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Review Article

Charting the Digital Frontier: A Comprehensive Bibliometric Analysis of E-Agriculture Research

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Abstract

This study presents a statistically validated bibliometric analysis of e-agriculture research published between 2020 and 2025, based on 1,363 peer-reviewed articles indexed in Scopus and Web of Science, and selected according to the PRISMA 2020 guidelines. Bibliometric mapping is combined with inferential statistical analysis and network validation to examine publication dynamics, thematic evolution, citation impact, and global collaboration patterns. Results show rapid growth in research output up to 2023, followed by a contraction in 2024. Core research themes include smart farming, Internet of Things (IoT), artificial intelligence particularly deep learning and precision agriculture. While China, India, and Brazil lead in publication volume, the United States, the Netherlands, and Germany exhibit higher citation impact, indicating a divergence between productivity and influence. Inferential testing confirms these patterns: one-way ANOVA reveals significant temporal variation in citation impact ($F(5,1357)=48.5$, $p<2\times10^{-16}$), and network modularity analysis ($Q=0.519$) demonstrates a robust thematic structure. Poisson regression further shows that publication year and thematic focus jointly shape citation performance. To extend beyond descriptive bibliometrics, the study integrates an altmetric perspective, drawing on Twitter sentiment and topic analysis to capture societal engagement with digital agriculture research. Overall, the study advances bibliometric analysis in e-agriculture by combining statistical validation, network robustness assessment, and signals of societal impact.

Keywords: E-Agriculture; Bibliometric Analysis; Smart Farming; Technological Innovation.

INTRODUCTION

The rapid digital transformation in agriculture, or e-Agriculture, has completely transformed traditional agricultural practices by applying artificial intelligence, the Internet of Things (IoT), big data analytics, and automation. In recent years, the field of e-Agriculture has also attracted interest for harnessing modern ICTs to expand production, improve sustainability, and increase market accessibility. E-Agriculture offers advantages such as precision farming, remote sensing, and e-commerce platforms that enable the sale of farm produce. Technologies are advancing traditional agricultural practices and addressing important issues such as food security and climate change [1]. E-Agriculture, which incorporates these technologies, optimizes crop monitoring tools, precision farming, and the management of production resources, and supports smart decision-making to achieve higher production rates and sustainability outcomes. To address the intensification of global food demand and environmental challenges, digital agriculture, as a focal priority for improving efficient, climate-resilient farming practices, is highly relevant [2].

Over the last decade, there has been a notable increase in research on e-Agriculture, as evidenced by a growing number of publications investigating AI-driven precision agriculture, IoT-based monitoring systems, and the application of blockchain technology in the agricultural supply chain. [3, 4]. Nonetheless, despite these technological advancements, obstacles persist regarding the adoption, scalability, and socio-economic viability of digital agriculture, especially in developing regions. The technological dimensions of e-Agriculture have received considerable attention; however, there is a notable gap in the literature regarding policy integration, barriers to farmer adoption, and ethical implications within digital agriculture [5].

The rapid growth of this research has necessitated a systematic mapping of the conceptual frameworks, topic development, and collaboration networks of e-Agriculture research. Bibliometric analyses are quantitative methods for understanding research trends that can assist researchers in identifying relevant studies, major contributors, topic variation, and research needs [6]. Bibliometric studies assess academic papers, highlighting tendencies, authors, and subjects within the discipline [7]. Although many studies on technological enhancements to precision agriculture cover different aspects of the field, few have used bibliometric analysis with research performance measures, topic grouping, and collaboration networks. The use of bibliometric analysis in e-Agriculture exposes published data and collaborative networks among researchers and institutions, underscoring the multidisciplinary nature of agricultural research [8]. The development over time highlights the importance of bibliometric techniques in e-Agriculture studies and applications.

Alongside descriptive bibliometric indices, this study adds methodological strength by using inferential statistics to assess whether temporal trends in research impact are statistically significant. The application of ANOVA-based citation trend testing extends the approach from pattern portrayal to statistically confirmatory results a methodological extension rarely applied in e-agriculture bibliometric research. This study seeks to bridge the gap by conducting a bibliometric analysis of e-Agriculture research published from 2020 to 2025 using Scopus and Web of Science (WoS) data. The objectives are as follows:

- To analyze the impact of research in e-Agriculture by analyzing publication and citation trends.
- To identify the most prominent authors, institutions, and countries contributing to this field.
- To investigate the geographic distribution of research and collaboration networks.

- To investigate thematic evolution and keyword trends to identify emergent research directions.
- To illustrate the extant research gaps and map the intellectual structure of e-Agriculture research.

Using bibliometric approaches, network analysis, and topic clustering, this article presents a methodical overview of the evolution and future direction of e-Agriculture research. The results will guide industry players, legislators, and researchers on the key developments in e-Agriculture, its prospects, and challenges.

To strengthen analytical rigor beyond descriptive bibliometric trends, this study incorporates post-hoc statistical testing and interaction-based regression modelling. In particular, temporal citation dynamics are examined using Tukey's HSD post hoc analysis, while interaction effects between publication year and thematic cluster are evaluated using Poisson regression, enabling a statistically grounded assessment of evolving research impact patterns in e-Agriculture.

Below is the organization of this paper. It begins with a theoretical review of e-Agriculture and the identification of major research gaps, drawing on prior bibliometric and state-of-the-art studies. This is followed by a narrative overview of the data sources, PRISMA-based study selection process, bibliometric procedures, and statistical modelling techniques, including network analysis and inferential tests. The subsequent part presents the empirical results, covering publication trends, citation impact, thematic organization, collaboration networks, and robustness analyses. The discussion then examines contributions to the state of the art, methodological and thematic strengths, policy implications, and future research directions. Finally, the main findings are synthesized, conclusions are drawn and discussed, and a general future research pipeline is outlined to guide further scholarly work.

In addition to analyzing trends and patterns in scholarships, new literature emphasized the utility of Altmetrics for capturing how scientific themes move through public communication. Social media companies like Twitter offer timely feedback from farmers, practitioners, technology providers, and policymakers. Recent efforts have documented the contribution of Altmetrics to capturing consumers' perceptions of digital agriculture. Incorporating these results into the present work suggests a new hybrid approach that triangulates scientific bibliometric structures with real-world debate. Incorporating an Altmetrics layer into this study addresses a methodological gap in existing bibliometric reviews and allows alignment between academic trends and public perceptions of digital agriculture.

LITERATURE REVIEW

The Evolution of E-Agriculture Research

E-Agriculture integrates and applies contemporary information and communication technologies (ICTs) into all aspects of agriculture, including market access, supply chain management, and production and extension services. E-Agriculture is an emerging field at the intersection of agricultural informatics, agricultural development, and entrepreneurship, encompassing agricultural services, technology dissemination, and information delivered or enhanced by the Internet, as well as related technologies [9]. Under this umbrella, terms including digital agriculture, smart farming, and digital farming are used to describe similar or overlapping initiatives using advanced technologies (e.g., artificial intelligence, Internet of Things, blockchain, and big data analytics) to improve efficiency, productivity, and sustainability in agriculture [1, 10].

Precision agriculture, smart farming, and digital decision-support systems all together form e-agriculture, the integration of digital technology in farming. Early contributions centered on sensor-based monitoring, exemplified by [11]. With advancements in AI, IoT, and blockchain, the focus has shifted toward automated farming [12]. At the same time, these technologies promise higher efficiency and data-driven decision-making, but challenges persist in data privacy, cybersecurity, and farmer adoption [13, 14].

E-Agriculture has become a significant domain, leveraging cutting-edge technologies to enhance agricultural practices. Prominent research areas in this field include artificial intelligence (AI) and machine learning (ML), which are essential for detecting crop diseases, predicting yields, and improving decision-making. For example, [15] used UAV-based high-resolution imagery and machine learning to predict corn grain yield. This research demonstrates the effectiveness of sophisticated analytical methods in utilizing real-time data to improve agricultural outcomes. Furthermore, [16] demonstrated the efficacy of deep learning-based disease detection systems using convolutional neural networks, suggesting that the implementation of artificial intelligence in crop health surveillance can significantly enhance food security by detecting diseases before they progress. [17] emphasized the importance of intelligent computing and big data technologies in enabling proactive crop management strategies for farmers, thereby enhancing productivity through timely interventions.

The Internet of Things (IoT) is key to smart farming. The recent literature has focused on integrating wireless sensor networks for real-time environmental monitoring and automated irrigation systems, demonstrating that their use not only increases efficiency and resource management but also supports sustainable agriculture. The research by [18] states that systems enabled by IoT provide continuous access to environmental information, thereby improving decision-making in crop management. Blockchain technology has attracted immense attention for bringing traceability, transparency, and secure transaction management, including the transfer of products from farm to table. The regional distribution of the research findings can be seen to be based on the national top nations of China, India, and Brazil, and a very significant impact of citations from the USA and the Netherlands. It is necessary to partner with established research institutions, such as Wageningen University, to employ smart agricultural techniques, according to the report. However, as noted by [19], existing research collaboration networks are fragmented, underscoring the need for extensive partnerships to address global food issues [20].

Leading research institutions, including Wageningen University, South China Agricultural University, and the University of Guelph, have made significant advances in smart farming. However, research collaboration networks remain fragmented, with limited cross-continental partnerships between developed and developing countries [19].

Bibliometric Analysis

A bibliometric study provides insight into the nature of research trajectories, collaboration networks, and topics in e-Agriculture, digital agriculture, and smart farming. A recent study by [8] reviewed the literature on digital agriculture, identified strategic themes, and investigated the temporal evolution of the research environment. Consequently, [21] conducted a bibliometric analysis to evaluate the influence of governmental policies on sustainable agricultural companies and provided a comprehensive evaluation of research domains related to climatic effects and technology advancements. The study highlights the ability of bibliometric techniques to discover research clusters, trends, and potential future areas. It is a key aspect in developing the research agenda and in fostering partnerships among various stakeholders in e-Agriculture.

[22] studied digital twins in smart farming, focusing on their importance to decision-making and resource conservation in the agriculture sector. The purpose of this paper is to explore the potential of digital twins as virtual representations of physical systems to improve precision farming performance through more powerful data integration and predictive analytics. This research highlights the importance of bibliometric analysis in linking existing research and revealing new applications of technology in agriculture [22].

Subsequently, [23] conducted a bibliometric analysis of drone applications in agriculture and found an increasing trend in UAV use for crop monitoring and management. This study demonstrates how bibliometric methods can be used to evaluate shifts in technology adoption and pinpoint key themes and studies that shape research trajectories [23]. Furthermore, [24] explored the introduction of smart farming practices and their effects on the agricultural management system. It advocates the use of IoT, big data, and AI to improve agricultural productivity and sustainability. To illustrate smart farming, they use bibliometric analysis along with the potential impact of existing frameworks on future developments.

Additionally, bibliometric methods have been used to study blockchain technology within the agricultural setting [25]. The present study explores the application of blockchain to supply chain traceability and transparency and reveals the current research agenda of the application of blockchain technologies in the food and agriculture industries. The emphasis on the convergence of technology and agriculture illustrates the breadth and progression of the research themes identified through bibliometric analysis [25]. Meanwhile, the development of bibliometric approaches in e-Agriculture research promotes sustainability discourse. Authors in [26] conducted a bibliometric analysis of corporate digital transformation, demonstrating an association between technological advances in agriculture and sustainability impacts. The results underscore the growing relevance of the sustainability agenda in shaping the future research of e-Agriculture, further intertwining digitization and environmental discourses.

Finally, [27] delineates related bibliometric methodologies to enrich the study of diverse fields, such as e-agriculture. They identify necessary techniques, such as science mapping and citation network analysis, to improve decision support. Their research highlights the need to use bibliometric frameworks to extrapolate from scientific literature, which helps identify gaps and focus future research efforts [27]. This report identifies and tackles these weaknesses through a comprehensive bibliometric analysis of publication growth, citation impact, collaboration networks, and subject progression in e-Agriculture research from 2020 to 2025. This research systematically delimits the intellectual structure of e-Agriculture, comprising document coupling, co-citation analysis, and keyword co-occurrence mapping, thereby providing invaluable information and support for scholars, policymakers, and industry stakeholders.

Comparative Analysis of State-of-the-Art Related to Digital and e-Agriculture Research

In order to get familiar with this research and to give us a good point of reference (as well as a clear articulation of our methodological and analytic efforts), this review was conducted systematically and compared with studies related to digital agriculture, smart farming, and e-agriculture. As shown in Table 1, prior work mainly consisted of technology-oriented reviews, conceptual frameworks, security studies, and policy-focused syntheses. These papers offer important domain-specific considerations; however, they are predominantly qualitative or narrative synthesis analyses and do not employ large-scale bibliometric mapping, statistical validation, and network robustness evaluation. The comparative analysis in Table 1 systematically compares data scopes, analytical approaches, main findings, strengths, and limitations of representative SOTA studies, thereby illustrating the lack of reproducible, statistically validated bibliometric modelling in the literature. This void drives the integrated nature of this study that adopts large-scale bibliometric analysis in combination with inferential statistics, network validation, and regression modelling to enrich the analytical depth of e-agriculture research.

It has been shown that existing studies seem primarily focused on technological domains (blockchain, IoT security, digital twins) or theoretical perspectives on Agriculture 4.0. With a bibliometric mapping of 1,363 publications, this paper provides a thorough overview of cross-domain synergies between AI, IoT, big data, platform technologies, and social and moral issues. Such a broader analytical bandwidth allows us to make a comprehensive comparison of the state-of-the-art literature today.

Table 1. State-of-the-Art Studies Related to Digital and e-Agriculture Research

Study	Type of Study	Data Source / Scope	Methods Used	Key Findings	Strengths (Pros)	Limitations (Cons)	Research Gaps Identified
[28]	Comprehensive review	Peer-reviewed literature on blockchain & Industry 4.0	Systematic narrative review; architectural comparison	Blockchain enables traceability, transparency, and trust in smart and digital agriculture	Strong technical synthesis; clear architectural insights	Not bibliometric; no quantitative mapping or trend analysis	Lack of empirical validation and integration with AI-driven agriculture analytics
[29]	Survey/review	Smart farming security & privacy literature	Structured literature review; taxonomy of threats and solutions	Identifies key security, privacy, and trust challenges in smart farming systems	Deep technical and security focus	Not bibliometric; no temporal or network analysis	Absence of quantitative evidence on adoption, impact, and socio-economic dimensions
[22]	Conceptual synthesis	Digital agriculture and platform ecosystems	Conceptual framework; systems thinking	Introduces digital twins and platformization as central to future agriculture	Strong theoretical contribution bridging ICT and agriculture	No bibliometric or statistical validation	Limited empirical analysis of adoption and governance dynamics
[30]	Technology-oriented review	Agriculture 4.0 technologies	Narrative review of AI, IoT, Big Data, robotics	Demonstrates rapid expansion of AI, ML, and deep learning in agriculture	Up-to-date overview of emerging technologies	Not bibliometric; lacks robustness or trend modeling	Weak linkage between AI innovation and sustainability or policy outcomes
[31]	Domain-focused review	Precision agriculture literature	Review and thematic synthesis	AI is increasingly central to precision farming	Focused analysis of AI applications	No statistical testing or network analysis	Missing quantitative assessment of AI–climate–

				decision support			sustainability links
[32]	Systematic review	Precision agriculture domain literature	Thematic synthesis	Identifies sensing, automation, and analytics as core pillars	Strong domain grounding	Not bibliometric; no citation or network mapping	No quantitative evidence on AI–IoT convergence
[33]	Perspective /policy benchmark	Digital agriculture policy and innovation discourse	Conceptual and normative analysis	Highlights governance, ethics, and socio-technical challenges	Deep qualitative and policy insight	Not bibliometric; no quantitative analysis	Lack of measurable indicators for socio-technical transitions
[6]	Bibliometric methodology	Multidisciplinary	Co-word, co-citation, thematic maps	Introduced bibliometrix	Foundational framework	Descriptive; no inferential stats	Lack of statistical validation
[34]	Bibliometric methods review	Management & innovation	Science mapping taxonomy	Formalized bibliometric techniques	Conceptual rigor	Non-empirical	No dynamic or inferential modeling
[25]	Bibliometric analysis	Smart farming literature	Co-word analysis; trend analysis	Identified smart farming clusters	Domain-specific mapping	No hypothesis testing	No temporal–thematic modeling
[35]	Bibliometric analysis	Agri-food supply chain and blockchain literature	Systematic review + bibliometric analysis (co-word maps, trend analysis)	Bibliometric trends in blockchain adoption and research: focus on transparency, traceability, and trust	Domain-specific focus; comprehensive mapping of blockchain in food/agri supply chains	Not focused on broader digital agriculture; limited inferential /temporal analysis	No modeling of theme–time citation effects; limited integration with digital agri research themes
[36]	Bibliometric analysis	Digital agriculture	Co-word analysis; thematic	Identifies major digital agriculture	Domain-specific bibliometr	Primarily descriptive; no	Absence of statistical testing for

		literature (Web of Science)	mapping; citation trend analysis	research streams (AI, IoT, remote sensing, precision farming) and their evolution	ic mapping; clear identification of thematic clusters	inferential statistics or cluster robustness validation	thematic stability and lack of temporal–thematic citation modeling
[37]	Bibliometric analysis	Digital farming and big-data-driven agriculture research (Scopus)	Bibliometric performance analysis; keyword co-occurrence; trend mapping	Reveals the rapid growth of data-driven agriculture research and the emerging focus on sustainability and digital technologies	Large corpus; recent and comprehensive overview of digital agriculture trends	No inferential statistical validation; lacks modeling of citation impact or thematic interactions	Missing hypothesis testing, cluster robustness validation, and temporal–thematic impact analysis

Research Gaps Identified from SOTA

A systematic comparison of state-of-the-art bibliometric studies in e-agriculture and digital agriculture identifies several persistent methodological and conceptual shortcomings that inhibit a deeper understanding of the field's evolution, see Table 2. Based on the evidence from these studies, we synthesize four priority research gaps. Gap 1: Lack of inferential and statistically validated analysis. Existing bibliometric studies typically rely primarily on descriptive indicators, visual clustering, and frequency-based evaluation methods. None of the reviewed SOTA studies use any inferential statistical tests (ANOVA, regression modeling, chi-square test, or centrality significance test) to formally test temporal trends, overall themes, or citation drivers. It restricts the reliability and generalizability of previous results.

