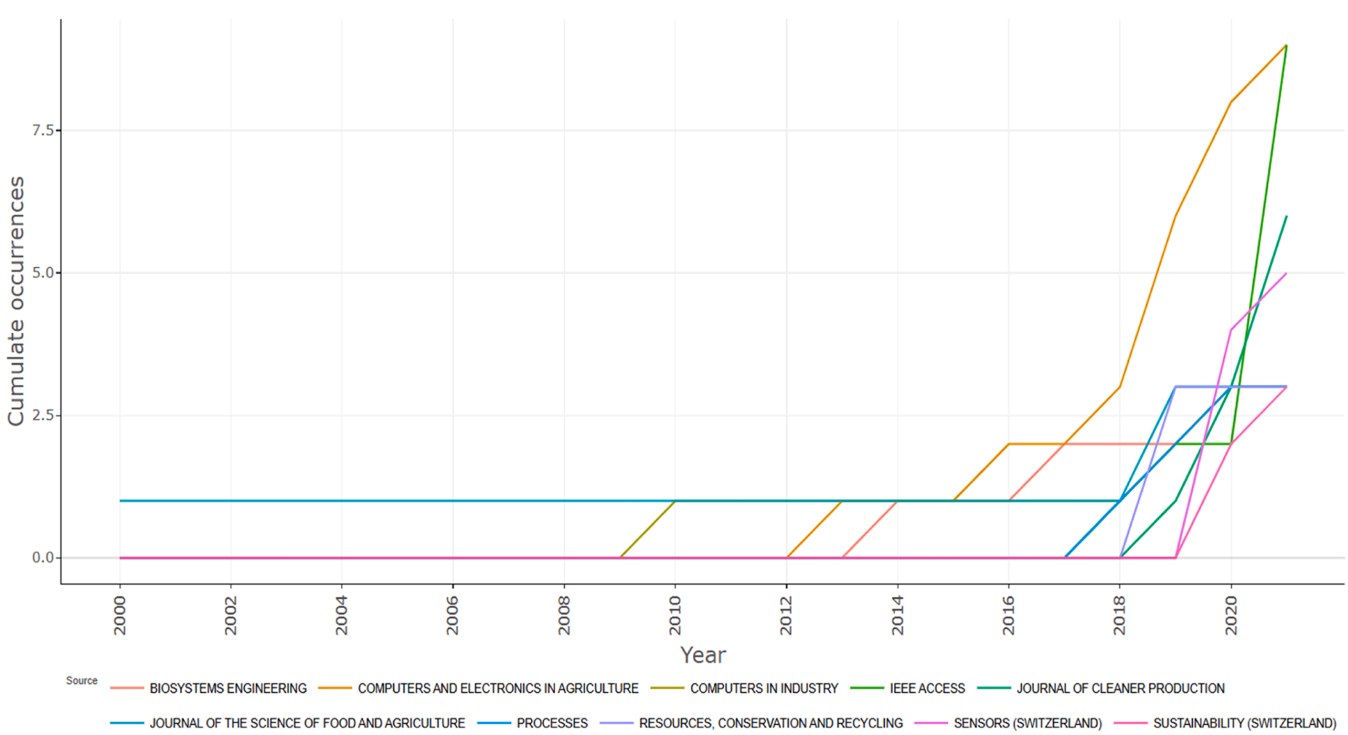

Fig. 4. Growth of Journals in the last two decades.

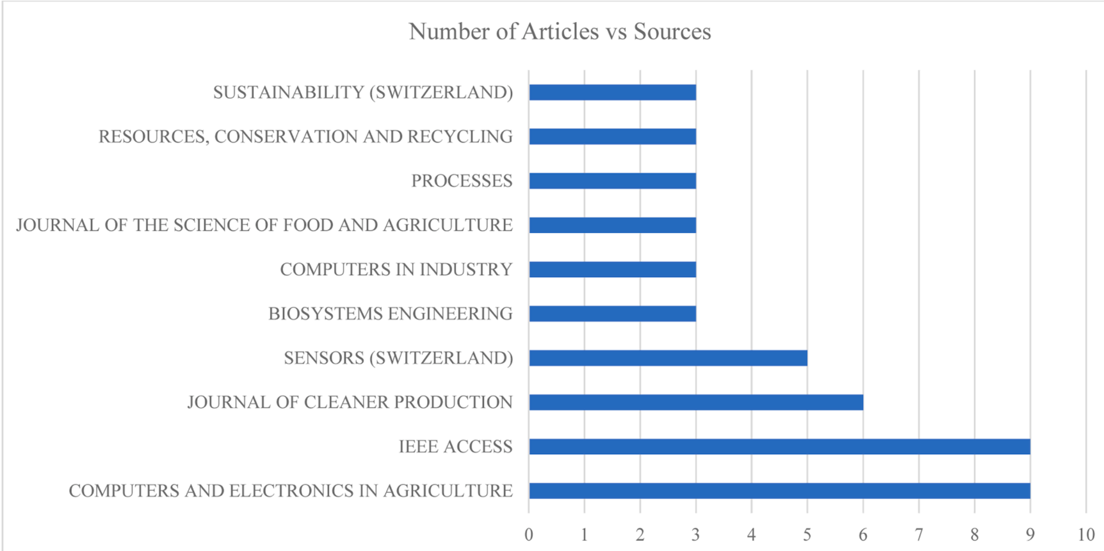

Fig. 5. List of top ten relevant journals.

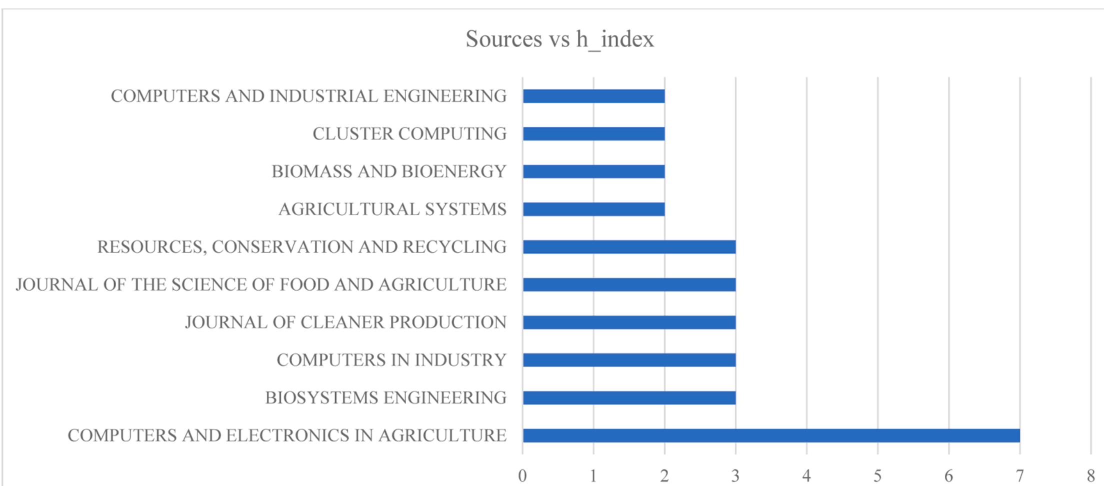

Fig. 6. List of top ten impactful journals.

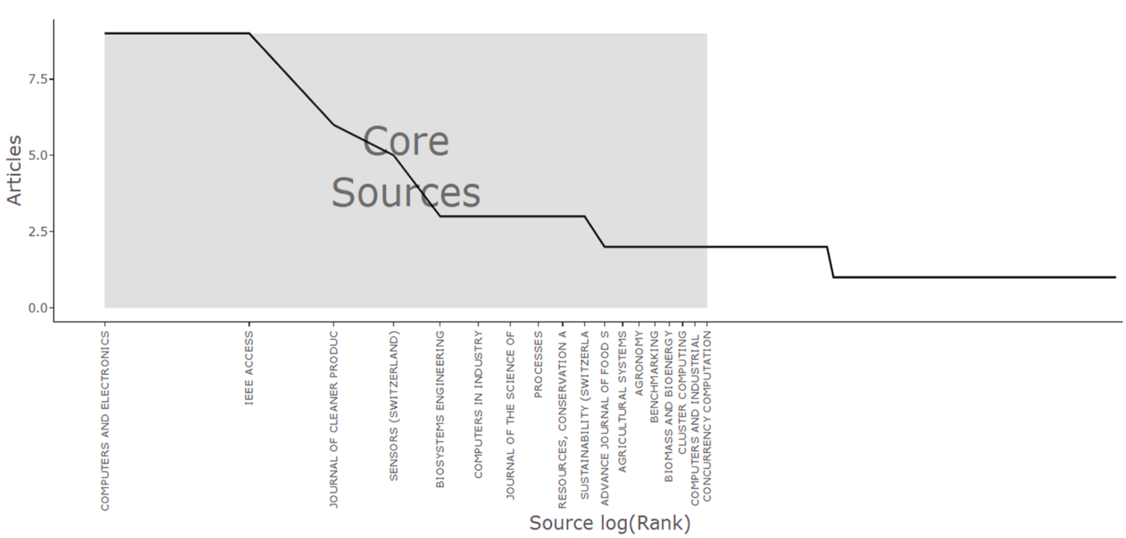

Fig. 7. Core journals.

