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Navigating the Landscape of Artificial Intelligence in Agricultural Extension Services: A Bibliometric Analysis

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Abstract

Artificial Intelligence (AI) is increasingly adopted in agricultural extension services to enhance knowledge sharing, improve decision-making, and promote sustainable farming methods. This study presents a bibliometric analysis of the global research landscape on the application of AI in agricultural extension. Using data from two major sources, Web of Science and Scopus databases, we analyzed publication trends, co-authorship network, bibliographic coupling, and co-occurrence network from 1997 to 2024. The findings reveal a slow but steady rise in publications. Indonesia, the United States of America, India, China, and the United Kingdom emerged as the top five countries in publication count, with notable contributions from developed and underdeveloped countries. The co-authorship and bibliographic coupling networks represent a high level of collaboration among the participating countries with global access to research on AI in agricultural extension. Keyword analysis highlights a strong emphasis on technological innovation in AI-driven agricultural extension, with an emerging focus on areas such as machine learning, farmers' knowledge, adoption, agricultural practices, and climate-smart agriculture. We recommend that stakeholders in the agricultural sector invest in the development of localized and context-aware AI applications. In addition, strengthen capacity-building efforts to ensure widespread and equitable adoption of these technologies in rural advisory services.

Keywords
Artificial Intelligence, Agricultural Extension, Machine Learning, Smart Farming

1. Introduction

Agricultural extension has played a key role in educating farmers on the best farming practices worldwide. However, the limited number of these extension officers, as well as rural accessibility in developing countries, has greatly affected their functions. Unfortunately, the majority of the farmers reside in the rural areas, and a greater percentage of the farmlands are in the rural communities. Agricultural extension workers serve as a bridge between academia, the industry, and the farmers, thus bringing the latest technology and best farming techniques to the farmers. As emphasized by Madaswamy (2020), farmers require timely, customized, and location-specific information to effectively manage their production, reduce risks, and market their produce to suitable market opportunities.

Artificial intelligence (AI) according to IBM (2024), is the technology that allows computers and machines to mimic human abilities such as learning, understanding, solving problems, making decisions, being creative, and operating independently. AI has evolved through derivative concepts that have emerged for a long time from AI to machine learning, deep learning, and generative AI (Gen AI). AI in agricultural extension is therefore, the use of AI technologies to support and enhance the delivery of agricultural extension services. AI helps in providing decision support services, predictive analytics, chatbots and virtual assistants, disease diagnostic Apps for crops and animals using image recognition, and so on. In short, AI in agricultural extension aims to make advisory services more efficient, accessible, and tailored to farmers' needs. Agricultural advisory systems and agricultural data analysis are effectively done using machine learning algorithms (Logesh & Domnic, 2024). In modern agriculture practices, machine learning facilitates data-driven decision making by enabling precise crop management, resource-efficient farming, yield optimization, and the early detection of potential crop failures. Ben-Ayed and Hanana (2021) highlighted that to achieve food security with the projected world population coupled with climate change, a harsh socioeconomic situation, and resource scarcity, the intervention of forecasting strategy and computational tools like AI is needed.

Information and Communication Technology (ICT) has acted as a catalyst for modern agricultural practices such as smart farming, precision agriculture, digital agriculture, and e-agriculture which serve as the foundation for AI applications in agriculture. AI has become a household name with its application in almost every field of human endeavor, and agricultural extension is not an exception. This study uses literature from the Web of Science Core Citation and Scopus databases to analyze the trend of research publications on the application of AI in agricultural extension services. The study therefore, seeks to answer these research questions (RQs):

i. What has been the growth pattern of scientific publications on the application of AI in agricultural extension, and how has AI been applied in agricultural extension so far?

ii. Which countries have made the most significant contributions in the area of application of AI in agricultural extension, and what have been their collaboration patterns?

iii. What is the current research focus on the application of AI in agricultural extension?

2. Materials and Methods

The advanced search option on the Web of Science Core Collection database (https://www.webofscience.com/wos/woscc/advanced-search) and Scopus database (https://www.scopus.com/search/form.uri?display=advanced) were used to collect relevant articles for the study on the 8th of April, 2025. The Web of Science Core Collection database and Scopus were chosen because of the high quality and credibility of their content with a global coverage. They also have powerful tools for citation analysis. This makes it easier to track research output and trends in a particular research area. The Web of Science Core Collection and Scopus databases cover a wide range of disciplines. Figures 1 and 2 represent the detailed approach to how this bibliometric analysis of the application of AI in agricultural extension was conducted. A search query was logically formed to ensure that only relevant articles were returned.