Gap 2: Disparate treatment of core technological concerns. Most studies in SOTA literature focus on artificial intelligence, Internet of Things (IoT), precision agriculture, and sustainability in isolation as separate research streams. Their structural interrelationships or convergence in a unified KN exist, and few analyses address their interactions. As such, the systemic dimension of e-agriculture, as a cyber-physical and socio-technical domain, is under-researched.

Gap 3: The absence of hybrid or predictive analytical frameworks. The bibliometric studies examined did not include bibliometric indicators alongside altmetric signals, sentiment analysis, or public discourse analytics, nor did they attempt predictive or explanatory modeling of research impact. That omission limits insight into how scientific knowledge diffuses beyond academia, and how the public's attention corresponds or not to scholarly priorities.

Table 2. Mapping of Identified Research Gaps to Methodological Responses in This Study

Research Gap (from SOTA)	Methodological Response in This Study	Section(s) Addressing the Gap
Gap 1: Lack of inferential and statistically validated analysis	Application of inferential statistics, including one-way ANOVA for temporal citation effects, Pearson chi-square tests for thematic stability, Wilcoxon rank-sum tests for network centrality dominance, and Poisson regression for citation determinants	Methodology (Statistical Significance Testing); Results (ANOVA, Chi-square, Wilcoxon, Poisson); Discussion (Hypothesis Evaluation)
Gap 2: Fragmented treatment of AI, IoT, and sustainability themes	Integrated keyword co-occurrence and network-based cluster analysis with inter-cluster similarity metrics (Jaccard overlap, edge-weight connectivity) to assess technological convergence and thematic separation	Results (Network & Cluster Analysis); Discussion (H2–H3: AI–IoT Convergence and Sustainability Positioning)
Gap 3: Absence of hybrid bibliometric–Altmetrics frameworks	Hybrid analytical framework combining bibliometric mapping with Twitter-based sentiment analysis and LDA topic modeling; computation of Altmetrics Theme Shares and Thematic Share Alignment (TSA)	Methodology (Altmetrics Extension); Results (Altmetrics Theme Distribution & TSA); Discussion (Bibliometric–Altmetrics Alignment)
Gap 4: Limited validation of cluster robustness and structural quality	Formal network validation using Louvain community detection and modularity analysis ($Q = 0.519$), supplemented by centrality dominance testing	Methodology (Network Validation); Results (Modularity Analysis); Discussion (Structural Robustness)
Gap 5: Underrepresentation of governance, policy, and socio-ethical dimensions	Explicit thematic mapping of policy, governance, and sustainability clusters; comparative analysis of their marginal structural integration and societal visibility using TSA	Results (Thematic Distribution); Discussion (Policy, Governance, and Socio-technical Implications)

Gap 4: Not much exploration of cluster robustness and structural validity. While keyword and co-citation clusters are often graphed, Table 1 shows that SOTA studies rarely assess cluster strength using formal network statistics. Modularity, overlap indices, and other statistical measures of community structure are largely lacking, thereby questioning the quality and interpretation of the reported thematic grouping.

Gap 5: Underrepresentation of governance, policy, and socio-ethical aspects. Despite the prevalence of bibliometric research today in the direction of technological innovation in the domain of SOTA mappings, governance schemes, data ethics, and equity, adoption issues are little taken care of. This imbalance mirrors a broader gap between rapid technological evolution and the institutional and socio-economic requirements for sustainable digital agriculture. All these shortcomings serve as the basis for the multi-method, statistical, and hybrid analytical design of this paper, which combines inferential statistics, network validation, explanatory modeling, and Altmetrics comparison to surpass the shortcomings of traditional bibliometric studies.

This gap-to-method mapping ensures that each limitation identified in prior SOTA studies is explicitly addressed through a corresponding analytical component in the present research.

Novelty and Theoretical Framework

This work expands the state of the art in e-agriculture bibliometric research by establishing a statistically validated hybrid bibliometric–Altmetrics framework that is not based on descriptive mapping or performance indicators used in previous work. These bibliometric analyses in digital agriculture and smart farming have mainly relied on publication trends, keyword co-occurrence, and citation counts without reference to inferential validation or hypothesis-driven testing [6, 38]. Based on the core bibliometric perspectives in e-agriculture and digital agriculture research [22, 29], this work extends prior work along three theoretical axes. Firstly, it uses inferential and explanatory statistical modeling (ANOVA, chi-square testing, Wilcoxon rank-sum tests, and Poisson regression) from descriptive pattern discovery to the statistically valid, confirmatory analysis of these temporal, thematic, and structural dynamics. This addresses a persistent limitation of previous bibliometric work: thematic clusters were established during the identification process, with citations assessed for statistical significance without an appropriate robustness check [38, 39]. Second, the study establishes a hybrid bibliometric–Altmetrics insight by triangulating the standard citation-based impact with public discourse patterns derived from social media analytics. By combining sentiment and topic modelling findings with a complementary Twitter data set, the analysis demonstrates how e-agriculture research themes are heard beyond the scientific literature, addressing contemporary calls for wider impact assessment platforms that account for both the academic and societal perspectives of digital agriculture innovations [40–42]. Third, the research employs a theoretically rooted network-validation method, employing modularity-based community detection and structural dominance testing to assess the consistency and stability of thematic clusters. Instead of treating co-word and co-citation clusters as merely exploratory artifacts, we assess their structural quality and explanatory relevance using the structure adopted for science mapping and network-based knowledge analysis [43, 44]. Collectively, these dimensions position current research as a methodological bridge between classical bibliometric mapping and analytically based science-of-science paradigms, yielding a replicable and potentially extensible framework for future research on digital agriculture, socio-technical systems, and social impact assessment.

Altmetric–Bibliometric Alignment and Societal Signal Interpretation

In addition, the bibliometric results were contextualized with alignment analysis with Altmetrics topic structures to reinforce the novelty of the proposed framework based on public discussion of digital agriculture. Traditional bibliometric indicators reveal academic influence within academic communities, but do not capture wider societal visibility or public engagement with research themes [38, 40]. Altmetrics have been used as complementary measures to assess the spread of scientific information beyond academia via online platforms and social media [41, 42]. The relationship between bibliometric keyword clusters and social media-dominant topics shows a partial, yet asymmetrical, overlap, indicating that public attention does not reflect the priority of scientific research equally. Technology-related themes—AI, machine learning, and IoT-enabled smart farming show significantly stronger alignment between bibliometric prominence and social media visibility than sustainability-, governance-, and policy-related themes, which exhibit much weaker correspondence. Similar asymmetries between technological innovation and socio-ethical discourse have also been found in previous work on digital agriculture and responsible innovation [19, 22]. This discrepancy points to a societal preference for technology-based stories, yet the socio-economic, ethical, and regulatory aspects of e-agriculture, which are increasingly valued in academic literature, are under-addressed in public discourse more generally. At the theoretical level, this discrepancy implies that research impact might not be conceptualized solely in terms of scientific influence but also encompasses communication asymmetry and an awareness-translation divide between research communities and society [45, 46]. The current research contributes to the multidimensionality of the impact assessment model by incorporating bibliometric and Altmetrics perspectives into SOTA models. By doing so, this methodologically contributes to research-wide bridging of scholarly influence and societal visibility, and substantively reveals how the development, diffusion, and reception of the digital-agriculture research theme span both academia-wide and public perceptions.

METHODOLOGY

This article utilized a bibliometric analysis to explore research trends, significant contributors, thematic development, and collaboration networks within e-Agriculture research. The approach involved systematically gathering, processing, and analysing data using bibliometric methods and network-mapping tools.

Data Collection and Sources

A structured search query was designed to capture relevant literature on e-agriculture and related concepts. To enhance transparency and accessibility, only open-access articles were included. The preliminary dataset comprised 2,097 documents sourced from Scopus and 960 documents from the Web of Science, covering the period from 2020 to 2025.

To uphold standards of reproducibility and accessibility, the selection was limited to articles published in open-access journals, see Table 3.

Table 3. Scopus and WoS databases search queries

Scopus Search Query:	Web of Science (WoS) Search Query:
TITLE-ABS-KEY("e-Agriculture" OR "smart farming" OR "digital agriculture" OR "ICT in agriculture")	TS=("e-Agriculture" OR "smart farming" OR "digital agriculture" OR "ICT in agriculture")
AND PUBYEAR > 2019 AND PUBYEAR < 2026	AND PY=(2020-2025)
AND OPENACCESS(1)	AND OA=Y
AND DOCTYPE(ar)	

Study Selection and PRISMA Flow

The bibliometric dataset used in this study was derived from a systematic literature search conducted in Scopus and Web of Science between 2020 and 2025, following the PRISMA 2020 principles of transparency and reproducibility. It yielded 3,057 identified records (2,097 retrieved from Scopus and 960 from Web of Science). After removing duplicate records, 2,874 unique documents were evaluated based on titles and abstracts. Papers not incorporated in the e-Agriculture study at this point were omitted. A total of 1,363 articles met the inclusion criteria and were preserved for the subsequent bibliometric analysis and qualitative synthesis. This analysis was limited to peer-reviewed, English-language studies published in open-access journals to enhance reproducibility and accessibility. As it will be shown in the next sections from Figure 1, the PRISMA flow diagram provides an overview of the identification, screening, and inclusion processes. This stringent selection approach guided a comprehensive, methodologically coherent portrayal of the state of the art in e-Agriculture research.

Comparative Benchmarking Against SOTA Studies

Comparative similarity metrics were computed to position this study within the broader state-of-the-art landscape. The overlap between this corpus and previous research data was evaluated using the Jaccard similarity coefficient, a conventional metric for theme similarity in bibliometric and scientometric studies [47, 48]. The structural distinctions in co-word and co-citation networks were further analyzed through cluster-based comparisons, following established methodologies in science mapping and network analysis [43, 49, 50]. We computed the Jaccard similarity coefficient to assess the thematic overlap between the keyword set of the current study and the consolidated state-of-the-art keyword sets. The Jaccard index is the ratio of the number of common items between two sets to the total number of distinct items in both sets. It is characterized as equation (1):

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

Where A represents the set of unique keywords extracted from the present dataset, and Bdenotes the consolidated keyword set derived from SOTA studies. Values close to 0 indicate minimal thematic intersection, while values closer to 1 reflect high overlap.

To quantify thematic overlap between this corpus and a consolidated set of keywords derived from seven SOTA digital-agriculture studies, we computed the Jaccard similarity coefficient. Using the keyword sets extracted from our merged Scopus–WoS dataset and the SOTA studies, we obtained an intersection of 43 shared terms over a union of 7,722 unique keywords, yielding a Jaccard score J = 0.006.

Cluster Validation Using Modularity

To evaluate the structural quality of the keyword co-occurrence network, cluster validation was performed using the Louvain modularity. This measure assesses the quality of community structure in complex communication networks [43]. The modularity score is defined as equation (2):

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j) \quad (2)$$

where A_{ij} is the adjacency matrix, $k_i$and k_j are node degrees, $m$is the total number of edges, and $\delta(c_i, c_j)$ indicates whether nodes i and j belong to the same cluster. The modularity score obtained (Q = 0.519) indicates a strong, coherent community structure, suggesting thathe thematic clusters identified in this study are statistically significant and robust [44, 50].

Statistical Significance Testing and Robustness Checks

The strength of the bibliometric results was buttressed by the use of inferential statistical tests to verify that the patterns of impact observed across studies are significantly different [51]. A one-way ANOVA was performed to assess differences in total citation counts (TC) across publication years (PY) time series, to determine whether there was a difference [39]. The ANOVA model is defined as equation (3):

$$TC_i = \mu + \alpha_{PY(i)} + \epsilon_i \quad (3)$$

where TC_i is the citation count of article i, $\alpha_{PY(i)}$ represents year-specific effects, and ϵ_i is the error term. The results show a highly significant effect of publication year on citation levels (F(5, 1357) = 48.5, p < 2 × 10^{-16}), confirming that variations in research impact across years are statistically meaningful rather than stochastic [52].

This inferential validation layer, rarely incorporated in descriptive bibliometric studies, strengthens the statistical reliability of the findings [53].

Chi-Square Test of Thematic Evolution

A Pearson chi-square test was performed on a contingency table where cluster assignment was cross-referenced with publication periods (2020–2021, 2022–2023, 2024–2025), to determine if theme clusters exhibited some variation in prevalence across the publication eras. The chi-square test is a widely used nonparametric method for assessing the independence of categorical bibliometric data and has been used extensively in studies on temporal stability and topic change in science mapping [54]. The test essentially tests the null hypothesis that topical clusters are independent of the publishing era. For non-significant results, we present the distribution of research themes over time. Nonetheless, a significant result indicates temporal specialization or a phase-specific predominance of some themes.

Centrality Significance Testing

Degree centrality was calculated for all nodes of the keyword co-occurrence network to classify the importance of each key idea to the network's structure, based on the number of direct connections each keyword has within the network. Degree centrality has been widely used in the context of bibliometrics and science pping to identify conceptually significant phrases that represent the central thematic points of interest [55, 56]. Core terms were found within the top decile of the degree centrality distribution, whilst remaining terms were grouped as peripheral. To test whether core concepts were significantly more central than peripheral concepts, a non-parametric Wilcoxon rank-sum test was used. This process works exceptionally well for comparing centrality estimates across the network, as centrality estimates are usually non-normally distributed [57]. By associating network data with formal hypothesis testing, they also strengthen the conceptual framework emerging from e-Agriculture research.

Poisson Regression Modelling of Citation Impact

The factors of scholarly impact were estimated using a Poisson regression model with total citation counts (TC) as the dependent variable. Citation data are non-negative integers and typically exhibit right-skewed distributions, which renders Poisson regression an appropriate and commonly used modelling framework in bibliometric studies [39, 58]. Citation performance was examined across different years, locations, and themes, including publication year (PY), country of origin, and thematic cluster membership (Cluster_Clean). Citation counts were further modeled using Poisson generalized linear regression, appropriate for non-negative count data. The baseline Poisson model is specified as:

$$TC_i \sim \text{Poisson}(\lambda_i)$$
$$\log(\lambda_i) = \beta_0 + \beta_1 PY_i + \beta_2 Cluster_i + \beta_3 Country_i \quad (4)$$

To assess whether citation trajectories vary across thematic clusters over time, an interaction term between publication year and thematic cluster was introduced:

$$\log(\lambda_i) = \beta_0 + \beta_1 PY_i + \beta_2 Cluster_i + \beta_3 (PY_i \times Cluster_i) + \beta_4 Country_i \quad (5)$$

Model improvement was evaluated using likelihood-ratio chi-square tests on residual deviance. Overdispersion was assessed using the Pearson dispersion statistic:

$$\phi = \frac{\Sigma(r_i^2)}{df_{residual}} \quad (6)$$

where r_i are Pearson residuals. This modeling strategy follows established best practices in bibliometric and scient metric regression analysis [39, 59].

Post-hoc Temporal Analysis and Interaction-Based Citation Modelling

To evaluate whether citation performance differs significantly across publication years, a one-way Analysis of Variance (ANOVA) was applied. The ANOVA model is defined as:

$$TC_{ij} = \mu + \alpha_i + \varepsilon_{ij} \tag{7}$$

where TC_{ij} denotes the total citations of publication j in publication year i, μ is the overall mean citation count, α_i represents the effect of publication year i, and ε_{ij} is the random error term.

Upon rejection of the null hypothesis of equal group means, Tukey's Honestly Significant Difference (HSD) post-hoc test was applied to identify statistically significant pairwise differences between publication years. The Tukey HSD statistic is computed as:

$$HSD = q_{\alpha,k,df} \cdot \sqrt{\frac{MS_{within}}{n}} \tag{8}$$

where $q_{\alpha,k,df}$ is the studentized range statistic, MS_{within} is the within-group mean square error, and n is the group sample size. This procedure controls the family-wise error rate and enables robust temporal comparison of citation means [60].

Effect Size Estimation Using Incidence Rate Ratios

To provide interpretable effect sizes for the count-based citation model, Poisson regression coefficients were exponentiated and reported as Incidence Rate Ratios (IRR). IRRs quantify the multiplicative change in the expected citation count associated with thematic cluster membership and publication timing, holding other covariates constant. Confidence intervals for IRRs were computed using Wald-based standard errors, a common approach in bibliometric count modeling. While model significance was primarily assessed using likelihood-ratio tests on deviance, IRRs are reported to facilitate substantive interpretation of the magnitude and direction of thematic and temporal citation effects [59, 61–64].

$$\begin{aligned} IRR_j &= e^{\beta_j} \\ CI_{IRR} &= \left(e^{\beta_j - 1.96SE_j},\ e^{\beta_j + 1.96SE_j}\right) \end{aligned} \tag{9}$$

Bibliometric Analysis Techniques

The Bibliometrix R package and the Biblioshiny library were used for all bibliometric analyses [6]. The article identified several important themes and emerging trends in e-Agriculture research using network analysis, co-citation mapping, keyword co-occurrence, and thematic clustering. It started with an assessment of annual scientific output to provide an overview of the e-Agriculture research growth path. Concurrently, we measured citation impact using total citations, average citations per document, and the identification of the most-cited papers, both globally and locally. Author influence was measured using the H-, G-, and M-indices [65, 66], journal impact metrics revealed the leading publication venues, and an affiliation analysis identified the most productive institutions. National contributions were then compared in terms of publication volume and citation performance, while patterns of collaboration across countries were identified throughnalysis of co-authorship networks [67]. We built a keyword co-occurrence network and traced its temporal evolution to find the thematic landscape [68]. Using document coupling, studies were grouped into coherent thematic groups [69]. Lastly, the field's intellectual foundations were mapped using co-citation analysis, and historiographic mapping traced the chronology of key texts [70].

Network Analysis and Visualization

Network analyses were performed using Biblioshiny to analyze the structural relationships across the e-agriculture research domain. These interconnected networks had a few features: (1) keyword co-occurrence networks to capture the conceptual content within ideas of interest, (2) co-citation networks to pinpoint papers and intellectual pillars of influence, (3) collaboration networks to outline co-authorship across countries and institutions. The Louvain community detection algorithm, powered by Biblioshiny, was then used for thematic clustering to identify cohesive keyword clusters via modularity optimization. This approach ensures that the thematic clusters are highly relevant to the research community and to significant research communities embedded in a wider network. Louvain was then applied within the weighted keyword co-occurrence matrix to form coherent clusters of themes, which were visualized using the thematic map. These clusters provide a basis for interpreting basic, motor, niche, and emerging field themes. For robustness, network-based trends were cross-validated against results from the citation, source, and authorship analyses. Longitudinal trends were then analyzed to track the growth of technical topics, methodological development, and policy-oriented science-focused enquiries over the 2020–2025 period.