specialized and exclusive examination of ASC. Fourteen authors have created single-authored works, while 615 authors have authored articles with multiple authors. This part includes the authors' citations and their work from the previous year as shown in Table 3. It demonstrates the contributions and impact of various authors in the field. The analysis reveals that Gunasekaran A, who published in 2020, has the highest total citations (TC = 160), indicating significant influence in recent years. This is followed by Kamble SS, whose work from 2020 has received 141 citations, and Wang J, whose 2016 publication has accumulated 126 citations. These figures highlight that research from these years has had a lasting impact on the academic community. Beulens AJM has contributed across multiple years—2010, 2013, and 2018—with the highest citation count (90) associated with the 2013 publication, signifying sustained academic influence over time. Liu Y and Wang J have also made consistent contributions, particularly in 2015 and 2016, with [90] research gaining substantial recognition with 126 citations. In contrast, some authors, such as Garg D, Luthra S, and Yadav S, have been more frequent contributors, particularly in 2020, but their citation impact remains relatively low, with each accumulating only 9 citations. Similarly, Wang X and Yadav S, who published multiple works in 2021, have garnered minimal citations (2 and 1, respectively), likely due to the recency of their publications and the time required for academic uptake.

Fig. 8 displays the top twenty authors with the most publications on the subject of the ASC. Wang X has the most publications, nine, followed by authors such as Gard D, Gunasekaran A, Wang J, and Yadav S, each with four publications. The statistics are followed by authors such as Kamble SS, Wang H, and Zheng L, each of whom has published three publications, while Aamer AM, who has written just two papers, is at the bottom of the list. Consequently, this part addresses the remaining part of the first RQ.

4.3. Keyword analysis

This section provides information on the relevance of various ASC, AI, and ML-related keywords. To examine the trend of current research on this topic, authors include various keywords in articles. It aids in tracking research trends and identifying research gaps. The supply chain keyword appears the most often, followed by the agricultural term. Keywords such as ML and industry 4.0 are discovered, however, they are insufficient since these technologies are relatively new. After analyzing all of the keywords, it is clear that they include concepts such as sustainable development, sustainability, and food safety, indicating that the significance of the field is not limited to the application of technology, but also includes concerns about the safety and security of the food industry.

Table 3
Authors publication year and citations.

Author	Year	Number of Articles	Total Citations
Beulens AJM	2010	1	33
Beulens AJM	2013	1	90
Beulens AJM	2018	1	34
Bouzembrak Y	2019	2	60
Bouzembrak Y	2020	1	2
Garg D	2020	3	9
Garg D	2021	1	1
Gunasekaran A	2018	1	34
Gunasekaran A	2020	3	160
Kamble SS	2018	1	34
Kamble SS	2020	2	141
Liu Y	2015	1	15
Liu Y	2016	2	73
Liu Y	2021	1	6
Luthra S	2020	3	9
Luthra S	2021	1	1
Wang J	2015	2	18
Wang J	2016	2	126
Wang X	2014	1	25
Wang X	2017	1	10
Wang X	2019	1	18
Wang X	2020	1	46
Wang X	2021	3	2
Yadav S	2020	3	9
Yadav S	2021	1	1

Keywords are distributed in relatively small groups based on their frequency of occurrence, forming distinct clusters— a process commonly referred to as cluster analysis [91–93]. This study employs MCA, as illustrated in Fig. 9, where each keyword cluster is treated as a class and subsequently merged based on the highest degree of similarity. The MCA method, a sociological approach [94], compresses high-dimensional data into a two- or three-dimensional space, facilitating the identification of keyword relationships. In this study, the clustering was performed using k-means clustering, with the number of clusters determined through the elbow method to optimize classification accuracy. The subject dendrogram derived from this clustering approach provides insights into the relationships between keywords in the ASC sector, revealing thematic proximity and divergence.

Notably, Fig. 9 highlights a clear distinction between the clusters at the top and bottom, indicating that some keywords share a closer conceptual relationship than others. The top cluster predominantly includes broader themes such as catering services, people, Industry 4.0, and food, whereas the bottom cluster is more technology-focused, comprising terms like optimization, AI, data mining, and neural networks. This segmentation suggests a divide between macro-level supply chain considerations and the technological innovations driving advancements in ASC. However, despite this apparent distinction, both clusters remain interlinked, illustrating the intersection of supply chain management with emerging digital technologies.

Furthermore, Fig. 9 and 10 were computed using hierarchical clustering techniques, ensuring a structured visualization of keyword relationships. The analysis underscores the interplay between conceptual and technological advancements in ASC research, providing a roadmap for future studies to bridge existing gaps between theory and application.

Between the two branches of the dendrogram, we observe the emergence of technical terms related to advancements in agricultural practices, particularly in precision agriculture, which plays a key role in optimizing farming operations. The central block of the dendrogram contains the highest number of subdivisions, connecting two significant sub-blocks with distinct characteristics. Within this central block, keywords such as supply chain, ASC, traceability, and IoT appear, illustrating their role in enabling more precise and technology-driven agricultural methods, including robotics and smart farming. The dendrogram highlights the interconnectedness of technologies, ASC, and various industries that are either directly or indirectly influenced by these advancements. While subject dendrograms, as noted by Andrew [95], offer an approximation of relationships between key themes, they do not fully capture the depth of their interconnections. Industry 4.0 and Agriculture 4.0, though rooted in the same wave of technological advancements [96,97], have evolved in parallel to address distinct industrial and agricultural challenges rather than simply being "current developments." Industry 4.0 focuses on automation, cyber-physical systems, and IoT-driven manufacturing, whereas Agriculture 4.0 applies similar principles to precision farming, smart irrigation, and supply chain digitalization.

Additionally, the ASC serves as a critical enabler for integrating technological innovations across the sector. Efficient supply chains enhance traceability, logistics, and resource allocation, thereby improving productivity and sustainability in agriculture. By linking upstream and downstream stakeholders, ASCs facilitate the seamless adoption of smart technologies and data-driven decision-making, reinforcing their role in modern agricultural transformation. Xu et al. [98], Frank et al. [99], and Raut et al. [100] have examined the use of new technologies in modernizing the supply chain and its many aspects. In addition to aiding in the transformation of the field, the fourth iteration

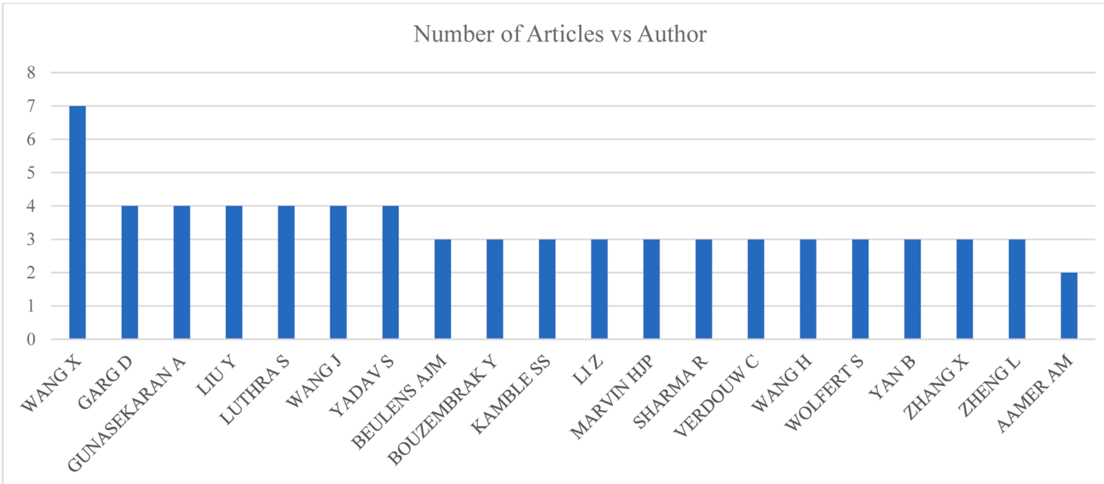

Fig. 8. List of top twenty authors with most publications.