2.1 Inclusion and Exclusion Criteria

The following inclusion and exclusion criteria were applied to filter the results returned by the query statement. The article's publication language was restricted to the English language, thus excluding articles published in non-English languages. Also, journal articles, conference papers, and book chapters were chosen as the document type. Review articles, editorial materials, letters, meeting abstracts, and others were excluded. Although 2025 has already witnessed a reasonable number of publications in its first quarter, it was excluded. Therefore, the publication years were set from 1997 to 2024 for the bibliometric analysis. After downloading the documents from the Web of Science Core Collection database and Scopus, the records were merged in Microsoft Excel, and duplicates were removed as detailed in Figure 2.

2.2 Bibliometric Analysis Tool

The VOSviewer bibliometric analysis tool was used to visualize the results. The final records after removing the duplicates, were imported into VOSviewer for the bibliometric analysis. Its strength in visual mapping, coupled with advanced bibliometric tools, makes it highly valuable for identifying research trends, uncovering relationships, and knowledge gaps in scholarly publications.

Figure 1. Bibliometric Analysis Flow Diagram

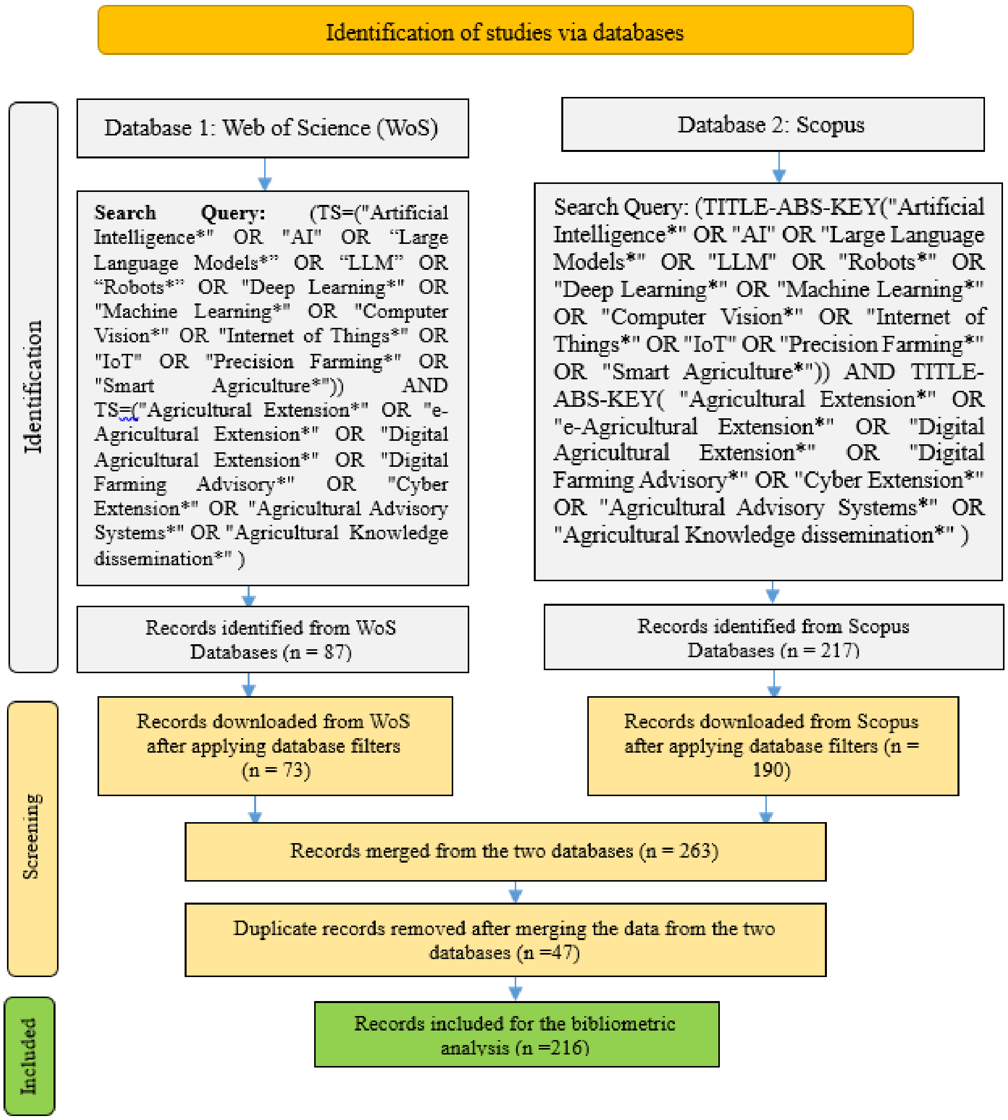

Figure 2. Literature Search Strategy

3. Results and Discussion

3.1 Publication Trend and Areas of Application

RQ1: What has been the growth pattern of scientific publications on the application of AI in agricultural extension, and how has AI been applied in agricultural extension so far?