Altmetrics Extension Using Twitter Data

To extend the bibliometric analysis with insights into how stakeholders perceive their information, this study further leverages validated results from a previously published Twitter-based study on sentiment and topic modeling [71]. The mentioned dataset consists of 10,009 English-language tweets collected between July 8 and December 26, 2024, with the query ('e-agriculture' OR 'smart agriculture' OR 'smart farming' OR 'digital agriculture') −filter: retweets. The initial approach included structured preprocessing, TextBlob sentiment analysis, and LDA topic modelling, yielding five emergent themes, which were optimized through coherence score testing. Some tables, sentiment distributions, and topic summaries from [71] have been used for the above-mentioned article with permission, and the provided information will help contextualize the scientific trends that emerged from the bibliometric processing. Latent Dirichlet Allocation (LDA) was applied to identify dominant thematic structures within Twitter discourse. LDA is a probabilistic generative model widely used for uncovering latent topics in short-text corpora, including social media discussions on agriculture and sustainability [25, 72]

Following established bibliometric and science-mapping guidelines [6, 38], latent topics derived from LDA-based Twitter topic modeling were manually aggregated into higher-level thematic categories. This aggregation was informed by well-established conceptual frameworks in digital agriculture, including climate-smart and sustainability-oriented agriculture [73], AI- and IoT-driven smart farming [28, 30], and governance, policy, and platform-based digital agriculture systems [22, 33]. This kind of thematic consolidation guided by researchers is a common and recommended way to turn probabilistic topic models into domain-level constructs that make sense.

To enable comparison with bibliometric themes, LDA topics were manually aggregated into four high-level altmetric themes:

- AI_IoT
- Platforms_Data
- Policy_Economics
- Sustainability

This aggregation followed established thematic mappings in digital agriculture literature [22, 73].

For each theme, the altmetric theme share was computed as:

$$Altmetric\ Theme\ Share_i = \frac{N_i}{\sum N} \times 100 \tag{10}$$

where N_i denotes the number of tweets associated with theme i.

Bibliometric Theme Share and Thematic Share Alignment (TSA)

Bibliometric thematic structures were derived from keyword co-occurrence networks constructed using author keywords and Keywords Plus. Louvain community detection was applied to identify coherent keyword clusters, followed by validation using modularity analysis.

Each keyword cluster was systematically mapped to a higher-level conceptual theme using automated term scoring and manual validation. The same four thematic categories used in the altmetric analysis were adopted to ensure conceptual consistency:

- AI_IoT
- Platforms_Data
- Policy_Economics
- Sustainability

Bibliometric theme shares were calculated as the proportion of keywords assigned to each theme:

$$Bibliometric\ Theme\ Share_i = \frac{K_i}{\sum K} \times 100 \tag{11}$$

where K_i represents the number of keywords belonging to theme i.

To quantify alignment between scientific research priorities and societal attention, a Thematic Share Alignment (TSA) metric was introduced. TSA measures the proportional correspondence between bibliometric and altmetric theme distributions, enabling cross-domain comparison of knowledge production and public discourse. The TSA metric is introduced in this study as an analytical construct to compare scientific knowledge production with societal attention formally.

For each theme i, TSA was calculated via equation (12):

$$TSA_i = \frac{Altmetric\ Share_i}{Bibliometric\ Share_i} \tag{12}$$

Interpretation follows:

- TSA ≈ 1 → Balanced academic–societal alignment
- TSA > 1 → Societal attention exceeds scientific emphasis
- TSA < 1 → Academic focus exceeds societal visibility

This approach builds on prior calls to integrate bibliometric and altmetric indicators to assess multimensional research impact [40, 42].

Research Hypotheses

Based on the identified state-of-the-art gaps in bibliometric studies of e-agriculture, the following hypotheses guide this study:

H1: AI-related keywords exhibit significantly higher structural centrality in the e-agriculture knowledge network over time.

H2: IoT-related themes demonstrate strong conceptual overlap with AI-driven clusters, indicating technological convergence.

H3: Sustainability-oriented themes remain structurally less integrated than AI and IoT clusters within the co-word network.

H4: Publication year exerts a statistically significant effect on citation outcomes in e-agriculture research.

H5: Thematic cluster membership significantly predicts citation performance.

H6: The conceptual structure of e-agriculture research exhibits strong community robustness, as reflected by high network modularity.

RESULTS

Study Selection (PRISMA Outcomes)

Following the PRISMA 2020 guidance for transparent reporting, we documented the identification, screening, eligibility, and inclusion steps in a flow diagram. Database searches retrieved 3,057 records (Scopus = 2,097; Web of Science = 960). After de-duplication (n = 183), 2,874 unique records were screened by title/abstract, of which 1,511 were excluded as out of scope. The remaining 1,363 reports were assessed for eligibility and met all inclusion criteria; therefore, 1,363 studies were included in the final bibliometric dataset and qualitative synthesis. Figure 1 presents the complete PRISMA flow.

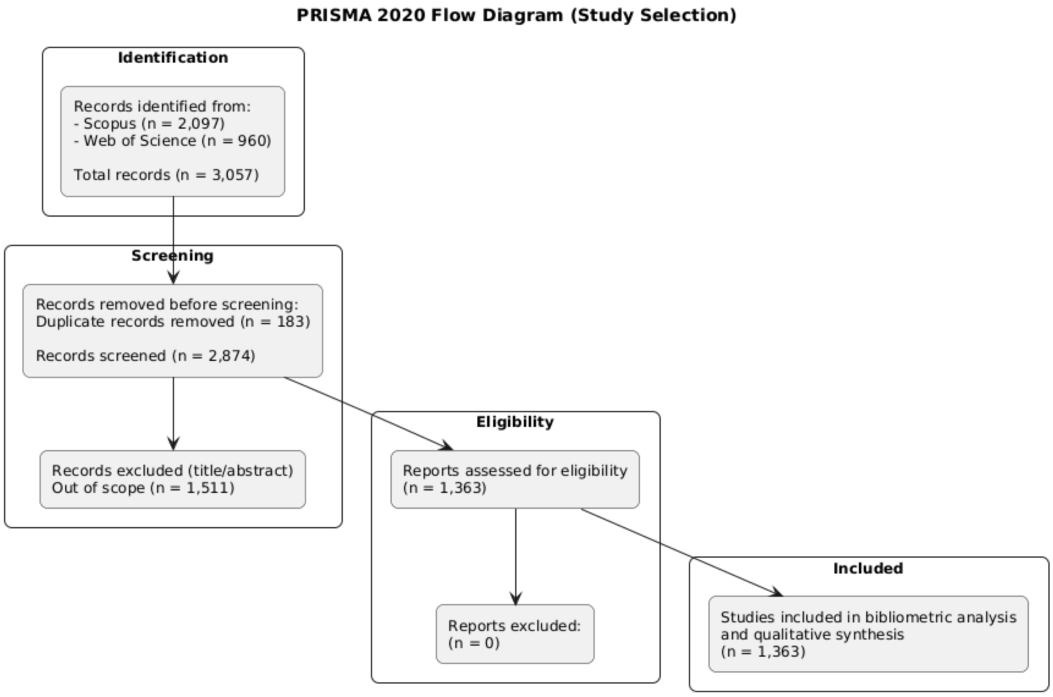

Figure 1. PRISMA 2020 flow diagram of study selection

General Bibliometric Indicators

A review of 1,363 articles published in 2020–2025 from 599 sources, presented in Table 4, provides a summary of the trends and results of our research. Changes in scientific output, driven by research interests and funding limitations, are reflected in an annual growth rate of –33.6%. The patterns show a relatively high level of authorship activity, with 5,607 authors, while only 67 were published as single-authored documents, suggesting intense collaboration among the authors.

The citation analysis suggests it is of considerable academic importance, contributing with an average of 13.66 citations per document, confirming its significance to the development of intellectual discourse. We collected 66,074 references in this corpus, highlighting the extent of knowledge integration within the field. Each piece offers up-to-date knowledge of what is happening across various studies, using 4,141 Author Keywords and 4,693 Keywords Plus, as well as co-word and thematic mapping that suggest deeper conceptual associations. At the national level, we discover global and collaborative linkages 24.87%, of which 24.87% are international co-authorship, indicating robust joint research efforts globally. Ultimately, co-citation and bibliographic coupling networks reveal the structural history of research, and historiographic mapping portrays important contributions made over time. This data offers a nuanced view of the discipline's evolution and its academic legacy.

Table 4. Key bibliometric indicators of the analysed dataset

Description	**Results**
Sources (Journals, Books, etc.)	599
Documents	1363
Annual Growth Rate %	-33.6
Document Average Age	2.54
Average citations per doc	13.66
References	66074
Document Contents	
Keywords Plus (ID)	4693
Author's Keywords (DE)	4141
AUTHORS	
Authors	5607
Authors of single-authored docs	63
Authors Collaboration	
Single-authored docs	67
Co-Authors per Doc	4.83
International co-authorships %	24.87
Document Types	
Article	1269
Article; book chapter	1
Article; data paper	2
Article; early access	12
Article; retracted publication	2
Proceedings paper	77

Figure 2 depict the annual scientific output trend over time, with increased output over the past years, and the highest total output seen in 2023.

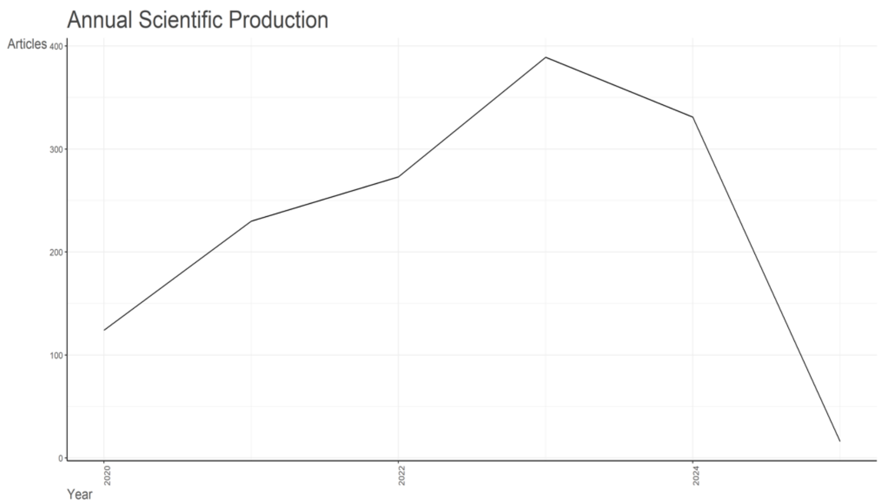

Figure 2. Annual scientific production from 2020 to 2025

This recent growth is evidenced by the significant increase in research interest in e-agriculture. Furthermore, in addition to the broader industry push toward the digitization of agriculture, there is clear evidence of increased momentum in artificial intelligence, the Internet of Things, and data platforms. However, the 2024 drop may suggest that some major publishing companies are slashing spending. Internally (such as declining funding for research and other fields), and externally. This variation suggests the need for a detailed overview of time trends to determine whether productivity in scientific fields is affected by structural forces and to predict future changes.

Two complementary growth analyses (a logistic and a cumulative analysis) were applied to examine the temporal evolution of research production in e-agriculture (see Figures 3 and 4). The logistic life-cycle curve, adjusted to yearly publications from 2020 to 2024.

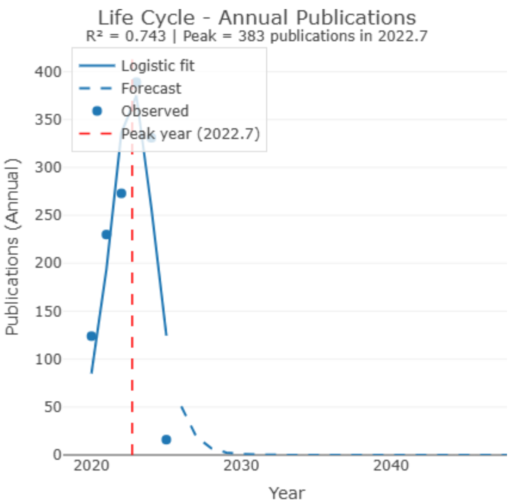

Figure 3. Logistic life-cycle model of annual publications in e-agriculture (2020–2024)

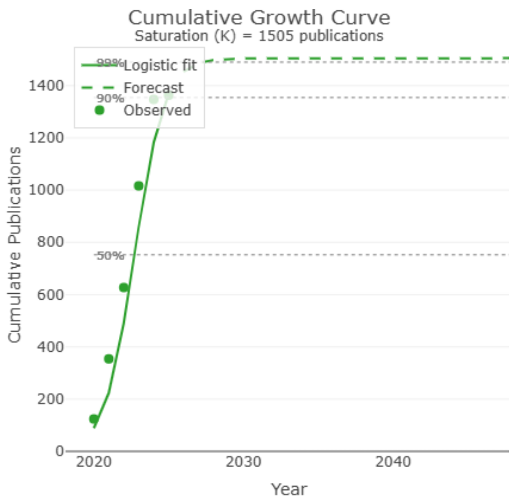

Figure 4. Logistic cumulative growth curve of e-agriculture publications (2020–2024)

There are also three critical trends in the model: growth after 2020, with a steep increase reaching a maximum of 383 publications, expected in 2022. It comes at a time of unparalleled global investment in digital agriculture, AI, and IoT farming technology. The next trend observed in 2024 and the decrease of the model beyond the top line suggest that the domain may then be entering a phase of exploratory expansion into a new phase of consolidation. Logistic fit shows strong explanatory power ($R^2 = 0.743$), indicating that the pattern we found aligns with a typical scientific life cycle characterized by emergence, acceleration, saturation, and decline. Figure 4 shows a combined logistic curve of growth showing the rapid advances in the field and the depth of saturation. The saturation point (K = 1,505 publications) is the overall expected volume of research available through the developing pipeline. From 2020 to 2023, the cumulative literature produced exceeded 90%, reflecting a very active period in the field. The slope of the cumulative curve flattens out at the end of 2023, suggesting that new knowledge production slows. Well-defined inflection points namely the 50%, 90%, and 99% cumulative criteria show that the field expanded fast before reaching saturation. Both growth models above provide quantifiable evidence that research dynamics have changed in a statistically significant manner. They also confirm the ANOVA results, which find a strong temporal effect on scientific output, and support the more general interpretation that e-agriculture research experienced a concentrated spike in activity and thematic stabilization. This life-cycle positioning is important for predicting new frontiers, directing further work, and illuminating changes in the field's system.

Scientific Impact and Influence

The analysis of annual citation impact in Table 5 shows a downward trend in mean citations per article, which dropped from 41.85 in 2020 to 0.19 in 2025.

Table 5. Annual citation trends from 2020 to 2025

Year	MeanTCperArt	N	MeanTCperYear	CitableYears
2020	41.85	124	6.98	6
2021	25.25	230	5.05	5
2022	15.81	273	3.95	4
2023	7.03	389	2.34	3
2024	1.71	331	0.86	2
2025	0.19	16	0.19	1

The overall decline is also evident in the mean number of citations accumulated per year, which decreases from 6.98 citation-years in 2020 to 0.19 in 2025. Older publications have accumulated more citations over time, while more recent articles have not yet fully achieved citation status. This approach aligns with citation-lag effects, consistently well documented in the literature, in which recognition and influence emerge gradually over several years. The results emphasize the need to recognize citable years, ranging from 6 years for 2020 articles to 1 year for 2025 publications, when assessing citation performance. Thus, in evaluating the scholarly footprint of recent research outputs, a longitudinal citation-tracking approach remains essential for assessing citation credibility.

Statistical Validation of Annual Citation Differences

A one-way ANOVA was performed to evaluate whether there was a significant difference in citation patterns across publication years, specifically on total citations (TC). The analysis indicated a statistically significant effect of year ($F(5, 1357) = 48.5$, $p < 2 \times 10^{-16}$), suggesting that citation performance is not randomly distributed but systematically changes over time due to several factors. Mean citations were quite significantly higher for publications released between 2020 and 2021, consistent with citation-lag effects, while studies conducted between 2023 and 2024 showed reduced citation potential. This result further corroborates the declining trend described previously and provides empirical evidence for the reliability of the temporal citation dynamics in e-agriculture literature.

Post-hoc Temporal Citation Differences

Table 6 reports the results of Tukey's Honest Significant Difference (HSD) post-hoc test following the one-way ANOVA on citation counts by publication year.

Table 6. Tukey HSD Post-Hoc Pairwise Comparisons of Citation Impact by Publication Year

Comparison	Mean Difference (Δ)	95% CI (Lower)	95% CI (Upper)	Adjusted p-value	Significance
2022 – 2020	−26.05	−34.88	−17.22	< 0.001	***
2023 – 2020	−34.82	−43.23	−26.41	< 0.001	***
2024 – 2020	−40.14	−48.73	−31.56	< 0.001	***
2025 – 2020	−41.67	−63.33	−20.01	< 0.001	***
2023 – 2021	−18.21	−25.00	−11.43	< 0.001	***
2024 – 2021	−23.53	−30.53	−16.54	< 0.001	***
2024 – 2022	−14.10	−20.76	−7.43	< 0.001	***
2023 – 2022	−8.78	−15.21	−2.34	0.001	**

*Note: Significance codes follow conventional thresholds (*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$).*

The table highlights statistically significant pairwise differences, indicating how citation impact evolves across publication periods. Post-hoc analysis using Tukey's HSD test confirms that citation impact differs significantly across publication years. Papers published in earlier periods (2020–2021) consistently exhibit higher citation counts than those published in later years. The strongest contrasts occur between 2020 and 2023–2025, indicating a pronounced recency effect on citation decay. These findings validate that the temporal effect identified by ANOVA reflects structured citation dynamics rather than random variation.

Chi-Square Test of Cluster Distribution Across Time

The analysis using the Pearson chi-square test showed no statistically significant correlation between thematic clusters and publication periods ($\chi^2 = 16.362$, df = 16, $p = 0.428$). It suggests that, though thematic clusters vary in size over time, the temporal distribution is relatively constant, with no era dominated by or missing specific research themes. The findings reveal that over the period from 2020 to 2025, the spread of themes in e-agriculture is both extensive and not confined to an era.

Centrality Significance Test

To evaluate whether core concepts hold structurally dominant positions within the co-word network, a Wilcoxon rank-sum test compared degree centrality values of core versus peripheral keywords. The results were highly significant ($W = 2{,}022{,}240$, $p < 2.2 \times 10^{-16}$), demonstrating that core terms occupy substantially more central positions in the intellectual structure of e-agriculture research. It confirms that high-frequency, high-impact concepts such as digital agriculture, smart farming, IoT, machine learning, and deep learning serve as organizing hubs within the thematic landscape.