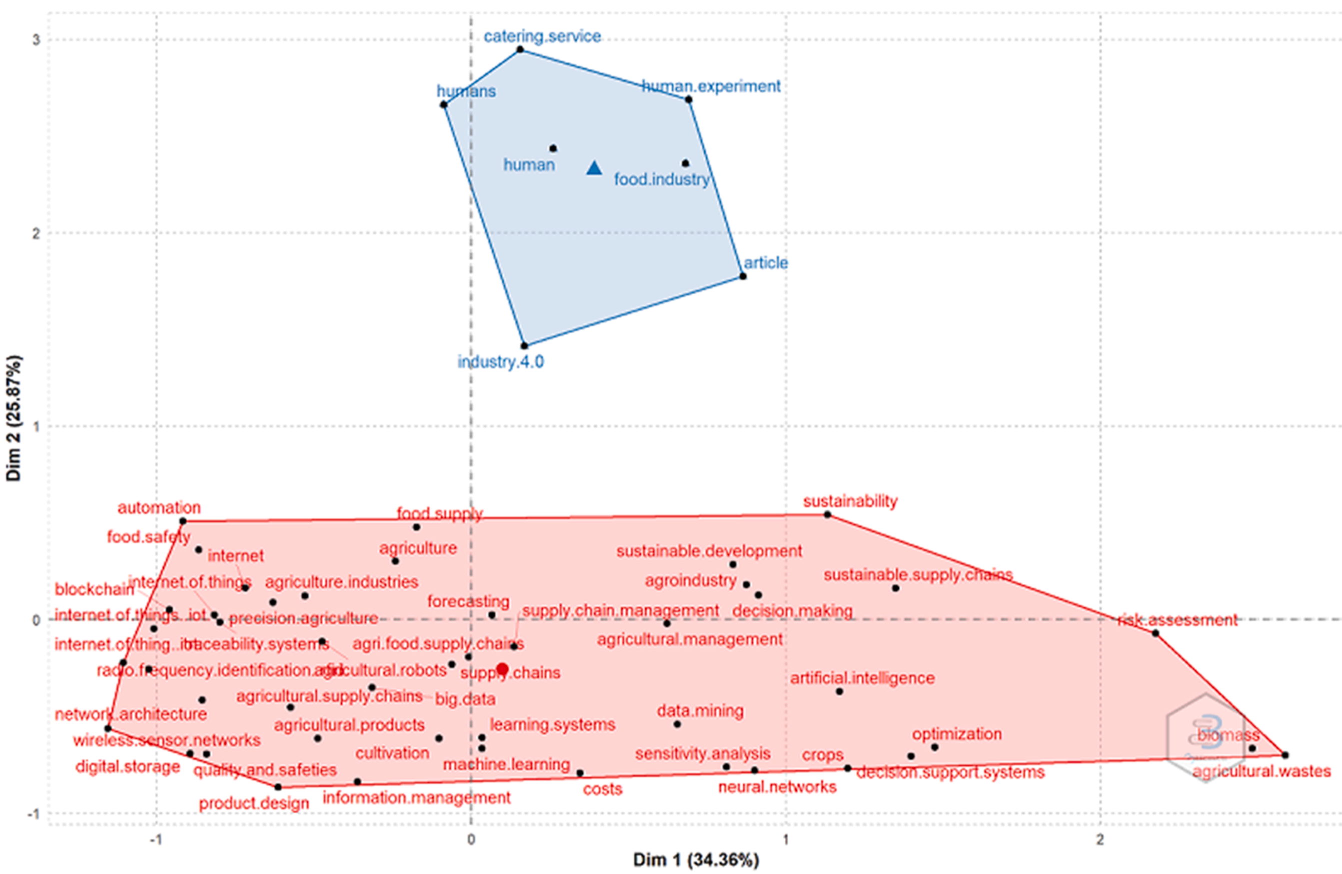

Fig. 9. Multiple correspondence analysis (MCA) of high-frequency keywords.

of the integration of agriculture and industry may also assist in resolving a number of issues that both sectors are now experiencing. In addition, Fig. 11 contains a word tree that highlights the interrelated critical domains in the evolution of intelligence in agriculture, i.e., the transition from agriculture 3.0 to agriculture 4.0. In the word cloud, we can see those terms such as supply chains, supply chain management, and IoT occupy a higher portion of the cloud, which demonstrates the authors' growing interest in this area. Additional terms of comparable prominence include agricultural robots, decision-making, and blockchain.

Thematic mapping highlights four distinct types of themes [101], and in this study, keyword associations were identified using semi-automated techniques [102]. These techniques involved the application of co-word analysis, where algorithms and data mining tools automatically extracted and clustered keywords based on their co-occurrence patterns within the analyzed publications. Specifically, the Biblioshiny package in R was employed to construct keyword networks, with a minimum frequency threshold set to ensure meaningful clustering. The co-occurrence matrix was generated using binary counting, meaning that a keyword was counted only once per document, regardless of repetition, to prevent overrepresentation. A normalized

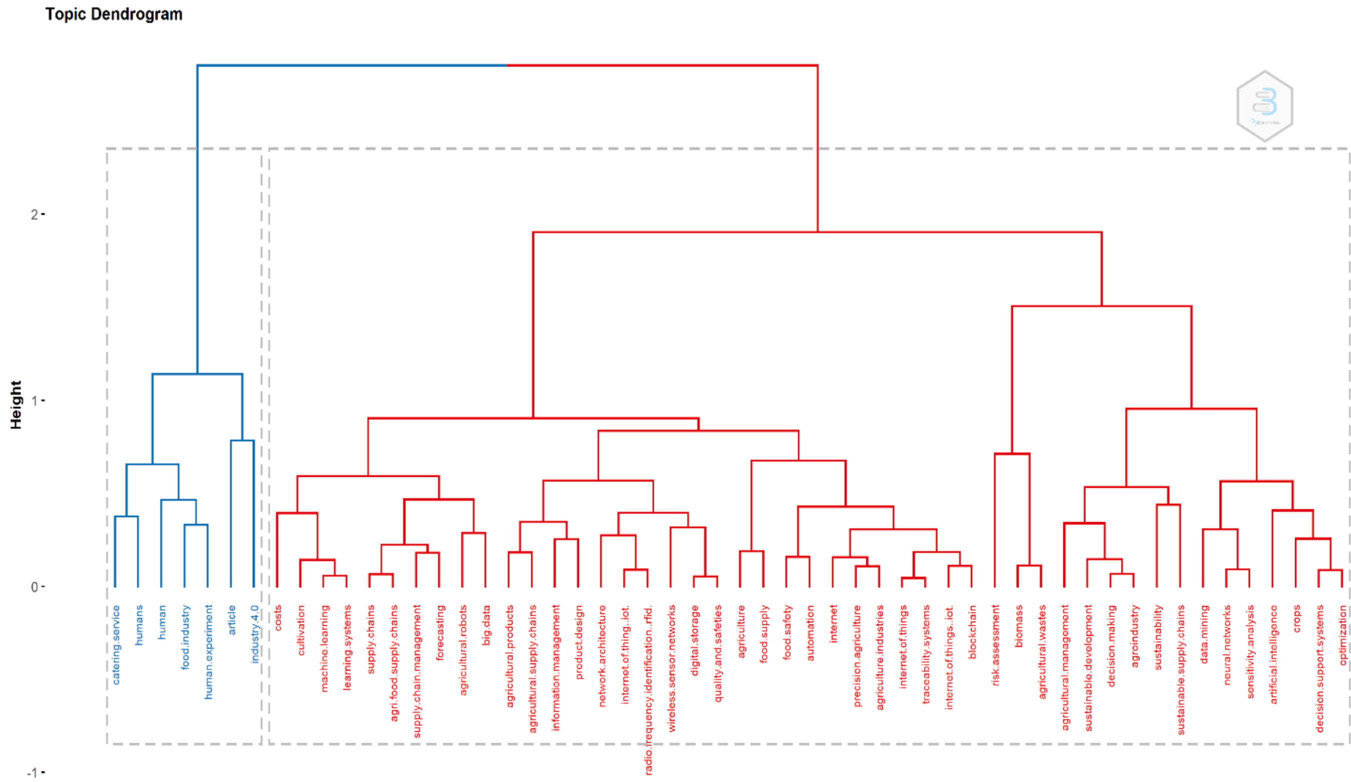

Fig. 10. Topic dendrogram.