The retrieved documents show a slow and fluctuating number of publications from 1997 to 2018 but a rising trajectory in publication count from 2019 to 2024, with little variation in the yearly publications output relating to AI in agricultural extension services. Similarly, the records indicate a growing number of citations from 2016 to 2023, with a decline in 2024. The consistent growth in publication count from 2019 to date results from the overwhelming acceptance of AI in our daily routines.

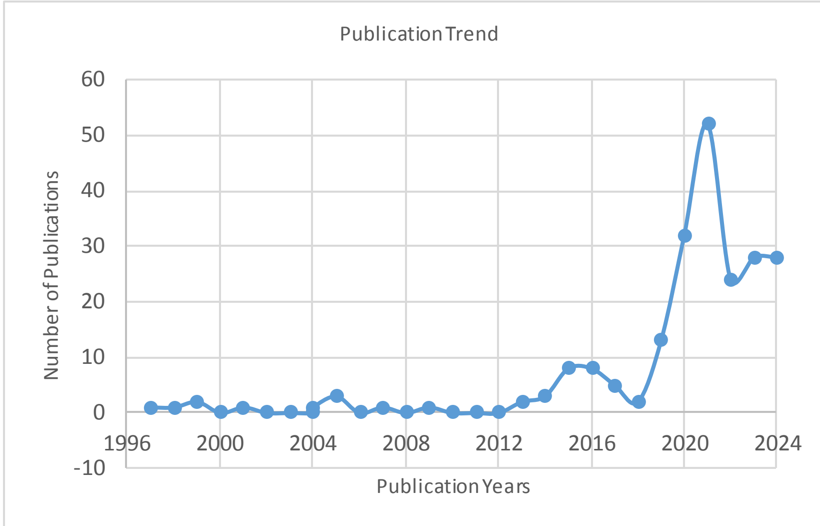

Figure 3. Publication Trend on Application of AI in Agricultural Extension

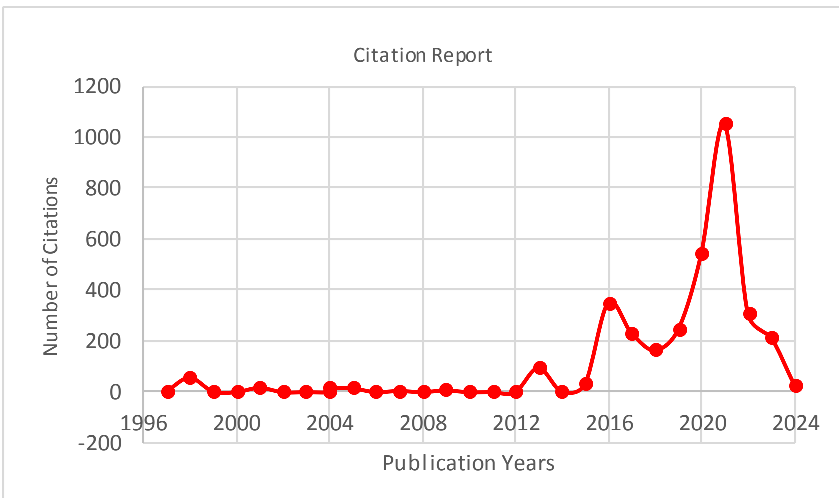

Figure 4. Citations Trend on Application of AI in Agricultural Extension

We review the screened articles to appraise how AI has been applied in agricultural extension services. Different areas of agriculture, such as crop production, animal husbandry, market predictions, weather forecasting, disease detection, and irrigation requirements, have applied AI through machine learning (ML) algorithms, thereby educating farmers on the best farming practices. Chatbots that assume the position of an agricultural extension officer are developed to provide automated, quick responses to farmers' queries, which gives the farmers the impression of virtually communicating with an extension officer. In India, they have the KissanAI (https://kissan.ai), a sophisticated multilingual AI platform that offers personalized, voice-based support for every agricultural need, empowering farmers, agribusinesses, governments, and nonprofit organizations around the globe. The International Crop Research Institute for Semi-Arid Tropics (ICRISAT) in collaboration with Microsoft India, also developed an AI Sowing App (Bizna, 2016; FAO, 2017) to guide farmers in Asia and Sub-Saharan Africa. The AI Sowing App provides participating farmers with sowing recommendations on the best dates for planting. These advisories are delivered via text messages to their mobile phones. Another AI-powered App that provides agricultural extension services to farmers is Plantix (plantix.net). It helps farmers to diagnose and treat crop diseases, thus improving farming knowledge and productivity.