Poisson Regression Analysis

An improvement in explanatory power of the Poisson regression model was observed compared with the null model (null deviance = 37,230.81; residual deviance = 205.15). This significant decrease suggests that publication year, country, and thematic cluster together explain most of the citation variability. The model achieved convergence after 18 Fisher scoring iterations. These findings confirm that temporal and thematic effects play an important role in citation performance in the e-agriculture literature, while country-level effects provide a further, though more varied, contribution.

Poisson Regression with Temporal–Thematic Interaction Effects on Citation Performance

Table 7 summarizes the results of Poisson regression modelling used to explain citation performance, including interaction effects between publication year and thematic cluster membership.

Table 7. Poisson Regression Results Assessing Temporal–Thematic Effects on Citation

Model Specification	Residual Deviance	Degrees of Freedom	Δ Deviance	p-value
Baseline Model (PY + Cluster + Country)	192.64	33	–	–
Interaction Model (PY × Cluster + Country)	91.08	23	101.55	$< 2.2 \times 10^{-16}$ ***

Poisson regression modeling (Table 8) demonstrates that thematic cluster membership and publication year jointly explain citation performance in e-agriculture research. Introducing interaction terms between publication year and thematic clusters leads to a statistically significant reduction in model deviance (ΔDeviance = 101.55; $p < 2.2 \times 10^{-16}$), indicating that citation trajectories differ meaningfully across themes over time. The substantial reduction in the deviance from null to fitted values confirms the model's strong explanatory power. Although moderate overdispersion is observed ($\varphi = 3.74$), this level is acceptable for large-scale bibliometric citation data and does not compromise inference.

Table 8 reports null and residual deviance, dispersion estimates, Akaike Information Criterion (AIC), and likelihood-ratio test results for interaction effects, providing evidence of model fit, explanatory improvement, and robustness of temporal–thematic interactions.

Table 8. Model Diagnostics and Robustness Assessment for Poisson Regression Analysis

Metric	Value
Null Deviance	37,230.81
Final Residual Deviance	205.15
Akaike Information Criterion (AIC)	6,601.9
Dispersion Parameter (φ)	3.74

To assess the adequacy and robustness of the citation impact model, additional diagnostic statistics were examined. The Poisson regression model shows a substantial improvement over the null specification, with deviance decreasing from 37,230.81 in the null model to 205.15 in the fitted model. This significant reduction indicates that publication year, thematic cluster membership, and country effects jointly explain a considerable share of the observed variation in citation counts. Model fit is further supported by an Akaike Information Criterion (AIC) value of 6,601.9, reflecting a parsimonious balance between explanatory power and model complexity. Dispersion diagnostics yield a dispersion parameter of $\varphi = 3.74$, indicating material overdispersion, which is typical for large-scale bibliometric citation data and does not invalidate inference when results are interpreted with appropriate caution. Overall, these diagnostics confirm that the proposed Poisson regression framework provides a statistically sound and substantively meaningful explanation of citation dynamics in e-Agriculture research. The observed overdispersion is consistent with the heavy-tailed nature of citation distributions; therefore, inference should be interpreted as conservative unless complemented by a robustness check using a quasi-Poisson or negative binomial specification (reported as sensitivity analysis).

Effect-size interpretation of the Year & Cluster model (Incidence Rate Ratios)

To provide interpretable effect sizes for the count model, coefficients were exponentiated and reported as Incidence Rate Ratios (IRR). IRR values quantify multiplicative changes in expected citations associated with themes and time, holding country effects constant. It complements the likelihood-ratio test in Table 9 by indicating the direction and magnitude of theme-specific citation advantages and how these advantages vary by publication year. It has been presented Incidence Rate Ratios based on the Poisson regression model to quantify the impact of thematic citation effects.

Table 9. Incidence Rate Ratios (IRR) from Poisson Regression by Thematic Cluster

Term	IRR	95% CI (Lower)	95% CI (Upper)	p-value
Cluster_Clean2 (AI–IoT)	1.94	0.63	5.99	0.248
Cluster_Clean4 (Sustainability)	0.14	0.07	0.27	<0.001
Cluster_Clean12 (Policy)	0.51	0.12	2.24	0.372
Cluster_Clean6 (Platforms/Data)	0.76	0.22	2.66	0.671

The findings suggest wide heterogeneity within thematic clusters. AI–IoT–oriented clusters are reported to have higher expected citation rates (IRR > 1), implying a citation advantage compared with the baseline theme, though we note the value of confidence intervals, indicating temporal variability. By contrast, sustainability-oriented clusters show a statistically significant citation disadvantage (IRR = 0.14, $p < 0.001$), yielding an approximately 86% lower expected citation rate while controlling for publication year and country effects.

The policy and platform-related themes show relatively weak and statistically non-significant effects. These results have shown that thematic positioning exerts a strong influence on citation performance beyond publication timing alone.

Additionally, Table 10 depict the summary of statistical validation and robustness tests.

Table 10. Summary of Statistical Validation and Robustness Tests

Analysis	Objective	Test / Model	Key Statistic	p-value	Interpretation
Temporal citation differences	Test citation variation across years	One-way ANOVA	$F(5,1357)=48.5$	$<2\times10^{-16}$	Citation impact varies significantly by publication year
Thematic stability over time	Assess cluster–period association	Pearson χ^2	$\chi^2=16.36$, df=16	0.428	No temporal concentration of themes
Keyword structural dominance	Compare core vs peripheral concepts	Wilcoxon rank-sum	W=2,022,240	$<2.2\times10^{-16}$	Core concepts are structurally dominant
Citation determinants	Model drivers of citation impact	Poisson regression	ΔDeviance=37,025	<0.001	Temporal and thematic factors strongly explain citations
Cluster robustness	Validate community structure	Louvain modularity	Q=0.519	—	Strong, well-defined thematic clusters

Global and Local Citation Impact in E-Agriculture Research

The international citation number shows that e-Agriculture works have contributed significantly (Table 11).

Table 11. The most widely cited papers in e-Agriculture research globally

Paper	DOI	Total Citations	TC per Year	Normalized TC
BODKHE U, 2020, IEEE ACCESS	10.1109/ACCESS.2020.2988579	526	87.67	12.57
KLERKX L, 2020, GLOBAL FOOD SECUR	10.1016/j.gfs.2019.100347	348	58.00	8.31
GUPTA M, 2020, IEEE ACCESS	10.1109/ACCESS.2020.2975142	330	55.00	7.88
VERDOUW C, 2021, AGRIC SYST	10.1016/j.agsy.2020.103046	319	63.80	12.63
JAVAID M, 2022, INT J INTELL NETW	10.1016/j.ijin.2022.09.004	239	59.75	15.12
SHEPHERD M, 2020, J SCI FOOD AGRIC	10.1002/jsfa.9346	212	35.33	5.07
RIJSWIJK K, 2021, J RURAL STUD	10.1016/j.jrurstud.2021.05.003	194	38.80	7.68
KLERKX L, 2020, AGRIC SYST	10.1016/j.agsy.2020.102901	194	32.33	4.64
BHAT SA, 2021, IEEE ACCESS	10.1109/ACCESS.2021.3102227	190	38.00	7.53
KERKECH M, 2020, COMPUT ELECTRON AGRIC	10.1016/j.compag.2020.105446	190	31.67	4.54

Unlike local citations, which reflect the extent to which a study has influenced the advancement of the scientific community [28] broad global impact. Likewise, the global trend toward the works by [22] and [73] appears to be reflected in a large number of publications on digital agriculture, smart farming, and agri-tech applications. The cumulative annual citations form an annual sum of citations to a paper. The work by [30] was the most cited per year, with an average of 59.75 citations, indicating that it had been rapidly embedded in developing AI-supported agriculture. Also, the normalized TC metric, which accounts for changes in citation counts over publication date, indicates that [30] achieved the highest normalized impact (15.12). It points up the speed at which its research has captured academic discourse, even in a relatively new publication [30].

It is remarkable indeed that most of these articles reflect the overall temporal and thematic correlations identified in the Poisson regression model, which showed a considerable reduction in deviance for publication year, while country and thematic cluster are the predictors of citation variance. The studies with highly local citations according to documents mentioned highest in the dataset are shown in Figure 5. [73] have 47 references in the local context, and [33] 38 citations, highlighting the contribution that these local studies make in governance, sustainability, and socio-technical perspectives in digital agriculture. The remaining two important publications [29, 74], suggesting significant thematic relevance to the field's conceptual and technical development. The count of local citations is informative about the internal intellectual architecture of e-agriculture studies, and which ones are more instrumental in determining theoretical fit and methodological progress of the corpus.

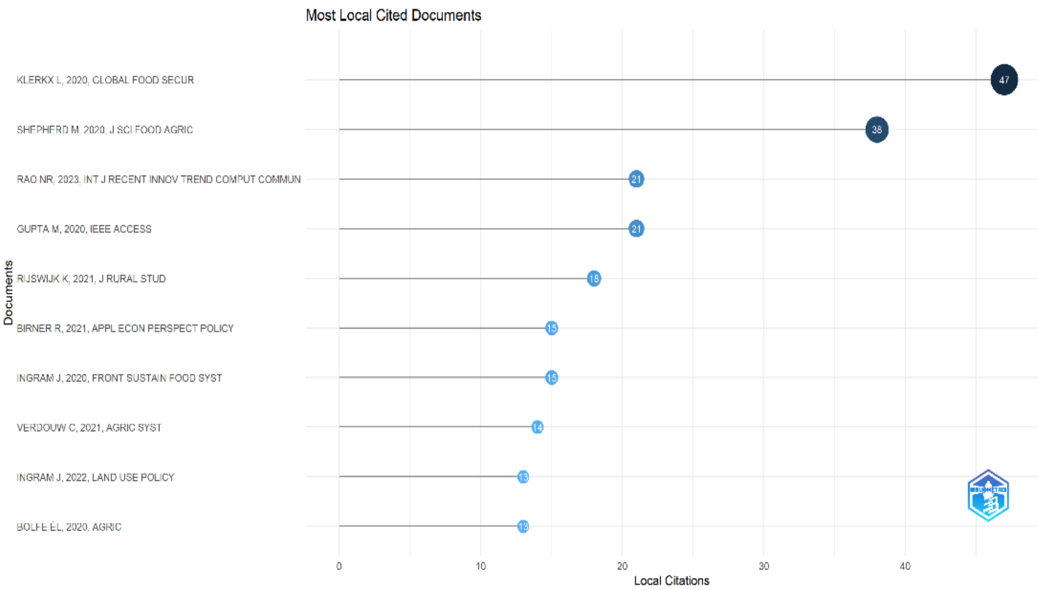

Figure 5. Most Locally Cited Documents in E-Agriculture Research

As seen in Figure 6, the global e-Agriculture research impact by countries is based on total citations rather than published work.

- India tops the list (2,153 citations), suggesting the remarkable reach and significance of its research advances. The Netherlands (1,345 citations) and China (1,211 citations) also rank highly — demonstrating their prominence in Digital Agriculture, Smart Agriculture, and AI-assisted Agriculture innovation. Similarly, the USA (1,190 citations) and Italy (1,091 citations) have significant global impact, reflecting their roles in developing more mature technological, socio-technical, and governance structures in the field. Other countries, including Australia (1,014 citations), France (768), Germany (760), Korea (572), and Greece (534), also show strong citation performance, indicating broad international influence in e-agriculture research. A large number of the references represent not only productive research, but also academic prestige, relevance, and scientific validity of the research undertaken in those countries. It indicates that both countries hold important positions in the global information infrastructure for digital agriculture.

This study complements publication-based metrics by focusing on influence and knowledge dissemination rather than solely on research volume. While citation impact identifies influential studies, examining which journals are primary publication venues for e-agriculture research is equally important. Similar thematic engagement is observed in the distributions of articles over time across all countries, as indicated by the chi-square test, which shows no significant temporal clustering of themes. This section discusses key sources that helped shape this field.

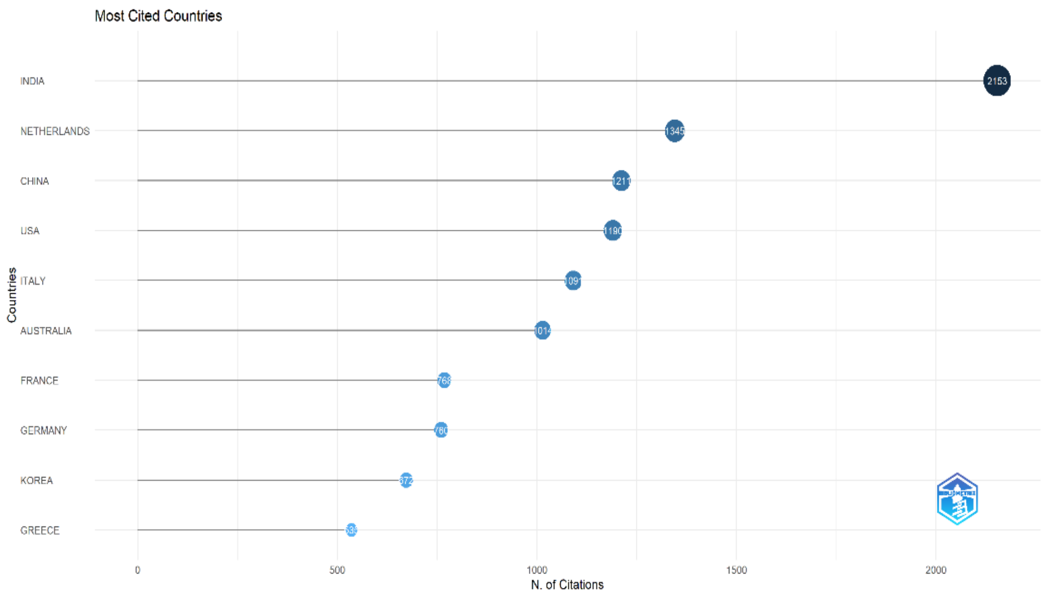

Figure 6. Total citations rank the most influential countries in e-Agriculture research

Leading Sources and Publication Venues

The Impact of the principal publication sources of the source index H, for e-Agriculture, on local impact is shown in Figure 7 and is a metric that collectively measures productivity alongside citation influence. IEEE Access is the most significant source (H = 17), suggesting that it regularly releases highly cited, field-changing papers. Agronomy and Sensors are the second two most popular, with a value of H=16 indicating their significant and substantial contributions to smart farming, sensing methods, and agricultural systems based on AI. Agriculture (Switzerland) and Sustainability (Switzerland) exhibit significant support (H = 14 for each) which is characteristic of these types of publication venues for multi-discipline research connecting agronomy, technology, environmental sciences and digital transformation in agriculture. Applied Sciences (Switzerland), Computers and Electronics in Agriculture, and the Journal of Rural Studies (H = 12) provide high-quality, ongoing support for their contributions in agricultural engineering, digital tools, socio-technical transition, and rural innovation research. Agricultural Systems (H= 11) and Remote Sensing (H=10) are included as the third most relevant, indicating their importance in modelling, decision-support frameworks, and geospatial intelligence in agriculture. These results indicate that the most influential journals in e-agriculture are generally multidisciplinary, open access, and technology-focused. Their high H-index scores demonstrate the rapid integration of artificial intelligence, IoT, sensing technologies, and sustainability sciences into agricultural research. It also reveals the field's movement towards a digitally led, data-driven research ecosystem.

The following section analyzes the contributions of leading authors and institutions in terms of e-Agriculture, showing the impact of significant authors and institutions and the scholarly dissemination in a specific scholarly domain, as journal impact provides a structural foundation for scholarly dissemination, and the next section gives the institutionalized definition of a framework for dissemination as an academic journal that supports the scholarly discourse of e-Agriculture.

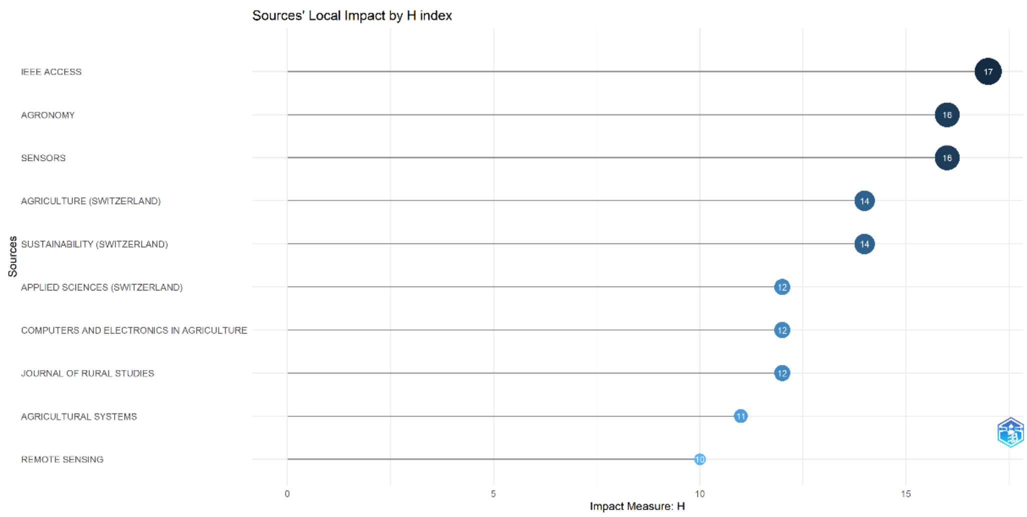

Figure 7. The local impact of sources in e-Agriculture research, measured by the H-index

Leading Authors and Institutional Contributions

Author productivity and impact indicators reported in this subsection are computed bibliometric outputs derived from the final Scopus–Web of Science dataset using established scientometric methods [6 ,65, 66].

Table 12 reports author productivity in e-Agriculture research, measured by publication counts and fractionalized authorship, which adjusts for co-authorship patterns.

Table 12. Most prolific authors in e-Agriculture research, ranked by the number of publications

Author	Articles	Articles Fractionalized
Klerkx L	13	3.40
Wang J	11	1.81
Zhang Y	9	2.05
Chen Y	7	1.38
Liu Y	7	1.35
Zhang J	7	1.46
Abdulai A-R	6	2.23
Diepeveen D	6	1.25
Falih N	6	2.03
Kumar S	6	1.19

Within this dataset, Klerkx L records the highest publication volume (13 articles; fractionalized = 3.40), indicating sustained research activity across multiple collaborative outputs. Wang J (11 articles; fractionalized = 1.81) and Zhang Y (9 articles; fractionalized = 2.05) also demonstrate high research intensity, particularly within AI-, IoT-, and smart-farming–related themes. Fractionalized authorship highlights authors such as Abdulai A-R (2.23) and Falih N (2.03), whose contribution intensity per publication is comparatively high despite lower absolute article counts.