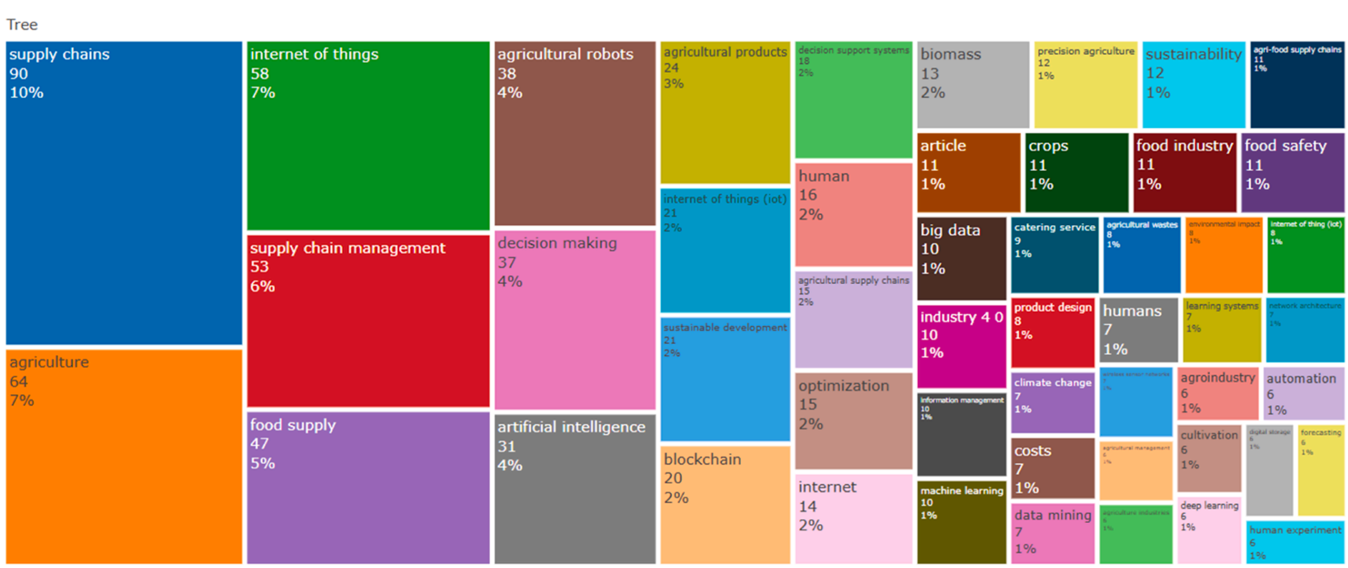

Fig. 11. Word tree.

association strength measure was applied to determine the degree of connectivity between keywords, enabling the identification of thematic clusters. This process facilitated the identification of dominant research themes by emphasizing frequently occurring and contextually significant keywords while filtering out less relevant terms not highlighted by the authors. The resulting clusters reflect the thematic structure of research in this domain, helping to distinguish core topics from emerging areas of study. Fig. 12 illustrates a strategic diagram showing these key terms. In particular, Keywords Plus, which provides deeper insights into the subject matter, reveals emerging topics such as 'IoT in agriculture' and 'robots in agriculture,' signaling the advancement of the discipline [103,104].

In the early 21st century, technological advancements started playing a crucial role in promoting sustainability, as reflected in the keywords frequently appearing in publications from that period, such as 'agriculture,' 'sustainable development,' 'sustainability,' and 'supply chain.' However, over the past eight years, there has been a noticeable shift, with keywords like 'AI' and 'blockchain' becoming increasingly prominent in discussions related to agriculture, as shown in Fig. 13. Despite the growing interest in these areas, ASC and related subjects have historically received limited attention, only gaining significant focus in recent years.

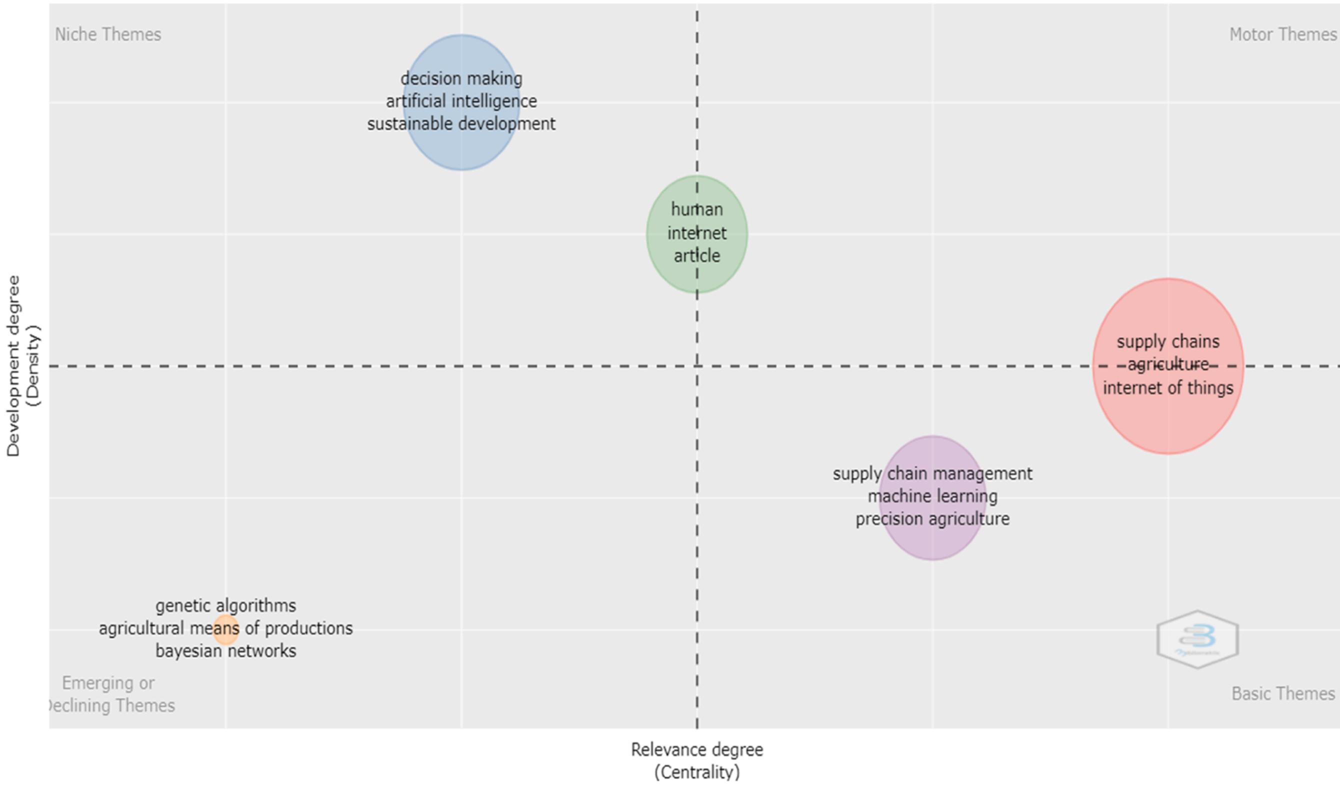

Fig. 12. Strategic diagram (Thematic map).