The introduction of large language models (LLMs) such as ChatGPT and Deepseek has been explored by farmers in search of agricultural advisory support. Ibrahim et al. (2024) evaluated the responses by ChatGPT to farmers' questions on irrigated lowland rice cultivation from farmers in Kano State, Nigeria. It was observed that ChatGPT provided the best responses compared to the selected agricultural extension officers. Even though ChatGPT failed in other areas, such as seed rate, fertilizer application rate, and planting time. It implies that AI chatbots specifically trained for such a purpose could offer alternative support to agricultural extension officers. This correlates with the findings of Tzachor et al. (2023), who explored ChatGPT for generating technical guidance for cassava farmers in Nigeria. They suggested an ideal development process that involves human experts at every stage to provide a safe and responsible use of LLMs in global agriculture. Due to the sparse application of LLMs in the agricultural extension domain based on the unstructured nature of agricultural data, Kpodo et al. (2024) proposed a novel question and answers benchmark dataset called agricultural extension question and answers (AgXQA). This novel dataset enhances the development of specialized language models for agricultural extension and the agricultural domain in general.

Another recent application of AI in agricultural extension services is the use of the Internet of Things (IoT) based devices. IoT devices have been applied in helping farmers in pest and insect detection, unmanned aerial vehicles for crop surveillance, irrigation, crop status, and even used for soil preparation (Ayaz et al., 2019), thereby aiding farmers in adopting best farming practices. Habibie et al. (2021) suggested that satellite remote sensing, geographical information systems (GIS), and analytical hierarchy process (AHP) based multicriteria analysis can be effectively applied in agricultural extension services to identify suitable land for enhancing maize production.

In disease diagnoses and management, AI has been extensively applied in developing various crop and animal disease detection systems through machine learning algorithms and computer vision techniques. Some are designed as mobile applications (Johannes et al., 2017; Loyani & Machuve, 2021; Mrisho et al., 2020; Petrellis, 2019; Ramcharan et al., 2019; Ranjith et al., 2017; Sanga et al., 2020; Verma et al., 2019) to facilitate access to these programs, allowing farmers and agricultural extension workers to utilize their phones for access. Samuel (2022) introduced an ensemble Seasonal AutoRegressive Integrated Moving Average (SARIMA)-Compact Classification Tree (CCT) machine learning algorithm. The SA-CCT model was designed to provide agricultural extension agents and farmers in South-West Nigeria with early and reliable predictions of black pod disease.

Robotics has also been investigated in crop disease detection and classification. Anwar et al. (2021) explored designing a robotic arm system for detecting and classifying various tomato leaf diseases using an experimental framework. The system exhibited advanced capabilities by detecting and classifying tomato plant diseases, indicating a high level of diagnostic accuracy and computational intelligence. Furthermore, robots are applied in the harvesting of crops (Aljanobi et al., 2010; Bac, 2015; Bechar & Vigneault, 2016; De-An et al., 2011; Ling et al., 2004; Wan Ishak et al., 2010). These harvesting robots can harvest crops using the best harvesting practices. In addition, numerous plant factories utilize robotic systems for sorting, transferring, and handling plants, as well as for quality control and post-harvest operations (Shamshiri et al., 2018).

3.2 Analysis of Countries' Publications and Collaboration

RQ2: Which countries have made the most significant contributions in the application of AI in agricultural extension, and what have been their collaboration patterns?

Indonesia, the United States of America (USA), India, China, and the United Kingdom (UK) were ranked the top 5 Countries with many publications on AI applications in agricultural extension services. However, the USA, UK, China, India, and Kenya are ranked the top 5 countries based on the total link strength computed by VOSviewer as represented in Table 2. The co-authorship network shows a high collaboration among the participating countries. However, these country pairs have the highest collaborations as indicated by the thick lines linking them together: USA-China, India-Japan, China-Thailand, UK-China, Uganda-USA, Kenya-Uganda, and USA-Germany. This may largely be attributed to the technological advancement of most of these countries, coupled with their interest in agricultural production. In addition, most of these countries have some of the highest populations in the world. The bibliographic coupling network shows six major clusters as indicated by the color codes: green, yellow, red, blue, purple, and light blue, represented in Figure 6. The network points to a global research access in the applications of AI in agricultural extension services, where different countries reference other countries' research output.