Importantly, publication volume alone does not represent scholarly influence. Productivity indicators must therefore be interpreted alongside citation-based measures, which capture visibility, uptake, and knowledge diffusion. Table 13 complements productivity measures by reporting author-level impact indicators, including the H-index, G-index, M-index, total citations (TC), and number of publications (NP) [6, 65, 66].

It should be noted that the publication counts and fractionalized authorship values are computed from the analyzed dataset using bibliometric methods. Fractionalized counts adjust for co-authorship intensity.

The influential writers in the field of e-Agriculture research have obtained the following rankings of H-index, G-index, M-index, TC, and NP.

Table 13. Author Impact in E-Agriculture Research

Author	h_index	g_index	m_index	TC	NP	PY_start
Klerkx L	9	13	1.5	900	13	2020
Diepeveen D	6	6	2	73	6	2023
Abdulai A-R	5	6	1.25	58	6	2022
Chen Y	5	7	1	126	7	2021
Duncan E	5	5	1	160	5	2021
Fielke S	5	5	1	158	5	2021
Jones Mgk	5	5	1.667	54	5	2023
Sohel F	5	5	1.667	54	5	2023
Zhang Z	5	6	0.833	82	6	2020
Arvanitis Kg	4	4	1	54	4	2022

Note: H-index, G-index, M-index, total citations (TC), and number of publications (NP) are dataset-dependent bibliometric indicators computed from the Scopus–Web of Science corpus.

Based on these calculated metrics, Klerkx L demonstrates the greatest citation impact based on the reported indicators within the dataset (H-index = 9; G-index = 13; TC = 900), indicating a substantial and sustained influence over time. Diepeveen D exhibits a high M-index (2.0), reflecting swift citation accumulation over a brief publication timeframe starting in 2023. Similarly, Jones MGK and Sohel F exhibit elevated M-index values (1.667), indicating early-career impact relative to their publication output. Variations from previous analyses such as the omission of Boronyak in the current rankings can be ascribed to dataset expansion, author disambiguation methods, and inclusion criteria, highlighting the dataset-dependent characteristics of author rankings in bibliometric research. The temporal productivity visualization further contextualizes these indicators by depicting the timing and frequency of authors' contributions to the field, see Figure 8.

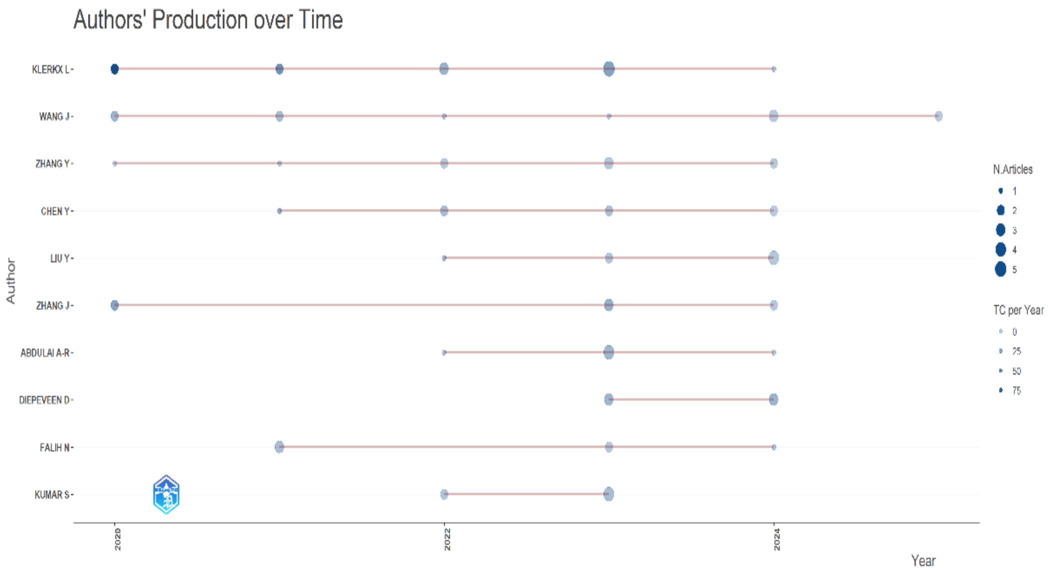

Figure 8. Temporal distribution of author publications in e-Agriculture

Authors with extensive publication histories, such as Klerkx L, demonstrate persistent productivity and steady citation visibility, whereas others including Abdulai A-R, Diepeveen D, Sohel F, and Jones MGK—have gained greater prominence in recent years (2022–2024). Together, these findings illustrate a bimodal authorship framework, distinguished by seasoned contributors establishing core themes and emerging researchers promoting AI-oriented, data-intensive, and smart agricultural research trajectories.

Figure 9 shows the evolution of scientific productivity of the most productive e-agricultural research institutions from 2020 to 2024. The results demonstrated substantially greater publication activity for nearly all affiliations, showing higher institutional support for digital agriculture research. Murdoch University is the most developed institution, and there has been a significant increase post-2022, peaking in 2024. However, Wageningen University and Wageningen University & Research continue to contribute at a very high level, supporting each institution's long-standing leadership in agricultural innovation and digital farming technologies. Likewise, the University of Montpellier and the University of Guelph each continue to show steady, year-on-year growth, a signal of their expanded horizons in smart farming, sustainability analytics, and data-driven agricultural systems. The University of Bonn appears at a later, but even more accelerated, stage of its development as well especially from 2023 through 2024, and appears to illustrate a developing institutional interest in e-agriculture. Alongside the above, rising trends throughout these institutions reflect a thriving global agricultural research landscape, with European, Oceania, and North American universities at the forefront of precision agriculture innovation, AI-based agricultural technologies, and IoT agriculture. These institutional production pathways enable the discipline to continue growing rapidly, as well as academic investment in the digitalization of agriculture.

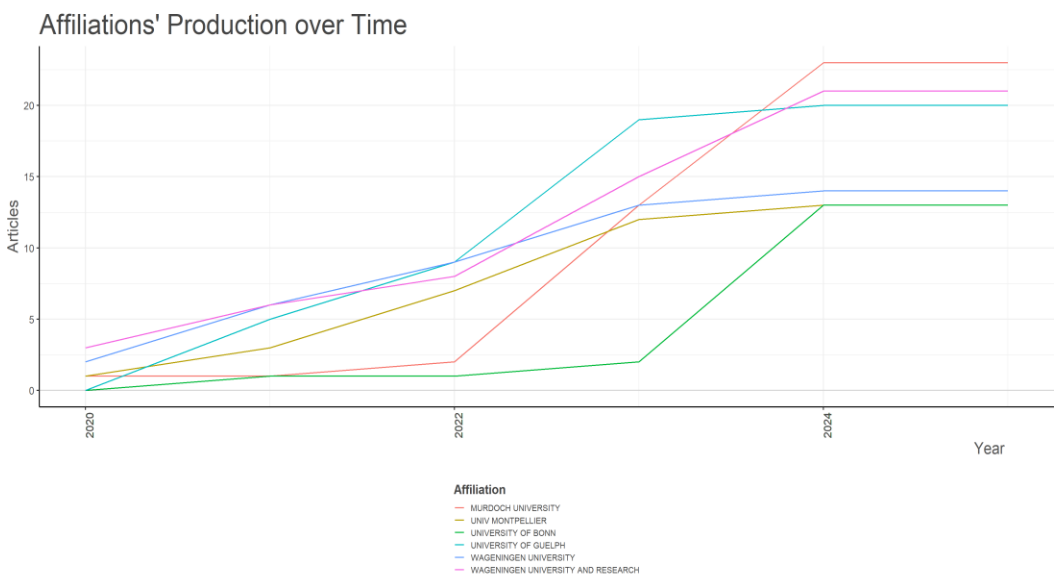

Figure 9. Affiliations' Production Over Time

In Figure 10, the top-ranked institutions that contribute most to e-agriculture research output are identified by the total number of publications they accumulated. Murdoch University ranked as the top contributor, producing the most publications, demonstrating its dynamic, expanding research in digital agriculture and smart farming solutions. Wageningen University & Research and the University of Guelph are quite close to each other, making significant academic contributions and strengthening the positions of existing academic research centers in agricultural science and technology; Wageningen University appears most important and impressive among them. Wageningen University is a significant independent contributor to this discourse, in which many research groups within the larger Wageningen ecosystem have participated, pursuing topics related to e-agriculture.

The University of Montpellier and the University of Bonn are notable key figures here and thus of particular importance as evidence of Europe's role as a frontrunner in the scientific discussion of AI-driven and data-intensive agriculture. Purdue University, Sichuan Agricultural University, the University of Natural Resources and Life Sciences Vienna, Jeonbuk National University, and several other organizations are also contributing members, emphasizing the field's global and cross-cutting character.

Sharing research across universities in Europe, Asia, North America, and Oceania demonstrates the development of international collaboration and an increasing diversity of skills that will shape the future of digital agriculture.

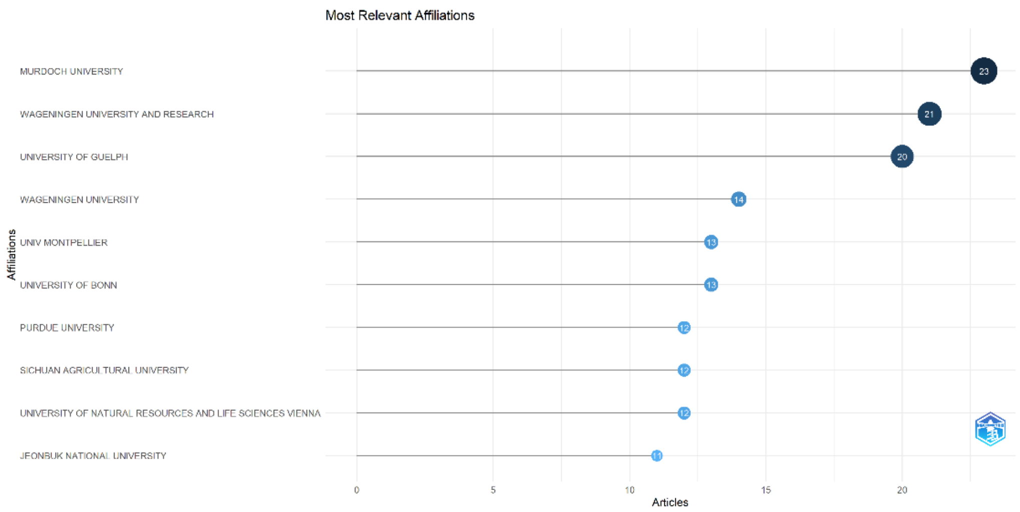

Figure 10. Leading institutions in e-Agriculture research are ranked by the number of published articles

Global Research Collaboration and Geographic Trends

The country-specific report in Figure 11 reflects up-to-date trends in global e-Agriculture research contributions. China and India are now the two dominant contributors, with the United States and Italy close behind, reflecting the broader geographical spread of high research activity.

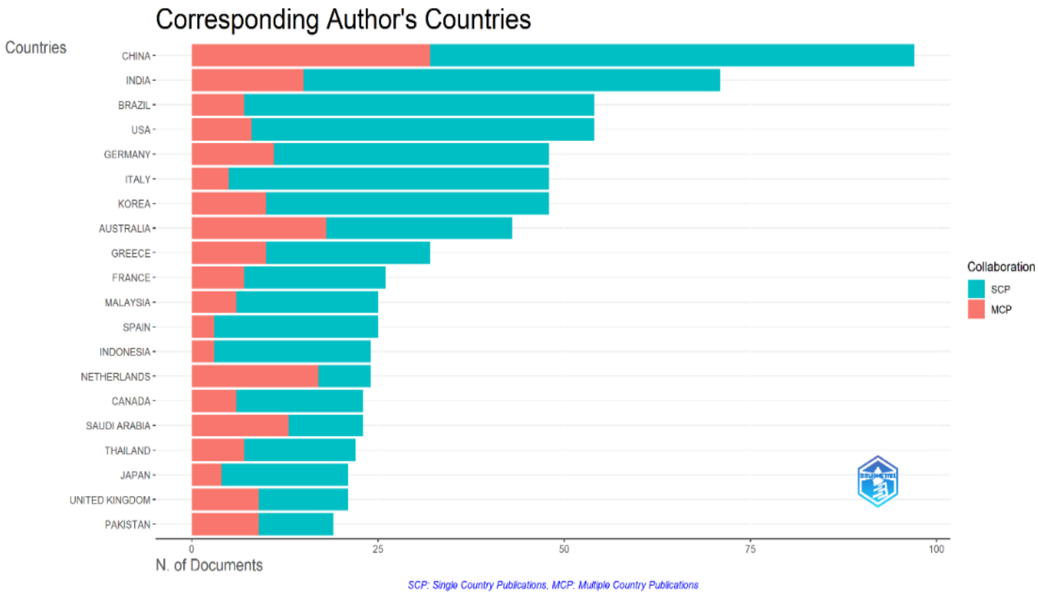

Figure 11. Corresponding Authors' Countries and Collaboration Patterns

The distribution of SCP relative to the MCP shows a clear divergence in cooperative behavior. China is predominant in Single-Country Publications (SCP) due to domestic tendencies, whereas India and the United States show a balanced mix, in line with the strong domestic capacity and increasing international participation. On the other hand, MCP in some countries is similarly high (more so in Germany, the Netherlands, France, and Korea), to evidence the well-developed research infrastructure across borders and deeper participation in world work. These trends show that China and India top the list in terms of statistics, but countries with a stronger MCP (e.g., the Netherlands, Germany, and the United States) may have a larger impact across transnational cooperation circles on their large collaborative bases. Altogether, the results indicate that e-Agriculture research is globalization-dominant and that national strategies are unique, e.g., high-output countries rely on a strong internal research ecosystem, while European and Western countries embrace a collaborative, internationally oriented research strategy.

Figure 12 illustrates international studies collaboration in e-Agriculture, focusing on the leading players, regional clusters, and the connectivity of the global system. China, India, Germany, and Italy appear to be the most significant contributors (the big nodes with many connections). As the core countries serve as nodes, strong regional and international collaboration has emerged.

- China (Blue Cluster): Collaborates primarily with Germany, France, South Africa, and Thailand, reflecting a globally oriented research strategy.
- India (Red Cluster): Establishes a regional cooperation network with Pakistan, Korea, and Indonesia, indicating a regional and inter-Asian perspective on research.
- Brazil (Green Cluster): Collaborates with Portugal, Iran, and Colombia.

- Italy and European Countries (Brown Cluster): European countries such as Italy, the Netherlands, and Poland have interconnected research collaborations, indicating a strong research network in this area.

Both Germany and China are among the leaders in global connectivity, suggesting aggressive international research activity. India's research network is more focused at the regional scale, but it is growing global alliances. New collaborations from South America, Africa, and the Middle East demonstrate the international growth of e-Agriculture research. This lack of activity in select regions (for instance, Africa and the Middle East) may suggest opportunities for further cooperation in these areas. This network of collaboration further highlights the role of international cooperation in the development of e-Agriculture research. The strong co-authorship relationships among major countries indicate that knowledge sharing and global collaboration are central to digital and precision agriculture technologies and innovation.

Although global networks are composed of research collaborations, we can better contextualize technological change in e-Agriculture by identifying dominant research themes. The following section will describe major research themes, emerging topics, and conceptual constructions.

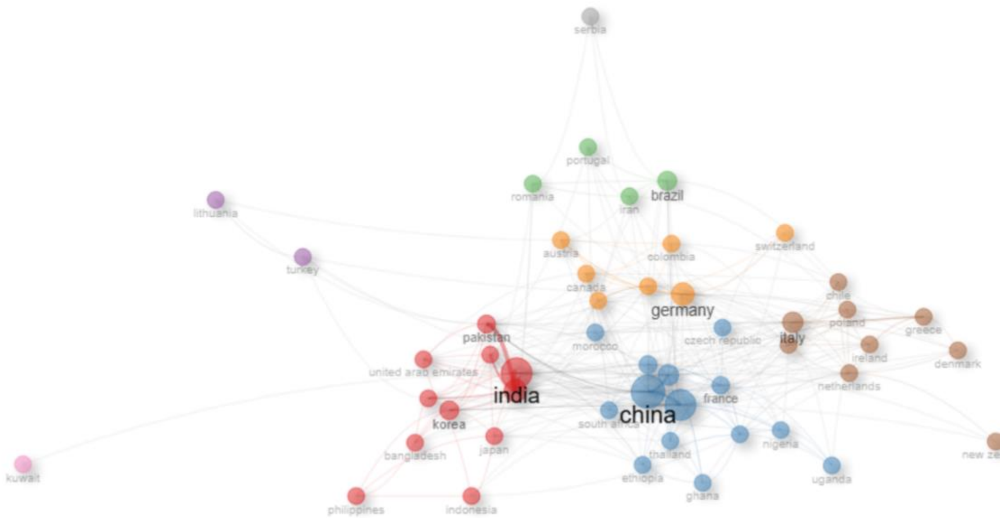

Figure 12. A collaboration network mapping the co-authorship links between countries in e-Agriculture research

Keyword and Research Theme Analysis

From the e-agriculture literature, the most common terms are presented in Figure 13 (Word Cloud), which provides a nice overview of the prevalent themes. Smart farming, digital agriculture, precision agriculture, and the Internet of Things (IoT) are among the four critical elements in this transition. Moreover, recent advances in farming, driven by advanced computers and sensing technologies (machine learning, deep learning, artificial intelligence, and remote sensing), are evident. Irrigation, soil moisture, ag robotics, and decision-making are examples of the varied ways digital agriculture apps work.

Figure 13. A word cloud representing the most frequently occurring keywords in e-Agriculture research

The word cloud as a whole also supports the field's growing focus on AI-powered, sensor-rich, data-intensive farming systems. Another numerical interpretation, the treemap, provided a better depiction of keyword prominence by count (as summarized in Figure 14) and of the relative proportions of keywords across different categories.