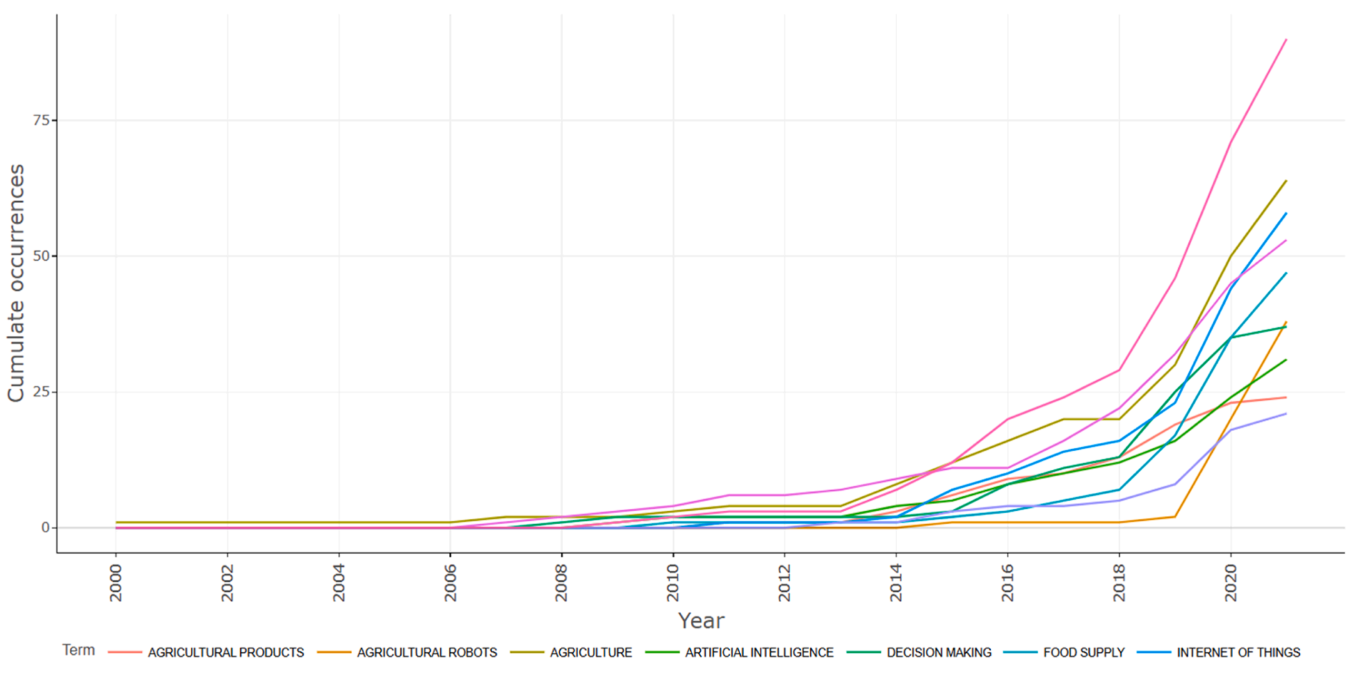

Fig. 13. Growth of keywords in the last twenty years.

4.4. Analysis of major countries and their collaboration

This section is significant because it illustrates the contributions made by various nations based on the volume of their publications, citations, and collaborations. Altogether, Fig. 14 and Table 4 show how deeply many nations have invested in terms of publication in the use of IoT, AI, ML, and other cutting-edge technology to address the ASC and its various facets. Since Chinese Premier Jiabao Wen started the rapid growth of the IoT in 2009 [105] resultant China occupies the top spot with more than a hundred publications [90,106]. The United States, India, the United Kingdom, and Italy are the next nations in the statistics with 60, 47, 28, and 23 publications respectively. Numerous nations

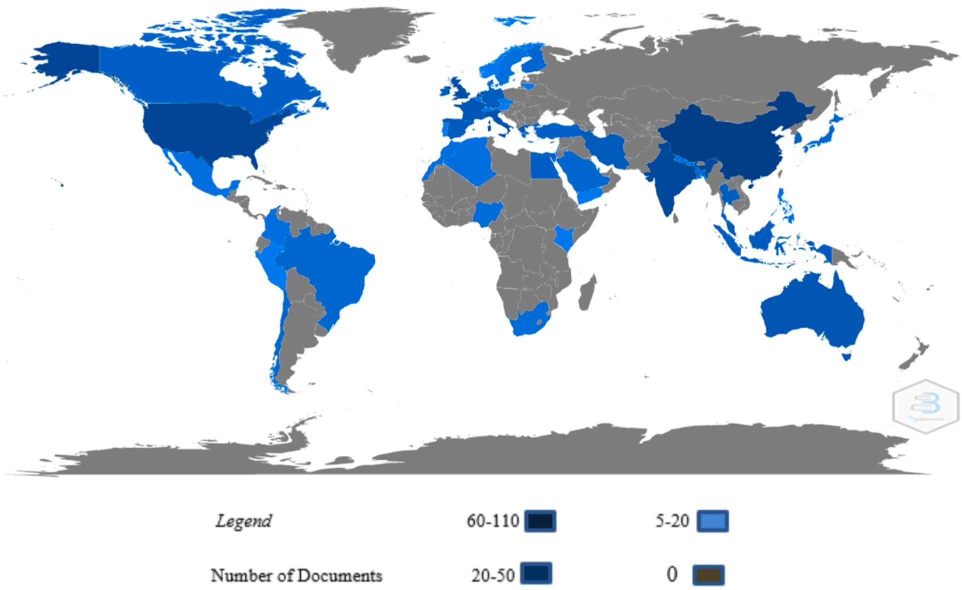

Fig. 14. Countries' scientific production distribution.

Table 4
Countries' scientific publications.

Country	Frequency
CHINA	110
USA	60
INDIA	47
UK	28
ITALY	23
NETHERLANDS	23
AUSTRALIA	16
FRANCE	13
GREECE	12
MALAYSIA	11
GERMANY	10
IRAN	10
IRELAND	10
INDONESIA	9
SPAIN	9
THAILAND	8
SOUTH KOREA	7
CANADA	6
EGYPT	6
TURKEY	6

have begun to work in this area; for instance, Spain, Egypt, Indonesia, Thailand, and Canada have started to take research interest in ASC. ASC with AI and ML is being greatly boosted by the nations that have seen an increase in population and are having trouble keeping up with the demand for agricultural goods.

Although many nations remain inactive in this research domain and have not yet contributed significantly to publications, active research nations can facilitate knowledge transfer by collaborating with less-involved countries. Fig. 15 illustrates the international research collaboration network, where blue hues represent cross-border research partnerships. The pink lines connecting countries vary in thickness, indicating the strength of these collaborations. A clear pattern emerges: nations with a higher number of publications tend to attract more research partnerships. China, the United States, and India collectively contribute to more than half of the global publications in this field and, consequently, exhibit the highest levels of international collaboration. By fostering partnerships between leading research nations and those with limited engagement, scientific knowledge can be disseminated more effectively, encouraging wider participation and ultimately increasing the global research impact of underrepresented countries.

Table 5 displays the total and the average number of citations for

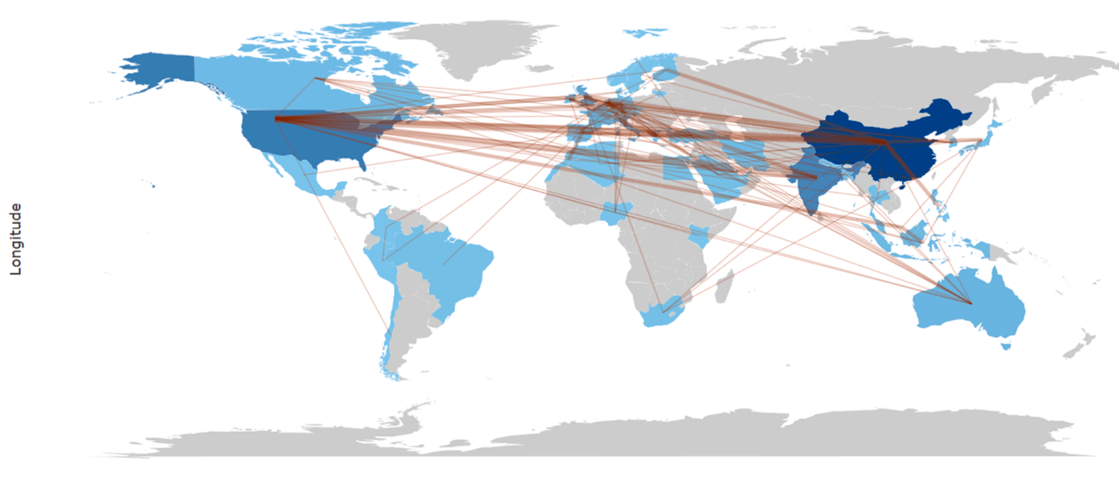

Fig. 15. Countries' collaboration network.

Table 5
Countries' total citation.

Country	Total Citations	Average Article Citations
NETHERLANDS	949	86.27
CHINA	619	15.47
USA	341	31.00
GREECE	277	46.17
ITALY	176	19.56
INDIA	157	11.21
FRANCE	150	21.43
SWEDEN	136	136.00
UNITED KINGDOM	81	10.12
LITHUANIA	52	52.00
SPAIN	51	10.20
QATAR	45	22.50
DENMARK	43	43.00
JAPAN	42	21.00
IRAN	40	13.33
KOREA	35	8.75
BRAZIL	34	17.00
COLOMBIA	22	11.00
NIGERIA	7	3.50
FINLAND	6	6.00

each nation; it reveals that China is second in this ranking, closely followed by the Netherlands. China publishes roughly five times as much as the Netherlands, while the Netherlands generates articles with more effect, as seen by the fact that China has fewer citations than the Netherlands. Other than China and the Netherlands, nations such as the United States, Italy, Greece, and India have received a significant number of citations. These nations might benefit from the improvement in the agricultural industry. Many nations must modernize their agricultural practices by moving from antiquated practices to cutting-edge technology to address the issue of feeding an ever-growing population.