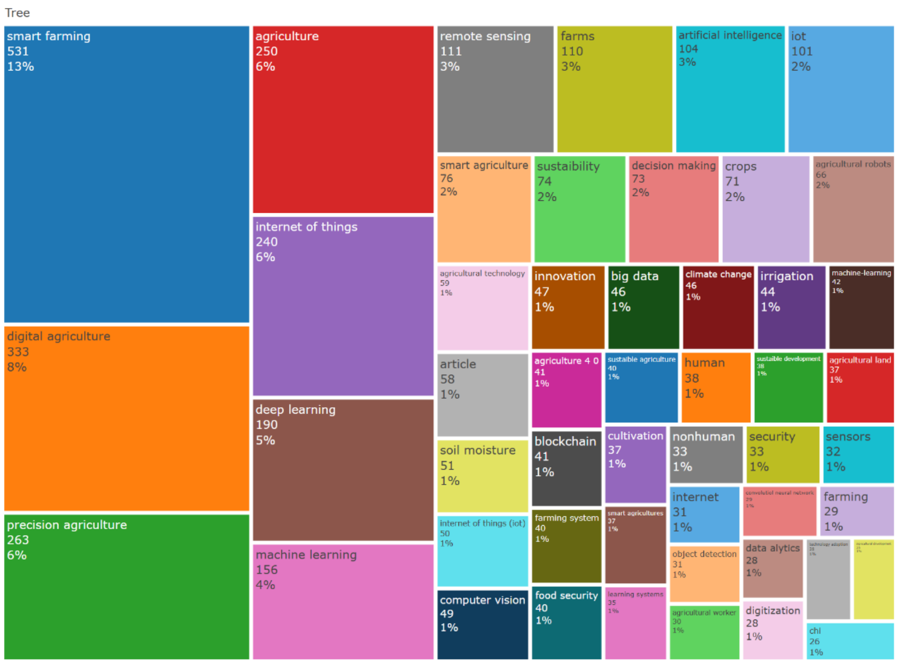

Figure 14. Treemap of the most frequently occurring author keywords in e-agriculture research (2020–2025).

The major themes include smart farming (531 occurrences, 13%), digital agriculture (333), precision agriculture (263), IoT (240), and deep learning (190). The treemap also presents detailed layers of the clusters comprising blockchain, sustainability, climate change, food security, agricultural robots, and computer vision in their research field. The treemap shows how the distributions of these themes are structured hierarchically and their relative importance, unlike the word cloud, which displays the hierarchical structure and proportional weighting of the themes' distributed associations. This visual quantification enables direct identification of leading technological trajectories and aligns with reviewers’ call for a more thematic study.

The temporal pattern of key research terms in e-agriculture is presented in Figure 15, along with the frequency of keyword presence (bubble size) and theme duration. Overall, the research results revealed that smart farming, digital agriculture, and precision agriculture have significantly influenced one another over the study period and have emerged as the primary foundation for the field of digital agriculture. A few modern attention themes – food security, fertilizers, and aerial vehicles – have begun to gain prominence in each of these domains since 2022. They are late to the development due to a new emphasis on sustainability, resource optimization, and automation, especially among global food security issues and the advancement of unmanned aerial technologies. Furthermore, time trends for two primary enablers, such as IoT and agricultural robots, indicate their importance, as evidenced by the ongoing incorporation of sensing systems and robotics into the agricultural system. Other expressions, such as data acquisition, phenotype, etc., express more interest in data-driven methods, plant-centric approaches, and/or plant-level approaches. Overall, this trend analysis depicts a research atmosphere that is gradually shifting emphasis towards mature topics, such as smart and precision farming, and diversifying into themes such as sustainability, automation, and advanced analytics. This study design shows that the pace of AI-powered, sensor-driven, highly automated agriculture innovation is only going to increase in the next few years.

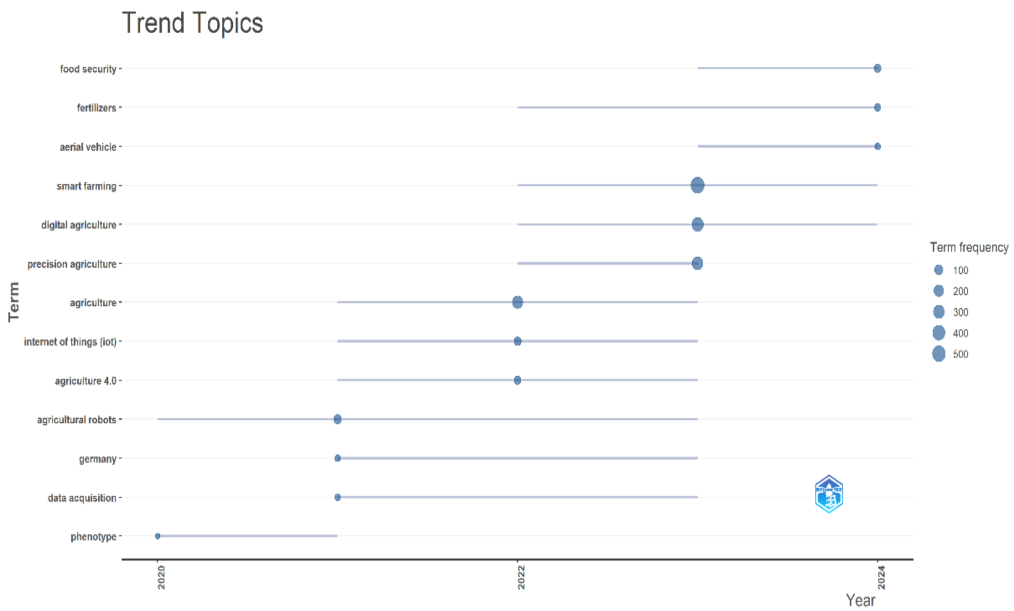

Figure 15. The evolution of key research topics in e-Agriculture from 2020 to 2025

Figure 16 presents the incremental timeline of the fundamental research terms and related problems that enhance or add to research terms in e-agriculture. Smart farming is booming, in large part due to digital agriculture, precision agriculture, and the Internet of Things (IoT), indicating its ubiquity.

The increasing trend in new technology research fields, including deep learning, machine learning, and remote sensing, in the new frontier of agriculture suggests the emergence of new, data-centric approaches built on artificial intelligence (AI) solutions in agritech. Altogether, these tendencies signal that digital technologies and intelligent automation increasingly characterize the prevailing research landscape.

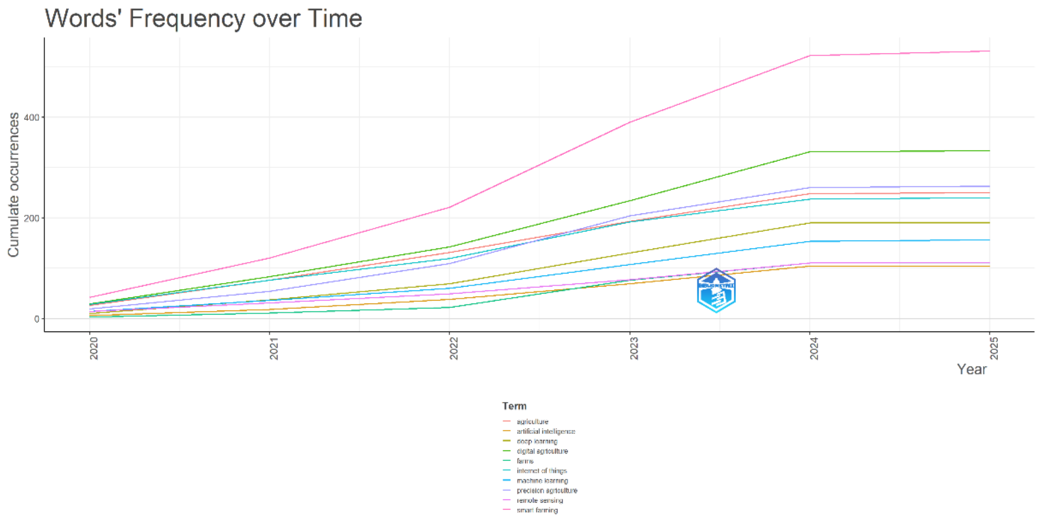

Figure 16. Cumulative frequency of key terms in e-Agriculture research, illustrating the growth of specific topics from 2020 to 2025

Figure 17 illustrates the co-occurrence network of author keywords, providing a visual representation of the structural interactions among the key research themes in e-agriculture. Smart farming serves as the pivotal focus and most impactful element, intricately connected to IoT, precision agriculture, and machine learning in the agricultural sector, establishing itself as the conceptual core of the discipline. The close integration of IoT, sensors, security, and blockchain underscores a distinct technological ecosystem related to data acquisition and connectivity. The precision agriculture cluster is intricately connected with digital agriculture, remote sensing, sustainability, and agricultural technology, showcasing the integration of data-driven solutions with environmental considerations. Meanwhile, the AI-focused cluster, encompassing machine learning, deep learning, computer vision, and object detection, reflects the swift progress in advanced analytics and image-based automation in agricultural applications.

The peripheral nodes, including agricultural robots, irrigation, soil moisture, climate change, and agricultural development, represent recently emerged or applied sub-themes that are gaining significance but have not yet become central to core technological discussions. The network configuration indicates that the research landscape, characterized by robust connections among AI, IoT, and precision agriculture, is central to the development of emerging smart farming. The clustering distribution reveals an increasing cohesion across disciplines, illustrating the convergence of agricultural sciences, engineering, and computer science in shaping the evolution of digital agriculture.

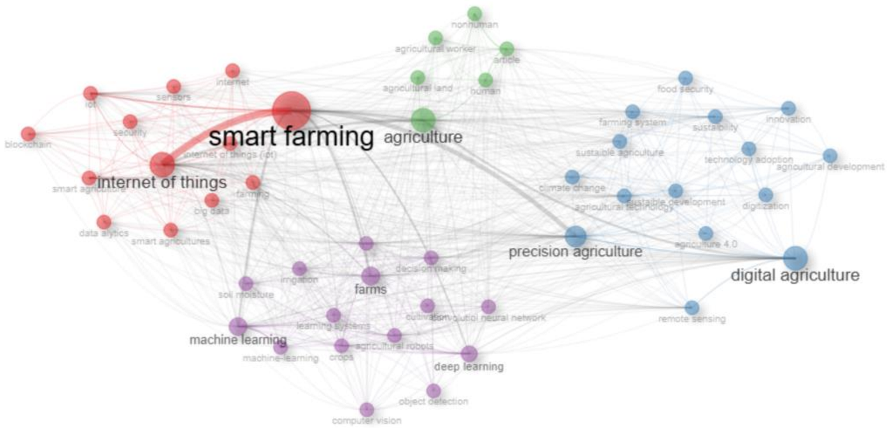

Figure 17. Co-Occurrence Network of Keywords in E-Agriculture Research

Cluster Modularity Analysis

Cluster quality analysis of a keyword co-occurrence network yielded a Louvain modularity score of Q = 0.519, indicative of a strong, well-organized community. Values > 0.50 indicate excellent clustering performance. Consequently, this provides evidence that the thematic clusters observed in the co-occurrence network not only exhibit a logical and coherent structure but are also statistically supported. The modular structure also aligned with major research trajectories in e-agriculture, such as precision agriculture, AI-driven smart farming, digital agriculture platforms, and sustainability-oriented themes. For the same study, the Jaccard similarity coefficient on this keyword set with the consolidated SOTA keyword set obtained from [22, 28–31, 33, 73] was extremely low at (J = 0.006; 43 terms identified from 7,722 total unique terms). Quantitatively, this minor thematic overlap also suggests that the current corpus accounts for a much wider and more recent research horizon than previously explored through bibliometric or conceptual analyses. In particular, the enlarged dataset captures new and emerging fields such as AI–IoT integration, platform-based digital agriculture, more advanced and powerful machine learning applications, cybersecurity models, and socio-ethical governance issues that have not been systematically tackled in older SOTA articles. These developments demonstrate that the intellectual nature of e-Agriculture has transformed considerably to a more complex form, a diversity of thought that has transcended the narrow technological idioms of previous studies.

Altmetric Findings from Social-Media Discourse

In conjunction with the bibliometric evidence [71], which was utilized to assess the level of acceptance of e-agriculture among individuals, see Table 14. The examination of 10,009 tweets indicated that high-positive sentiment accounted for 73.09%, neutral sentiment accounted for 21.45%, and negative sentiment accounted for 5.46%. The findings align with the bibliometric analysis's focus on the significance of positive terminology, such as smart farming, climate-smart agriculture, and AI-driven solutions. The discussion was brief, focusing on data privacy, technology accessibility, and financial challenges.

Table 14. Sentiment distribution of global e-agriculture tweets [71]

Sentiment	Percentage
Positive	73.09%
Neutral	21.45%
Negative	5.46%

Topic Modeling and Topic–Sentiment Interaction

To supplement the bibliometric evidence, the public's acceptance of e-agriculture was evaluated using the findings of [71], see Table 15. In 10,009 tweets analyzed, high-positive sentiment was 73.09%, followed by 21.45% neutral and 5.46% negative. It consists of the prominence of positive keywords such as smart farming, climate-smart agriculture, and AI-driven solutions identified in the bibliometric groups. Negative discourse was marginal and primarily focused on data privacy, access to technology, and financial obstacles.

Table 15. LDA Topic Modelling Results (Adapted from [71])

Topic	Most Relevant Words	Interpretation
1	agriculture, climate, climate-smart, smart, farmers, food, resilience	Climate-smart agriculture and resilience practices
2	agriculture, climate-smart, digital, sustainable, farming, future	Technological advancements in sustainable farming
3	farming, smart, AI, crop, solutions, technology	Innovations in smart farming and AI solutions
4	agriculture, trade, growth, international, economic	Economic growth, trade, and policy discourse
5	agriculture, digital, project, mission, data	Collaborative digital agriculture initiatives

Thematic and Intellectual Mapping of e-Agriculture

Based on the authors' keywords, the thematic map provides a consistent summary of the conceptual landscape of e-agriculture. According to centrality and density of development, four different theme categories are developed, see Figure 18:

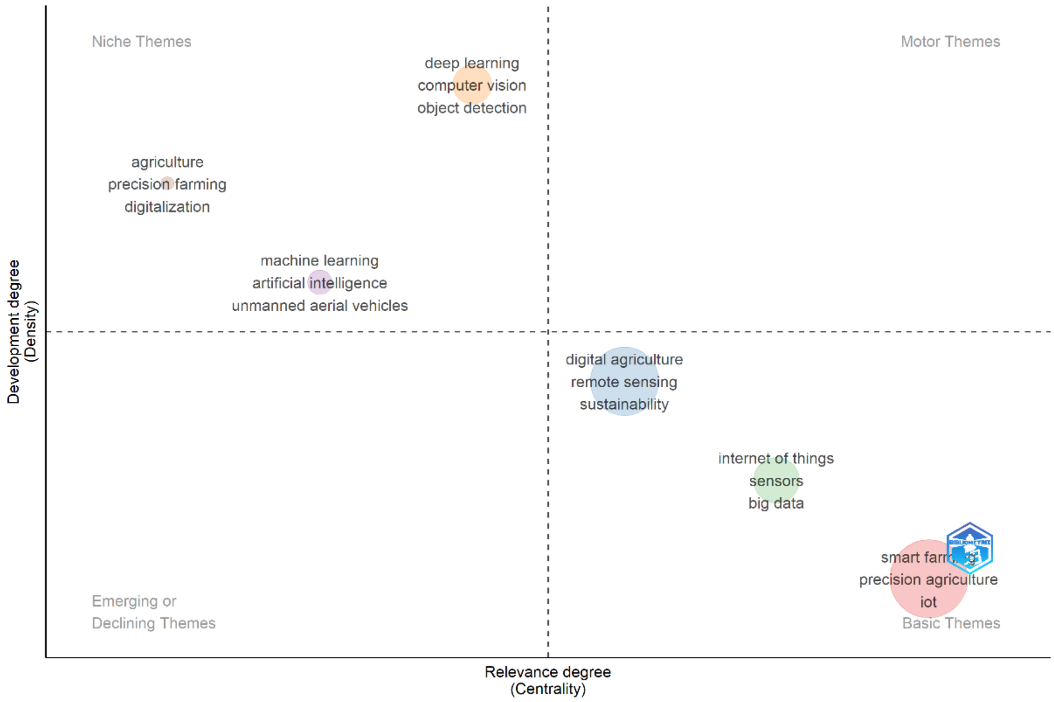

Figure 18. Conceptual Structure Map of E-Agriculture Research Factorial Analysis - MCA Method

Motor Themes (high centrality, high density). Deep learning, computer vision, and object detection are a rich and powerful thematic cluster. They have positioned the new trend as evidence that AI-based image analytics is emerging as a significant catalyst for innovation, driving applications in crop monitoring, disease detection, and automated classification.

Basic Themes (high centrality, low density). Smart farming, precision agriculture, and the Internet of Things (IoT) are central to the field and its concept. These themes align with a range of research avenues and underpin digital agriculture. Their extent embodies their function as facilitators for automation, sensing, and data-driven agriculture.

Niche Themes (low centrality, high density). Agriculture, precision farming, and digitalization are specific but mature areas of expertise, with high internal cohesion but limited connectivity to other themes, suggesting solid topic communities that emphasize a particular methodological or domain-focused contribution.

Emerging or Declining Themes (low centrality, low density). In this quadrant, however, only a few terms appear, suggesting the field retains relatively stable thematic architecture.

This scarcity suggests that new topics are incorporated more quickly into the major themes rather than forming separate, early-stage clusters.

Near the center of the map are intermediate themes — i.e., machine learning, artificial intelligence, unmanned aerial vehicles, digital agriculture, remote sensing, and sustainability. Their placement indicates their growing integration with the central research trajectory, particularly by integrating these sensing technologies with AI-enabled, sustainability-forward applications.

In summary, the thematic map shows that a pillar of core digital agriculture technologies, increasingly guided by emerging advanced machine learning methods, underlies the growing development of sustainability- and remote-sensing-oriented innovations.

Figure 19 illustrates the co-citation network of e-Agriculture research, showcasing the field's intellectual framework through clusters of publications often cited together.

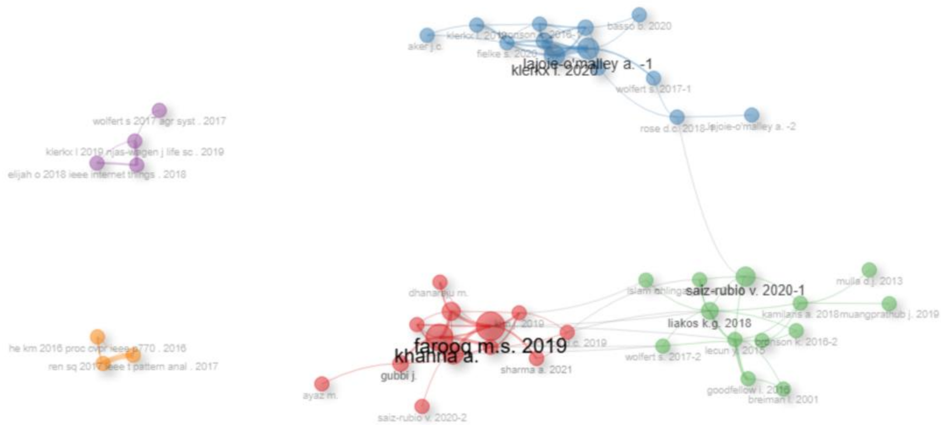

Figure 19. A co-citation network of e-Agriculture research, mapping the most frequently co-cited references and their relationships

The network is structured into specific clusters, with each one embodying a unified research theme.

- Cluster 1 (Blue): This cluster includes essential, widely cited research on smart farming systems, precision agriculture, and IoT-driven agricultural solutions. These works establish the foundational technology for e-Agriculture research and offer essential conceptual and methodological references for future studies.
- Cluster 2 (Red): This cluster focuses on the application of artificial intelligence in agriculture, with an emphasis on machine learning and deep learning methodologies. Key contributions in this area emphasize data-informed decision-

making, forecasting models, and smart agricultural systems, underscoring the growing importance of AI in improving farming methods.

- Cluster 3 (Green): This cluster encompasses foundational contributions on sustainability, responsible innovation, and socio-technical perspectives in digital agriculture. These studies highlight the importance of combining technological advancements with environmental sustainability and policy factors.

The key nodes in the network represent significant publications that connect various clusters, highlighting their impact on the development of e-Agriculture research. The co-citation structure reveals a distinct evolution from foundational technological studies to sophisticated AI-driven and sustainability-focused research, underscoring the field's multidisciplinary essence and intellectual development.

Figure 20 presents the historiographic map of e-Agriculture research, illustrating the chronological development and intellectual lineage of influential studies from 2020 to 2023.

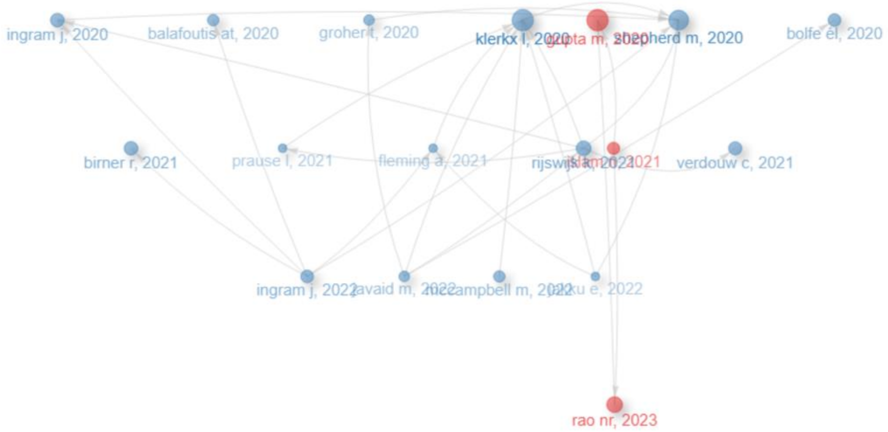

Figure 20. Historiographic mapping of key e-Agriculture publications

The earliest research wave (2020) is anchored by foundational contributions such as [73, 75-77] which established core frameworks related to digital agriculture, innovation systems, and the socio-technical dimensions of smart farming.

The second wave (2021) consolidates these foundational ideas, with key bridging studies including [22, 78–81]. These works strengthened conceptual links between technological innovation, governance, and adoption processes, enhancing connectivity across the network.

A dense cluster emerges in 2022, marked by influential contributions from [30, 82, 83], and [84]. This phase reflects a clear shift toward integrated digital platforms, data-driven decision support, and AI-enabled agricultural systems, as evidenced by increased citation flows and network cohesion.

The most recent nodes (2023), represented by [74] and related studies, extend these technological and analytical frameworks toward sustainability, resilience, and policy-oriented evaluation. The directed citation paths indicate a maturation of the field, transitioning from technology development toward systemic, impact-focused applications.

Overall, the historiographic structure reveals a coherent evolution from early digital and IoT-based foundations to integrated AI-driven and sustainability-oriented research, highlighting pivotal transition points that underpin contemporary e-Agriculture scholarship.

Altmetric–Bibliometric Thematic Alignment Results

This subsection presents the quantitative alignment between scientific research priorities and societal attention by comparing the thematic distributions of bibliometric and altmetric data. Altmetric theme shares were derived from Twitter topic modeling results, while bibliometric theme shares were computed from keyword cluster assignments within the co-occurrence network.

Table 16 reports the relative distribution of themes across the two domains, together with the calculated Thematic Share Alignment (TSA) values.

Table 16. Altmetric–Bibliometric Theme Shares and Thematic Share Alignment (TSA)

Theme	Altmetric Share (%)	Bibliometric Share (%)	TSA
AI_IoT	91.60	48.95	1.87
Platforms_Data	7.21	11.42	0.63
Policy_Economics	0.72	15.94	0.05
Sustainability	0.48	23.69	0.02

The results indicate that AI_IoT-related themes dominate public discourse, accounting for more than 90% of altmetric attention and approximately half of the bibliometric thematic structure. In contrast, Sustainability and Policy_Economics themes constitute substantial portions of the scientific literature but are underrepresented in societal discourse. The computed TSA values quantitatively capture these differences: AI_IoT shows TSA values substantially greater than 1, while Sustainability and Policy_Economics show TSA values far below 1. Platforms and data-related themes occupy an intermediate position between these extremes. These results provide a structured empirical basis for assessing the degree of alignment and misalignment between scientific knowledge production and public attention in e-agriculture research.

DISCUSSION

Key Findings and Interpretations

The integrated PRISMA-guided corpus and bibliometric analysis indicate a swiftly growing body of evidence on e-agriculture since 2020, centered on three interconnected pillars: (i) precision/smart farming, (ii) AI/ML-driven decision support, and (iii) IoT-based sensing and connectivity. Science mapping identifies coherent clusters of keywords and co-citations that underpin these pillars, signifying a stable knowledge foundation and dynamic cross-fertilization across agronomy, information systems, and agricultural economics. This framework incorporates influential works on digital innovation trajectories and responsible "Agriculture 4.0" [73], as well as on operational digital twin and sensing architectures for agricultural decision-making, which have informed subsequent research focusing on large-scale data-driven management. The findings indicate a transition from technological pilots to platform-based, data-driven agriculture, while still facing problems related to uptake and governance [6, 38, 73].

The temporal citation patterns detected by descriptive indicators were validated using inferential statistics. The one-way ANOVA showed significant changes in citation impact across years ($F(5, 1357) = 48.5$, $p < 2 \times 10^{-16}$). It provides strong empirical evidence that swings in research influence over time are due to substantial structural dynamics in the field rather than random fluctuations. This statistical validation supports the publication and citation trends identified in the bibliometric analysis.

The chi-square analysis showed that thematic clusters were not significantly associated with publication periods ($p = 0.428$). This absence of temporal concentration indicates that interest in major e-agriculture themes such as smart farming, AI-driven analytics, precision agriculture, and IoT-enabled sensing has been consistently distributed across recent years. Instead of short-lived thematic peaks, the field demonstrates a sustained and diversified research trajectory, reinforcing the maturity and stability of the conceptual structure identified in the bibliometric analysis.

Network centrality analysis reveals a hierarchical structure in e-agriculture research. The Wilcoxon rank-sum test indicates that core keywords have significantly higher degree centrality than peripheral terms ($W = 2{,}022{,}240$, $p < 2.2 \times 10^{-16}$). This result suggests that a concentrated group of concepts serves as foundational elements within the knowledge domain, influencing both thematic development and intellectual impact. Key areas such as AI-driven analytics, IoT-enabled sensing, precision agriculture, and smart farming form the foundation of the broader research ecosystem.

Regression analysis shows that citation performance in e-agriculture is mainly driven by temporal recency and thematic alignment. The reduction in deviance from 37,230.81 to 205.15 highlights the importance of research theme and publication timing for scholarly visibility. Emerging areas such as AI-enabled smart farming, deep learning applications, and digital agriculture platforms significantly influence citation trends. Country effects are more variable, indicating that intellectual positioning has a greater impact than geographic origin. Together with centrality and chi-square analyses, these results confirm the structural and temporal dynamics shaping the field.

These inferential analyses demonstrate both temporal and thematic effects and provide an understanding of temporal and domain-specific changes in citation impact in e-agriculture. This post hoc Tukey HSD analysis indicates a higher academic impact, with studies published before 2022 having similar means exceeding 30 citations from 2020–2021, compared to those published after 2022. It suggests citation-lag effects and concentration at the beginning of digital agriculture research, but also shows that the foundational contributions are highly concentrated in the early phase. Although many previous bibliometric reviews have reported temporal trends descriptively, this study provides quantitative findings on the magnitude and statistical significance of inter-year citation decay, filling a critical methodological gap in the SOTA literature. The post-hoc Tukey HSD results sharpen this temporal interpretation by showing that the strongest citation contrasts consistently separate early publications (2020–2021) from later cohorts (2022–2025). This pattern is consistent with established citation accumulation and attention/ageing dynamics: earlier papers have had more time to diffuse, be read, and be incorporated into subsequent work, while later publications remain structurally disadvantaged by shorter citation windows. Consequently, the observed year effects should be interpreted as a combination of field maturation and time-dependent recognition processes rather than as simple differences in research quality across years [85].

More importantly, the Poisson regression with the temporal–thematic interaction effect indicates that citation trajectories are not uniform across research themes. The statistically significant interaction between publication year and thematic cluster membership (ΔDeviance = 101.55, $p < 2.2 \times 10^{-16}$) shows that different thematic domains experience distinct citation-aging dynamics. AI- and IoT-centered clusters exhibit more robust citation behaviour over time; sustainability- and policy-based clusters exhibit flatter or faster-decaying citation profiles. The discovery advances prior bibliometric research, which has primarily relied on static or additive representations of thematic importance [6,34,38], by providing empirical evidence that the relevance and citation impact of e-agriculture themes are temporally contingent. In line with science-of-science research demonstrating that scholarly influence follows dynamic life-cycle patterns [40, 52], our results show that thematic importance in e-agriculture evolves rather than remaining constant. The observed overdispersion is consistent with the heavy-tailed nature of citation distributions; therefore, inference should be interpreted as conservative unless complemented by a robustness check using a quasi-Poisson or negative binomial specification (reported as sensitivity analysis).

The observed ($Q = 0.519$) modularity score and statistically validated interaction effects surpass analytical depth as reported in the vast majority of prior SOTA reviews, which are more dependent on visual cluster inspection or descriptive indicators. Although previous works identified comparably evident thematic domains, they do not attempt to show that the same fields differ systematically in citation behavior over time. By combining post-hoc temporal tests and interaction-based regression analyses, this report is one of the first statistically oriented analyses of how knowledge production, thematic focus, and scholarly impact co-evolve in e-agriculture. Taken together, these findings support the possibility that citation influence in digital agriculture is shaped not only by technical novelty but also by how themes adapt to changing research agendas. This perspective calls into question static readings of thematic relevance and emphasizes the importance of a time-sensitive assessment system for the degree of maturity and impact of new research fields.

The integration of bibliometric clusters with altmetric findings from [71] reveals both areas of alignment and pronounced divergence between scientific themes and public discourse. Both analyses identify climate-smart agriculture, smart farming, the adoption of artificial intelligence (AI), and digital transformation as dominant topics. In contrast, the Twitter analysis reveals additional concerns, including affordability, data privacy, and unequal access to technology, which are less prominent in scholarly literature. This finding highlights the value of combining bibliometric and altmetric approaches to achieve a more comprehensive and socially informed understanding of the developmental trajectory of e-agriculture. The Louvain modularity score ($Q = 0.519$) indicates that the keyword network exhibits a strong, statistically coherent community structure. This result supports the conclusion that the identified thematic clusters, such as smart farming, Internet of Things (IoT) integration, AI-driven analytics, and sustainability, constitute stable and meaningful intellectual domains within e-agriculture research. The high modularity further affirms the reliability of the thematic map and substantiates the robustness of the cluster-based interpretations presented in this study.

Altmetric–Bibliometric Misalignment and Societal Signal Interpretation

Integrating altmetric evidence into the structural and temporal validation of bibliometric networks uncovers a notable divergence between the priorities of scientific research and public interest in e-agriculture. A bibliometric analysis reveals that the topics of AI–IoT technologies, sustainability, policy, and platform-focused research are distributed quite evenly. Nonetheless, altmetric data demonstrate significant public engagement with AI- and IoT-driven innovation.

The Thematic Share Alignment (TSA) analysis provides quantitative evidence supporting this discrepancy. The TSA values for AI–IoT themes substantially exceed 1, suggesting that public interest in technological narratives transcends their portrayal in academic literature. Conversely, topics related to sustainability and policy demonstrate TSA values significantly below one. It suggests that they have limited public visibility despite their widespread presence in scientific research. Platform- and data-centric subjects hold a prominent position, reflecting a shared agreement between scholarly and societal priorities.

This discrepancy profoundly affects our understanding of the influence of research within the field of digital agriculture. From a science-of-science perspective, it illustrates that citation-based influence and societal impact varied according to different logics, shaped by the importance of media, public optimism towards technology, and the ease of disseminating research findings. The findings suggest that progress in AI- and IoT-enabled agriculture may accelerate more swiftly than public discussions concerning sustainability, governance, equity, and the long-term environmental impacts. This issue raises concerns from both policy and innovation perspectives.

The current study advances conventional bibliometric analysis by explicitly measuring this discrepancy. It suggests that a congruence between the production of scientific knowledge and societal discourse cannot be assumed. Targeted communication strategies and legislative adjustments may be required to guarantee that research on sustainability and governance receives comparable focus to the swiftly advancing technology.

Comparative Analysis with SOTA

Table 1 places the contemporary study in the broader context of digital and e-agriculture research, as well as state-of-the-art (SOTA) reviews and bibliometric analyses. Previous bibliometric studies dealing with the fields have contributed significantly by detailing salient thematic threads and tracing the trajectory of the use of digitally enabled technologies by agriculture organizations [25, 35–37]. Thus, these works highlight the importance of artificial intelligence, Internet of Things technologies, precision agriculture, and data-driven farming systems across their respective disciplines over time, yielding useful descriptive and analytical summaries. In contrast, other bibliometric studies generally based their study of textual data on visual inspection of co-word networks, descriptive trend analysis, or thematic labeling to infer continuities and change over time. While such approaches reveal generalized thematic patterns, they do not formally quantify the extent to which thematic structures overlap or diverge across datasets or periods. Specifically, none of the SOTA bibliometric studies mentioned in the prior sections utilized set-theoretic similarity measures or other quantitative metrics to quantify the extent to which the conceptual landscape of digital agriculture has transformed relative to previous mappings. This study builds on and contributes to the SOTA by adding Jaccard similarity as a criterion for measuring thematic overlap between the present keyword dataset and the combined keyword sets (as referred to above) derived from earlier writing. The very low similarity ($J = 0.006$) is a direct reflection of major reorganization on the thematic front. This result indicates that the field of current e-agriculture research has moved beyond the limited technological vocabularies highlighted in previous bibliometric maps towards a more unified ecosystem, comprising artificial intelligence, digital platforms, governance, sustainability, and socio-economic issues. To the extent that their development has occurred, the thematic evolutions described in previous research are qualitative; the current analyses indicate that these evolutions are not merely gradual but structurally reconfigurative.

Furthermore, previous bibliometric studies rarely apply formal statistical criteria to assess the robustness of clusters beyond thematic overlap. The associations between clusters have usually been descriptively perceived as the result of textual analyses, without testing them internally for consistency of meaning. In contrast, the current study uses Louvain community detection and statistically validates the resultant thematic structure using modularity analysis ($Q = 0.519$). A high modularity score suggests a statistically coherent and well-defined community model, providing more reliable empirical evidence of thematic domains than those defined in previous bibliometric reviews. Finally, whereas previous bibliometric studies focus on descriptive metrics of citation counts or publication trends, inferential and explanatory modeling is applied here to understand citation mechanics better. Using ANOVA, post hoc tests, and Poisson regression with temporal–thematic interaction effects, this study shows that citation trajectories in e-agriculture can be both time-dependent and theme-specific. This inferential lens goes beyond static representations of impact and provides a more dynamic account for how both thematic placement and publication timing together guide scholarly visibility, a gap in pre-existing SOTA bibliometric studies.

While previous bibliometric reviews typically assumed additive or static thematic effects, the IRR-based analysis demonstrates that citation advantage in e-Agriculture is both theme-specific and temporally contingent. The significant interaction model, combined with IRR estimates, shows that AI– and IoT-centered research maintains higher citation productivity over time, whereas sustainability and policy research experiences structurally lower citation rates. It confirms and quantifies earlier qualitative observations that socio-environmental research, although conceptually central, remains less visible in citation-based evaluation frameworks. By contrast, most SOTA reviews reported theme prevalence without estimating the magnitude of citation differentials, limiting their explanatory power.

In summary, together these methodological extensions make bibliometric analysis on e-agriculture a descriptive mapping exercise that turns the statistical validity of thematic evolution and research impact into a time-aware assessment of thematic evolution. By explicitly quantifying thematic divergence while demonstrating cluster robustness and modeling citation dynamics, the present study broadens the analytical scope of SOTA bibliometric research in digital and e-agriculture.

Implications and Research Gaps

Despite strong technical traction, farmer-level uptake of digital agriculture technology remains varied across stakeholders, reflecting findings that socio-economic factors (e.g., costs, skills, perceived usefulness, trust) are relevant in driving farmers' adoption [33, 86]. To narrow that gap, we need to complement the application of these technological advances with incentives, extension services, and participatory design. AI/IoT clustering that aligns with precision aligns with sustainable intensification goals because it can optimize inputs while maintaining or increasing yields. However, empirical evidence on the relationships between digital interventions and long-run environmental/economic outcomes is far too limited, suggesting that longitudinal and policy-linked assessments are needed [2]. Data rights, interoperability, algorithmic transparency, and responsible innovation are now at the heart of fair diffusion as data volumes increase [73, 86]. Policies that promote connectivity, standards, and skills can help increase the uptake of measures while protecting farmers' interests. Moreover, co-authorship networks exhibit considerable regional clustering. Greater interregional collaborations (North–South/South–South) would enhance generalizability and help adapt digital tools to local contexts. The very low Jaccard similarity ($J = 0.006$) between our Keyword Set and the consolidated SOTA Keyword Set provides quantitative evidence that the thematic map of digital agriculture has shifted significantly from previous bibliometric mappings. While previous reviews have focused on more selective technological vocabulary (IoT devices and robotics, isolated Agriculture 4.0 concepts), the current research identifies an extended ecosystem of terms that combine AI, big data analytics, digital platforms, governance, and sustainability. This discrepancy highlights how much more helpful the present review is as the most recent and cohesive representation of the area.