4.5. Citation analysis

Citation analysis is a crucial component of bibliometrics since it reveals the intellectual interaction that took place between various authors to achieve their goals [107,108]. ASC analysis employing IoT, AI, and ML approaches is an area that is still in development. Fig. 16 shows that throughout the first five years of the twenty-first century, this subject had essentially no citations; nevertheless, from 2006 forward, this field began to expand in terms of citations. The output became even better, and during the last three years, this industry's citations have skyrocketed. Citations are up, indicating that the manufacturing quality has been becoming better over time. However, if we look at things commutatively, we can observe that this field has had citation trends of growth and collapse.

Since Authors have been often addressing these two factors in recent years, the number of citations for papers has significantly grown. As this field has gained massive acceptance over the last few years, there have been more publications, which has led to a rise in the number of citations. In the previous 15 years, there were relatively few citations. Generally, a citation is made based on three things: sources, authors, and documents. The number of times an article has been cited serves as a key indicator of its academic influence. When citations are counted across all sources, reflecting the overall impact of a publication in the broader research community, it is referred to as a global citation. On the other hand, when citations are limited to the dataset used in this bibliometric study, measuring the influence of a work within the specific research scope, it is termed a local citation [109]. Local citation analysis is often used to determine the relationship and connection between authors working in the same field and how their efforts are assisting in achieving one another's objectives. Local citations basically count the number of times a certain author (or document) is referenced in other papers that are also part of the collection. Citations are connected; some are based on authors, some on sources, and some on papers. In many instances, the citations consist of two or three, as seen in Fig. 17.

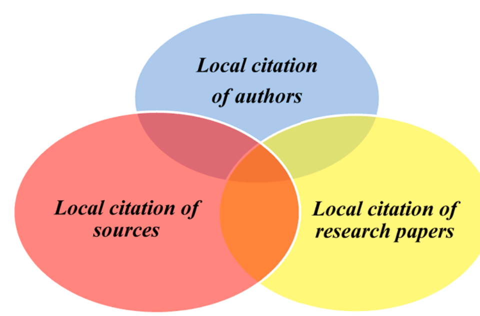

Fig. 17. Co-relation of local citations.

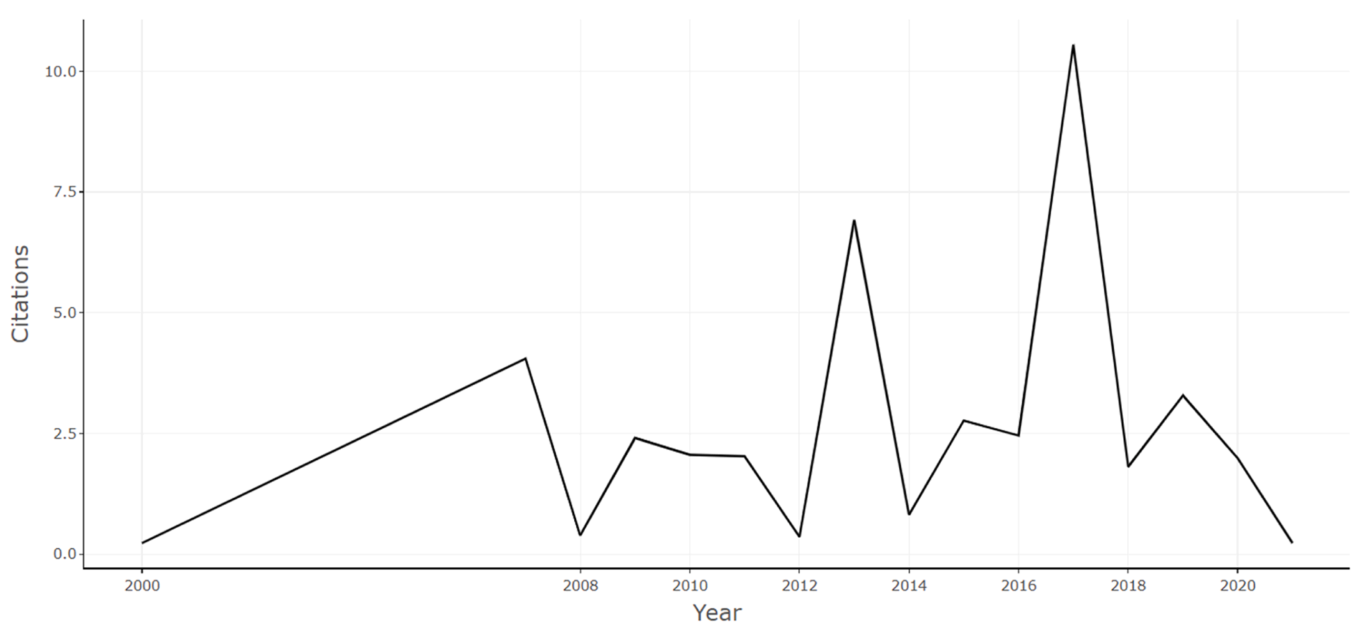

Fig. 16. Number of annual cited papers.

With a focus on Agriculture 4.0, this study examines key aspects of local citations within the ASC research domain. The author aimed to highlight significant scholarly contributions specific to this field, ensuring that the curated collection remains valuable for researchers. This bibliometric analysis is based on 187 documents, and the top 20 most locally cited authors, documents, and sources are presented in Figs. 18–20 respectively. Such an analysis helps researchers maintain a focused approach within a specific research domain rather than deviating into unrelated areas. In terms of author citations, Wang X has received the highest number of local citations (10), aligning with the findings in Section 4.2, which indicate that this author has also contributed the most articles and received the highest number of global citations in this field.

The papers that the author evaluated for the bibliometric study also mention Aganovic K, Ferrag MA, and Smetana S. Additionally, the local citation of sources is similar to the worldwide citation of the same sources. There have been 189 citations for Computers and Electronics in Agriculture, with 171 citations for the Journal of Cleaner Production and 113 citations for IEEE Access. According to Section 4.1 above, these journals have published the most articles overall, which has led to a higher number of citations than in other journals. Thus, the third RQ is addressed by the discussion in this section.

5. Discussion and implications

5.1. Discussion

This bibliometric study aimed to analyze the trends in publications, influential researchers, key research themes, and international collaborations within the context of the ASC, particularly through the lens of AI and related technologies. The findings shed light on the trajectory of academic focus and contributions in the ASC, providing insights into key contributors and emerging research areas. The analysis answers the RQs in the following way:

5.1.1. *What is the trend of publication, and who are the most influential researchers and authors in the last two decades?*

The trend of publications over the past two decades reveals a gradual but increasingly focused research effort in the ASC domain, especially with the integration of advanced technologies like AI, IoT, and robotics, as mentioned in Fig. 2. The study shows that Wang X emerges as the most influential author in terms of both volume and impact, with nine publications. Following closely behind are notable researchers such as Gard D, Gunasekaran A, Wang J, and Yadav S, each contributing four publications, as shown in Fig. 8. Additionally, Kamble SS, Wang H, and Zheng L are among the researchers who have authored three papers each. These key authors not only drive the research output but have also been highly cited, which signals their influence in shaping the academic discourse surrounding ASC, as illustrated in Fig. 7. The distribution of publication sources further underscores the specialized journals that dominate ASC-related research, with *Computers and Electronics in Agriculture, IEEE Access*, and the *Journal of Cleaner Production* contributing significantly, as highlighted in Fig. 4. Notably, the study reveals that the journal with the most articles published in ASC stands at nine, indicating that while there is growth, there remains substantial room for expansion in this research area, as seen in Fig. 3.