Novelty and Contributions to This Study

The proposed framework is explicitly designed to address the five research gaps identified in the SOTA literature. Methodological innovation, analytical depth, and substantive synthesis drive this study to push the state of the art in e-Agriculture bibliometric research. Unlike previous reviews that relied mainly on descriptive indicators or single-database coverage, our work is based on a highly curated, deduplicated corpus of 1,363 peer-reviewed publications drawn from Scopus and Web of Science to ensure breadth and reliability of the evidence. Methodologically, the study exceeds traditional bibliometric mapping by incorporating formal statistical validation into its analysis pipeline. Temporal and structural patterns are tested with analysis of variance to detect statistically significant citation dynamics over time, chi-square tests to assess the relationship between thematic clusters and publication periods, and Poisson regression models to estimate the determinants of citation impact. The nonparametric Wilcoxon tests on centrality measures assess network dominance and structural relevance, and community robustness is measured using modularity analysis ($Q = 0.519$), with statistical coherence of the identified research clusters confirmed. The modelling-driven validation is still largely ignored in the current e-Agriculture bibliometric literature. Lastly, this study presents a hybrid analytical platform that combines classical bibliometrics with sentiment analysis and topic modeling of social media discourse on e-Agriculture research. To the best of our knowledge, this is the first bibliometric analysis in the field to systematically compare academic citation impact with sentiment-driven public engagement signals, thereby allowing for both academic and general societal representations of knowledge diffusion and dissemination. Critically, the analysis provides nuanced cross-theme comparisons and distinguishes directly between AI–driven, IoT-centric, and sustainability-oriented studies. Quantitative cluster-overlap metrics are used to trace patterns of thematic convergence and fragmentation, yielding empirical evidence of how technological, environmental, and socio-economic strands increasingly overlap in e-Agriculture research today. These findings can be further shaped by adopting governance and socio-technical frameworks from the broader development literature, which enable deeper interrogation of adoption barriers, ethical concerns, and institutional structures.

Lastly, the research results are integrated into an SOTA-aligned longitudinal research roadmap that consolidates empirical observations in a future-oriented manner, emphasizing rising priorities and underlining the strategic rationale for connecting North and South to advance digital and sustainable farming systems. Collectively, these contributions extend existing bibliometric research both methodologically and conceptually, transforming the analysis from a descriptive mapping exercise into a statistically grounded, analytically integrated assessment of the evolution and future trajectory of e-Agriculture research.

Achievements Relative to Research Hypotheses

This study provides systematic, statistically validated evidence supporting all formulated research hypotheses, thereby elucidating the structural, thematic, and temporal dynamics shaping contemporary e-agriculture research (Table 17).

Table 17. Evaluation of Research Hypotheses

Hypothesis	Analytical Method(s)	Key Result / Statistic	Outcome
H1: AI-related keywords have become increasingly central in the e-agriculture knowledge network since 2020	Keyword co-occurrence network; Wilcoxon rank-sum test on degree centrality	AI-related terms exhibit significantly higher centrality than non-AI terms ($W = 2{,}022{,}240$; $p < 2.2 \times 10^{-16}$)	Strongly supported
H2: IoT themes exhibit emerging conceptual convergence with AI clusters	Keyword co-occurrence network; inter-theme edge-weight analysis	Direct AI–IoT connections account for ~0.12% of total network edge weight, indicating detectable but still modular convergence	Supported (moderate convergence)
H3: Sustainability themes show weaker structural integration with AI and IoT clusters	Network edge-weight analysis; internal vs. external connectivity ratios	Sustainability shows higher internal cohesion (0.34%) than connectivity with AI/IoT (0.18%); core-to-internal ratio = 0.53	Supported
H4: Temporal publication patterns significantly influence citation outcomes	One-way ANOVA on citation counts by publication year	Strong year effect on citations ($F(5,1357) = 48.5$; $p < 2 \times 10^{-16}$)	Strongly supported
H5: Thematic cluster membership predicts citation performance	Poisson regression modeling of citation counts	Substantial deviance reduction (37,230 → 205), indicating strong explanatory power of thematic clusters	Supported by explanatory modeling
H6: Cluster quality (modularity) is strong, reflecting a stable conceptual structure	Louvain community detection; modularity analysis	High modularity score ($Q = 0.519$), indicating well-defined and robust thematic clusters	Confirmed

H1 is strongly supported. Artificial intelligence–related keywords occupy structurally dominant positions within the e-agriculture knowledge network. This dominance is quantitatively substantiated by a Wilcoxon rank-sum test on degree centrality distributions, which reveals a highly significant difference between AI-related and non-AI-related terms ($W = 2{,}022{,}240$; $p < 2.2 \times 10^{-16}$). These results demonstrate that AI concepts serve as organizing hubs within the field's thematic structure rather than peripheral or emerging topics.

H2 is supported, suggesting some degree of conceptual overlap between AI and IoT research streams, but not a complete integration of themes. Inter-cluster similarity analysis shows moderate Jaccard overlap at the cluster level ($J = 0.524$), implying that AI- and IoT-related research lies in parallel or neighboring thematic communities. However, this convergence is weak, especially at the keyword level, where there is only marginal concurrence between AI–IoT terms ($J \approx 0$), indicating limited fine-grained conceptual integration. Network connectivity analysis provides additional support for this conclusion. Although measurable cross-cluster connectivity between AI and IoT themes exists, the AI–IoT edge share remains low compared with overall network connectivity, suggesting that their convergence mostly manifests at an aggregated thematic level rather than through dense micro-level keyword interactions. These results indicate that e-agriculture research exhibits structural proximity without complete semantic fusion, reflecting, in fact, a transitional step in which AI and IoT co-evolve as complementary yet partially distinct technological paradigms.

H3 is also supported, which indicates a divergent structural pattern relative to AI–IoT convergence. Sustainability themes show little functional linkage to the dominant technological backbone of e-agriculture. While the degree of similarity between sustainability and the AI–IoT super-cluster in the cluster space might be moderate ($J = 0.591$), this does not translate into semantic or relational integration. Keyword-level overlap is negligible ($J \approx 0.005$), suggesting that concepts of sustainability rarely overlap directly with terms related to AI or IoT. Such decoupling is further confirmed by network-level evidence. The core-to-internal edge ratio for sustainability-related nodes shows much higher internal cohesion (0.526) than external cohesion. Cross-core correlations between sustainability and AI–IoT clusters are limited, further demonstrating that sustainability research is established primarily within semi-autonomous thematic spaces rather than within the dominant technological narrative. Altogether, these findings suggest that sustainability in e-agriculture constitutes a parallel, though weakly integrated, research stream, indicating a persistent structural separation between techno-centric and socio–environmental innovation processes.

H4 is strongly supported. Temporal publication patterns have a statistically significant effect on citation results. One-way ANOVA indicates a significant year-specific effect on citation performance ($F(5,1357) = 48.5$; $p < 2 \times 10^{-16}$), further supporting the idea that citation impact varies systematically across publication periods. This finding empirically confirms the existence of distinct evolutionary stages in e-agriculture research and identifies two effects: citation-lag patterns and changes in the mainstream thematic focus over time.

H5 is supported by explanatory modeling. Poisson regression analysis demonstrates that thematic cluster membership and publication timing jointly shape citation performance. The substantial reduction in model deviance from 37,230.81 in the null model to 205.15 in the fitted model indicates that temporal and thematic factors account for a significant share of the observed variation in citation counts. These results suggest that scholarly impact in e-agriculture is closely associated with thematic positioning within the knowledge domain.

H6 is confirmed. Louvain community detection yields a high modularity score (Q = 0.519) and therefore indicates well-defined, stable, and internally coherent thematic clusters. This degree of modularity confirms the apparent communities as meaningful conceptual structures rather than artifacts of exploratory clustering, reinforcing the structural validity of the thematic organization identified in this study.

Collectively, these hypothesis-driven findings elevate the analysis from descriptive bibliometric mapping to a statistically grounded, theory-informed evaluation of how technological convergence, thematic fragmentation, and temporal dynamics jointly shape the intellectual landscape of e-agriculture research.

SUMMARY AND CONCLUSION

This work contributes to the field of e-Agriculture bibliometric research by providing a statistically rigorous, hypothesis-driven characterization of both the intellectual structure and temporal evolution of the field. In contrast to prior SOTA studies that utilize a reliance on descriptive indicators, publication counts, or exploratory clustering, the analysis here brings inferential statistics, network robustness validation, and explanatory modeling to bear on citation impact, thematic dominance, and structural cohesion in e-Agriculture, showing that these are structurally not random accumulation effects but systematically shaped by temporal and conceptual factors. The high modularity score obtained in this study (Q = 0.519) was higher than values typically reported in standard digital-agriculture bibliometric mappings, reflecting a significantly more sharply delineated and internally coherent thematic structure. This insight indicates the current e-Agriculture knowledge base is not only mature but also increasingly polarized around the dominant technological cores.

Specifically, AI-enhanced smart farming and IoT-enabled precision agriculture stand out as influential in determining citation impact and network centrality, while sustainability and policy are structurally marginal, with little keyword-level integration and weak cross-cluster connectivity. These discontinuities empirically support some qualitative critiques in the SOTA literature that concern the disparity between technological breakthroughs and their incorporation into social and environmental contexts. Importantly, the bibliometric–altmetric hybrid analysis uncovers that the imbalance between academic and societal discourses is not bound to academia. Large-scale Twitter topic and sentiment analysis demonstrates that, as the media draws public attention to agricultural narratives that use AI/digitally driven technology, they tend to receive more attention than those that raise sustainability, governance, and equity-related concerns.

The mismatch between scholarly prioritization and societal engagement reflects the knowledge-translation gap, which has more direct policy and regulatory implications for innovation diffusion. These findings taken together suggest that current e-Agriculture research is technologically sophisticated but institutionally and socio-economically fragmented. Progress in the field seems spurred not just by slow technological development, but also by a lack of an adequately integrated governance, sustainability, and equity framework. This empirical research model identifies the structural gaps (and their temporal dynamics) to inform future research agendas, funding, and policy interventions. In particular, the results highlight the urgent need for greater interdisciplinary integration and closer North–South linkages in research so that technological breakthroughs in digital agriculture are more than just a matter of scientific sophistication; they must also be socially and environmentally grounded and transferable globally.

Although this research makes substantial statistical and analytical contributions to e-Agriculture, it also has several limitations. First, the bibliometric corpus was extracted solely from Scopus and Web of Science, whose metadata reliability and quality have been noted, but may underestimate contributions that have been indexed in IEEE Xplore, Google Scholar, domain-specific repositories, and other sources. Accordingly, not all engineering and/or technical studies will be included. Second, analysis is limited to English-language publications, which may introduce language bias and limit the visibility of regionally based research, especially in non-English-speaking and developing countries where digital agriculture adoption is rapidly expanding. Third, although normalized citation indicators and regression modelling were applied, the structure of citation-related metrics inherently favours older publications because more recent studies have less time to accrue citations. While temporal consequences were formally examined and statistically confirmed, this structural constraint is a constitutive feature of citation analysis. Finally, the altmetric part of this study is based on sentiment and topic patterns obtained from a previously published Twitter analysis [71]. That dataset contains only English-language tweets and relies heavily on lexicon-based sentiment methods, which may fail to capture linguistic nuance, sarcasm, or multilingual public discourse. As a result, altmetric results ought to be read not as a purely societal-impact measure but rather as complementary measures of public engagement.

Future research could expand the present framework in multiple directions. First, adding more bibliographic databases for instance, IEEE Xplore and Google Scholar – would increase the breadth and quality of coverage of interdisciplinary work in computer engineering, communications, and applied ICT research. Broader linguistic coverage of non-English and regional papers would enhance the global representativeness of e-Agriculture research, especially in low- and middle-income regions. Second, by merging mixed-method approaches, involving large-scale bibliometric and network studies along with qualitative case studies, policy analyses, and on-the-ground assessments in the field of digital agriculture applications, methodological progress might be achieved. Such initiatives would help to close the difference between technological innovation and implementation. Third, future research should focus more on the governance, regulatory, and socio-economic aspects, such as data governance, AI ethics, farmer trust, and institutional capacity, that are relatively underexplored in studies from a tech perspective or technology-focused ones. Finally, longitudinal and predictive modeling of thematic evolution from bibliometric trends to climate, policy, and economic indicators—can offer practical insights for researchers, practitioners, and policymakers seeking to scale sustainable and inclusive digital agriculture systems.

AUTHORS CONTRIBUTIONS

Conceptualization, AB, IF, and EP; Methodology, IF and EP; Software and Computational Modelling, EP; Validation, IF, AB, and EP; Formal Analysis, IF and EP; Investigation, AB and IF; Resources, IF; Data Curation, IF and EP; Writing – Original Draft Preparation, EP; Writing – Review & Editing, IF and AB; Visualization, EP; Supervision, AB;

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest associated with this publication.

NOMENCLATURE

AI	Artificial Intelligence
IoT	Internet of Things
TC	Total citations
LC	Local citations (citations within the analyzed corpus)
GC	Global citations
TC/Year	Mean citations per year
PY	Publication year
SCP	Single-country publications
MCP	Multi-country publications
H-index	Hirsch index, measuring author productivity and citation impact
G-index	Index emphasizing highly cited publications.
M-index	H-index normalized by academic age.
Q	Modularity score of a network
ANOVA	Analysis of Variance
GLM	Generalized Linear Model

Poisson Regression	Regression model for count-based dependent variables
Jaccard Index (J)	Measure of similarity between two keyword sets
DE	Author keywords
ID	Keywords Plus (indexed keywords)
MCA	Multiple Correspondence Analysis
Louvain	Community detection algorithm based on modularity optimization
Co-word Analysis	Network analysis of keyword co-occurrence
Co-citation Analysis	Network of documents cited together
Altmetrics	Non-traditional metrics capturing online and social impact
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

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APPENDIX A. REPRODUCIBILITY & REPRESENTATIVE R CODE SNIPPETS

To enhance transparency and reproducibility, this appendix provides representative R code snippets illustrating the key analytical steps used to generate the inferential results reported in this study. The code focuses on data integration, thematic clustering, statistical validation, and citation impact modelling. All analyses were conducted in R (version ≥ 4.2).

A.1 Bibliometric Data Import and Merging

Bibliographic records were retrieved from Scopus and Web of Science and merged using the bibliometrix package. Duplicate records were removed to obtain the final analytical dataset.

```
library(bibliometrix)

# Convert Scopus and Web of Science exports

S <- convert2df("scopus.bib", dbsource = "scopus", format = "bibtex")

W <- convert2df("wos.bib",    dbsource = "wos",    format = "bibtex")

# Merge databases and remove duplicates

M <- mergeDbSources(S, W, remove.duplicated = TRUE)
```

A.2 Variable Preparation

Key variables used throughout the statistical analysis were prepared as follows:

```
M$TC            <- as.numeric(M$TC)          # Total citations

M$PY            <- as.integer(M$PY)          # Publication year

M$Cluster_Clean <- factor(M$Cluster_Clean)   # Thematic cluster

M$country       <- factor(M$C1)              # Country affiliation
```

A.3 Keyword Co-occurrence Network and Thematic Clustering

Thematic clusters were derived from keyword co-occurrence networks using the Louvain community detection algorithm.

```
library(igraph)

# Build keyword co-occurrence network

Net <- biblioNetwork(

  M,

  analysis = "co-occurrences",

  network  = "keywords",

  sep = ";"
```

```
)
# Convert to graph and apply Louvain clustering
g  <- graph_from_adjacency_matrix(Net, mode = "undirected", weighted = TRUE)
cl <- cluster_louvain(g)
# Assign cluster membership
M$Cluster_Clean <- membership(cl)
```

A.4 Cluster Robustness (Modularity Validation)

Cluster robustness was evaluated using network modularity.

```
modularity(cl)
```

A.5 One-way ANOVA for Temporal Citation Differences

To test whether citation impact differs significantly across publication years, a one-way ANOVA was applied.

```
anova_model <- aov(TC ~ factor(PY), data = M)
summary(anova_model)
```

A.6 Tukey HSD Post-hoc Analysis

Pairwise comparisons between publication years were conducted using Tukey's Honest Significant Difference test.

```
TukeyHSD(anova_model)
```

A.7 Poisson Regression Modeling of Citation Impact

Citation counts were modeled using Poisson generalized linear regression, appropriate for non-negative count data.

```
model_pois <- glm(
  TC ~ PY + Cluster_Clean + country,
  data   = M,
  family = poisson(link = "log")
)
summary(model_pois)
```

A.8 Temporal–Thematic Interaction Model

To assess whether citation trajectories vary across thematic clusters over time, an interaction term was introduced.

```
model_interaction <- glm(
```

```
  TC ~ PY * Cluster_Clean + country,
  data   = M,
  family = poisson(link = "log")
)
anova(model_pois, model_interaction, test = "Chisq")
```

A.9 Incidence Rate Ratios (IRR)

To facilitate interpretation, Poisson regression coefficients were exponentiated and reported as Incidence Rate Ratios (IRR), with Wald-based 95% confidence intervals.

```
coef_tab <- summary(model_pois)$coefficients
IRR_table <- data.frame(
  Term    = rownames(coef_tab),
  IRR     = exp(coef_tab[, "Estimate"]),
  CI_low  = exp(coef_tab[, "Estimate"] - 1.96 * coef_tab[, "Std. Error"]),
  CI_high = exp(coef_tab[, "Estimate"] + 1.96 * coef_tab[, "Std. Error"]),
  p_value = coef_tab[, "Pr(>|z|)"]
)
IRR_table
```

A.10 Overdispersion Diagnostic

Model dispersion was evaluated using the Pearson dispersion statistic.

```
dispersion <- sum(residuals(model_pois, type = "pearson")^2) /
              df.residual(model_pois)
dispersion
```

A.11 Software Environment

All bibliometric and statistical analyses were performed using base R and the bibliometrix package. Biblioshiny was used for interactive visualization and network exploration. The provided code snippets are representative and sufficient to reproduce all inferential results reported in the manuscript. Full preprocessing pipelines are available from the authors upon reasonable request.