5.1.2. *What are the major research themes, keywords, and the most promising sources of publication around ASC?*

The major research themes identified through Biblioshiny-based keyword analysis include sustainability, supply chain management, AI, and blockchain technology, as depicted in Fig. 9. The co-occurrence network analysis highlights the evolution of these themes over time, revealing notable trends in technological adoption within ASC. A temporal keyword trend analysis indicates that while AI and blockchain have gained traction over the past eight years, the study finds a comparative underrepresentation of ML and AI applications directly linked to ASC. This is evident in Fig. 13, where terms such as predictive analytics, deep learning, and AI-driven decision support systems appear less frequently despite their recognized potential in enhancing productivity, risk assessment, and supply chain efficiency. This gap suggests an opportunity for future research to systematically explore AI and ML integration in ASC, particularly in areas such as:

- Supervised and unsupervised learning models for crop yield forecasting and disease prediction

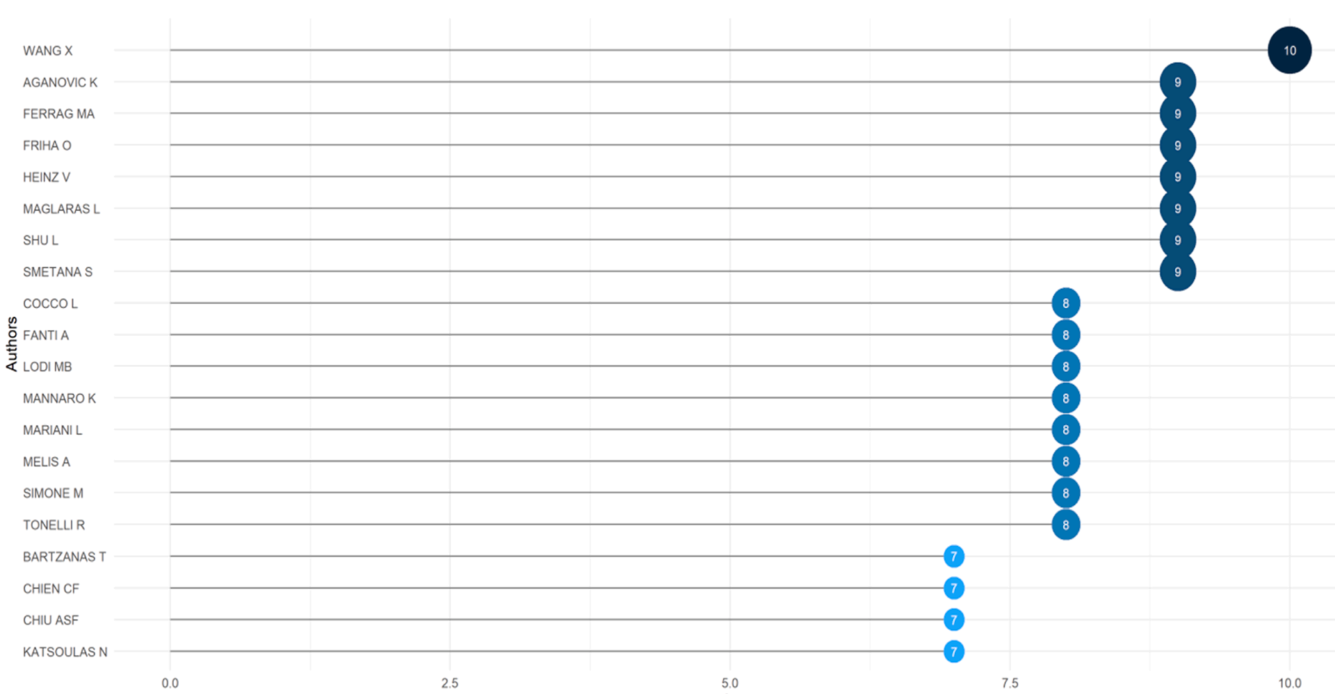

Fig. 18. Local citation of authors.

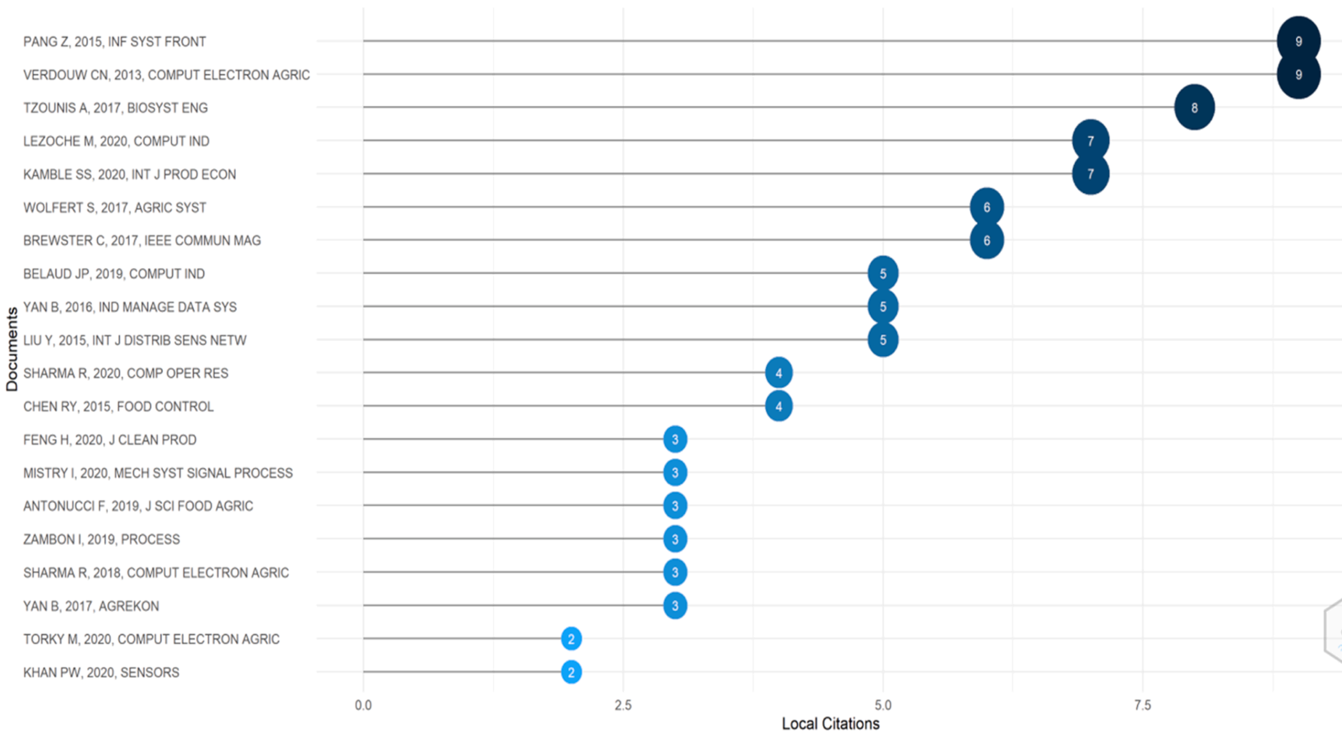

Fig. 19. Local citation of documents.

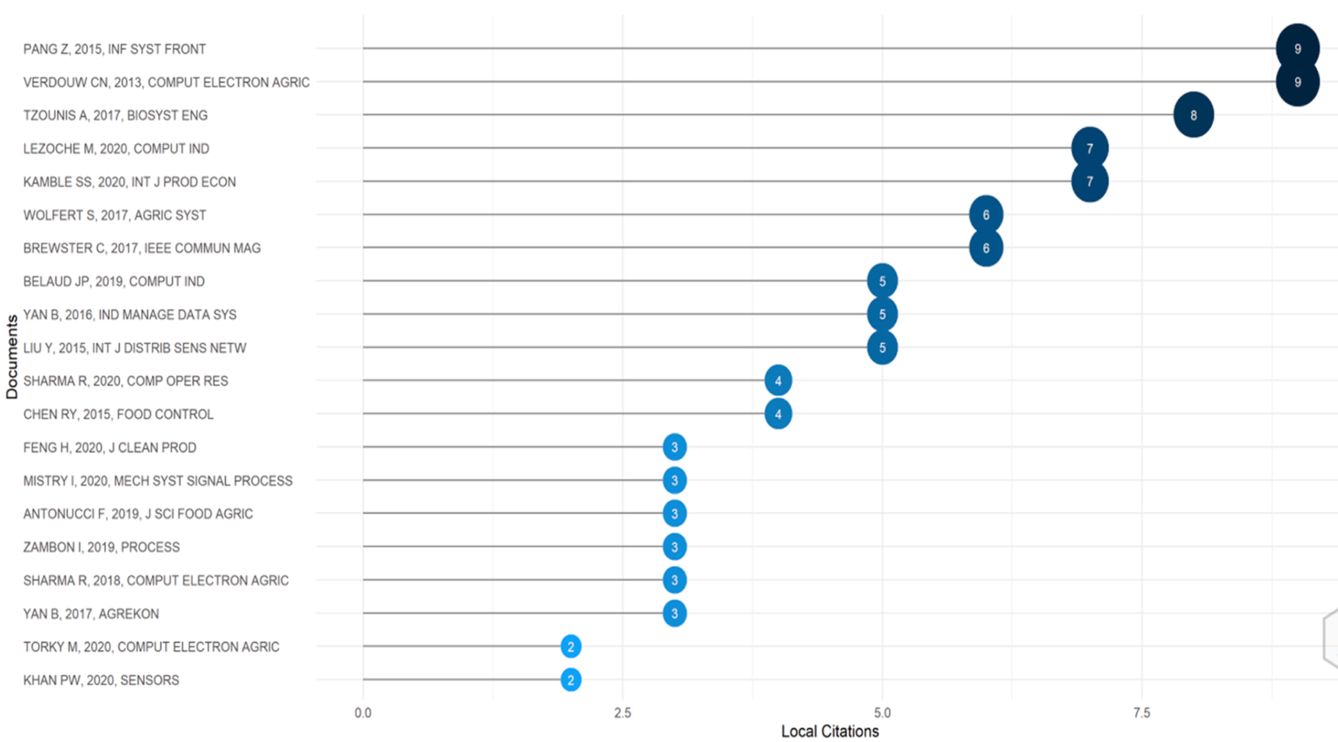

Fig. 20. Local citation of sources.

- Reinforcement learning-based optimization for real-time decision-making in supply chains
- Federated learning frameworks to address data privacy concerns in ASC digitization
- Blockchain-AI convergence for enhancing traceability and smart contract automation in agri-food networks

The thematic mapping analysis, as illustrated through the hierarchical clustering dendrogram, reveals two distinct phases of technological development in ASC:

Phase 1. Traditional Digitalization – Characterized by the adoption of IoT, remote sensing, and robotics, where drones and automated machinery primarily facilitated precision agriculture and real-time farm monitoring.

Phase 2. Intelligent Automation & Data-Driven Agriculture – An emerging trend marked by the integration of AI, blockchain, and ML-driven analytics, emphasizing predictive modeling, automated decision support, and decentralized data management.

Both phases are crucial in shaping the future trajectory of ASC. The transition from rule-based IoT automation to intelligent, data-centric decision-making represents a shift toward sustainable, resilient, and adaptive agricultural ecosystems.

5.1.3. What is the trend of research collaboration, and which countries are the leading researchers in this field?

In terms of international collaboration, the study highlights a global interest in ASC research, with China leading in the number of publications—over 100—likely driven by the need to address the challenges posed by its large population, as seen in Fig. 14. This aligns with China's strategy of leveraging technological innovation to enhance agricultural productivity. Other countries making significant contributions include the United States (60 publications), India (47 publications), the United Kingdom (28 publications), and Italy (23 publications). These nations are responding to similar population and sustainability challenges, which further fuels research and development in ASC technologies. Countries such as Spain, Egypt, Indonesia, Thailand, and Canada are emerging players in ASC research. Although their output remains lower in comparison, their growing contributions indicate an expanding interest in addressing ASC challenges using cutting-edge technologies. However, despite these contributions, many other nations are still underrepresented in ASC research, highlighting the need for broader global engagement, as discussed in Fig. 16. When it comes to collaboration, the Netherlands ranks first, indicating that Dutch researchers are not only prolific but also highly engaged in international partnerships, as illustrated in Fig. 15. Notably, the Netherlands' publications are more frequently cited than China's, suggesting that Dutch research has a significant impact in the field. In addition to the Netherlands and China, countries such as the United States, Italy, Greece, and India have demonstrated substantial collaborative efforts, further contributing to the cross-national exchange of knowledge in ASC research. This growing collaboration is essential, as the challenges posed by ASC require a concerted global effort to ensure food security and supply chain sustainability.

5.2. Implications

The findings of this bibliometric study highlight several policy implications across the pre-production, production, and post-harvest phases of the ASC. While predictive analytics, AI, IoT, drones, and blockchain present significant opportunities, their effective implementation requires targeted policy interventions to address barriers related to infrastructure, accessibility, standardization, and regulatory compliance.

Pre-Production Phase: Encouraging Digital Transformation and Capacity Building

- Subsidies and financial incentives: Government policies should promote the adoption of AI and IoT through subsidies, tax incentives, or low-interest loans, enabling better decision-making and resource management.
- Investment in digital infrastructure: Expanding high-speed internet and cloud-based agricultural platforms in rural areas is essential for real-time data sharing and predictive modeling. For example, Xu and Zhang [110], Xu [111], Xu [112], and Xu [98] demonstrated the effectiveness of predictive analytics in forecasting agricultural price trends using neural networks.
- Training and capacity building: Policies should focus on farmer education and digital literacy programs to enhance the adoption of AI-driven analytics and smart planning tools.

Production Phase: Strengthening Regulatory Frameworks for Smart Farming Technologies

- Standardized regulations for drone and sensor usage: Establishing clear guidelines on airspace management, data privacy, and cross-border drone applications can facilitate precision agriculture while ensuring compliance.
- Incentives for sustainable farming practices: Governments should encourage the adoption of sensor-based irrigation, AI-driven pest control, and robotics through tax breaks or grants, helping reduce environmental impact and improve efficiency.
- Public-private partnerships (PPPs): Collaboration between governments, research institutions, and agritech companies can accelerate the development and large-scale deployment of smart farming technologies.

Post-Harvest Phase: Enhancing Traceability, Compliance, and Global Standards

- Blockchain-based traceability policies: Policies should support the implementation of secure and interoperable blockchain platforms, ensuring food safety and transparency in supply chains.
- AI-driven regulatory compliance: Governments should integrate AI-based real-time monitoring to enforce food safety regulations, reducing food loss and improving product quality during storage and transportation.
- International standards for digital trade: Policymakers should focus on harmonizing digital trade policies to enhance cross-border traceability and compliance in global supply chains.

Global Collaboration for Inclusive Technological Adoption

International cooperation is essential to ensure technological advancements benefit regions facing food security challenges. Policymakers should foster global partnerships through:

- Knowledge-sharing initiatives for AI-driven agricultural innovations.
- Standardized regulatory frameworks for blockchain-based traceability and food safety.
- Joint investments in R&D to promote sustainable agricultural practices worldwide.

By aligning policy frameworks with technological advancements, governments can enhance food security, improve resource efficiency, and foster sustainable agricultural practices, ensuring a resilient and future-ready ASC.

6. Conclusion, limitations, and future scope

This study provides an in-depth bibliometric analysis of AI technologies within the ASC. By exploring publication trends, key authors, collaborative networks, and technological themes, the research reveals the growing influence of Agriculture 4.0 on the sector. AI-driven technologies, in particular, are highlighted as crucial components of modern agricultural systems. The findings underscore the increasing role these technologies play in enhancing decision-making, streamlining operations, and improving efficiency across various stages of the supply chain. IoT is seen as a foundational technology for connecting devices and systems throughout pre-production, production, and post-harvest processes, allowing for real-time monitoring and automation. Meanwhile, the potential of ML to address future challenges in the ASC is noted, especially in areas such as predictive analytics for crop yields, irrigation management, weather forecasting, and demand estimation. The study reinforces the importance of these innovations for the continued advancement and sustainability of global agricultural practices.

6.1. Limitations and future work

While this research follows a rigorous methodology, certain limitations must be acknowledged. Firstly, the study focuses on AI techniques in the ASC, but keywords related to other emerging technologies, such as blockchain and deep learning, were not explicitly included. As a result, some relevant studies on these advancements may have been overlooked. Secondly, the research covers the period from 2000 to 2021, a timeframe deliberately chosen to analyze the evolution of AI in ASC over a 21-year span. This period was selected to capture the gradual adoption trends, key inflection points, and technological breakthroughs that shaped AI-driven innovations in ASC. However, developments post-2021 are not included, which may limit insights into more recent advancements. Lastly, the reliance on the Scopus database, while extensive, excludes studies from other sources such as Web of Science or Google Scholar, potentially missing relevant contributions from niche or emerging fields.

6.2. Future research directions

To build on this study, future research should incorporate additional keywords to capture the role of blockchain, deep learning, and other advanced technologies in ASC. Expanding the search strategy would provide a more comprehensive view of how various innovations interact and contribute to supply chain transformation. Additionally, extending the analysis beyond 2021 would allow for a comparative assessment of recent developments against the historical trends identified in this study. Given that AI adoption in ASC showed gradual acceleration with spikes at certain points, it would be valuable to investigate whether this momentum has continued, slowed, or taken new directions in response to emerging challenges. Finally, utilizing multiple databases would help ensure a broader representation of the literature, reducing potential biases and capturing a more diverse set of scholarly contributions. By addressing these aspects, future studies can provide deeper insights into the evolving landscape of ASC technologies.

CRediT authorship contribution statement

Abhishek Kashyap: Writing – original draft, Methodology, Data curation, Conceptualization. **Om Ji Shukla:** Validation, Supervision, Software, Resources, Formal analysis. **Surya Prakash:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation. **Rupesh Kumar:** Writing – review & editing, Validation, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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