Table 1. Top 10 Countries Ranked by Publication Count

SN	Country	Documents	Percentage (%)
1	Indonesia	32	14.81
2	United States of America	27	12.50
3	India	23	10.65
4	China	15	6.94
5	United Kingdom	14	6.48
6	Kenya	11	5.09
7	Nigeria	10	4.63
8	Australia	9	4.17
9	South Africa	9	4.17
10	Bangladesh	8	3.70

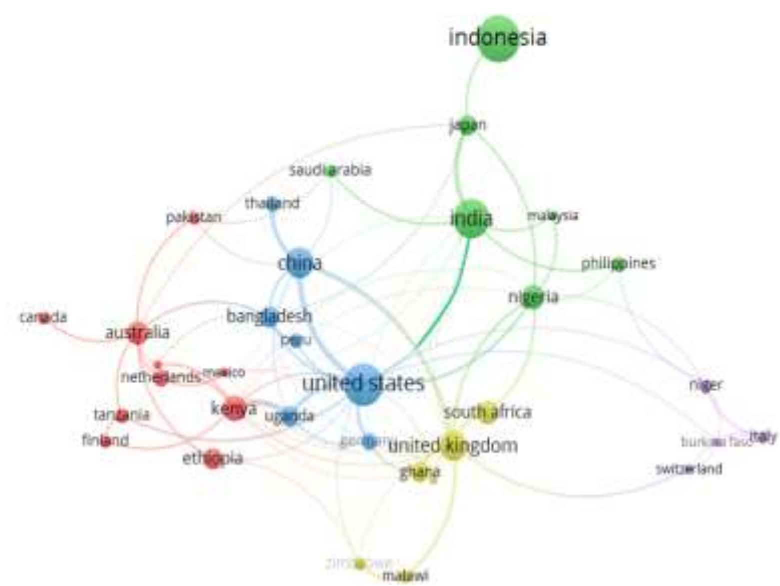

Figure 5. Co-authorship Network by Countries

Table 2. Top 15 Countries Ranked by Total Link Strength

Country	Documents	Citations	Total link strength
United States of America	27	617	920.04
United Kingdom	14	216	639.98
China	15	440	523.67
India	23	253	495.25
Kenya	11	280	453.49
Australia	9	334	397.77
Bangladesh	8	161	395.89
Japan	7	180	392.77
Germany	5	84	370.00
Nigeria	10	93	313.93
Uganda	7	584	312.79
South Africa	9	172	227.01
Ghana	7	140	198.13
Netherlands	5	325	195.67
Zimbabwe	3	80	192.5

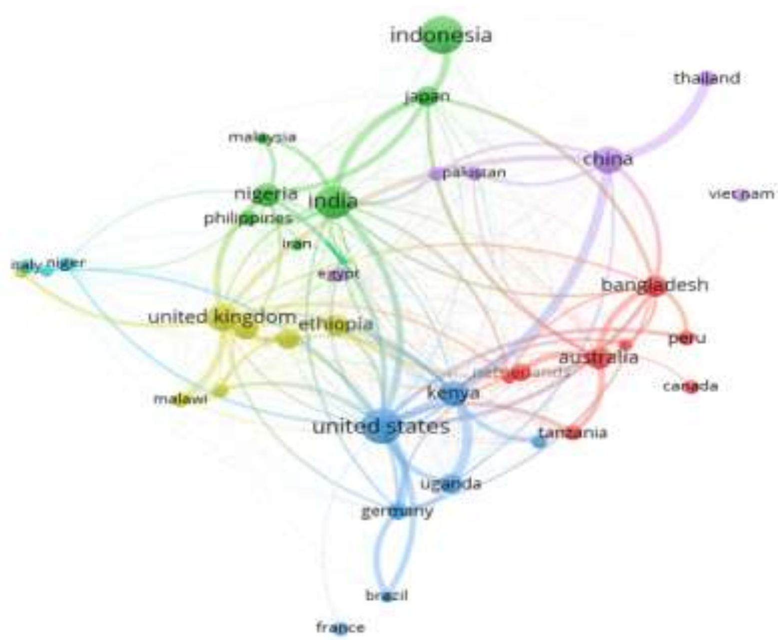

Figure 6. Bibliographic Coupling by Countries

3.3 Keyword Co-occurrence Analysis

RQ3: What is the current research focus on the application of AI in agricultural extension?

Figures 7 and 8 represent the keyword co-occurrence on the application of AI in agricultural extension. Research on AI in agricultural extension services has covered many aspects of agriculture. These studies focus on developing AI-driven solutions that improve farm efficiency, reduce environmental impact, and support adaptation to climate variability. Dominant keywords include agricultural robots, agricultural extension, climate change, artificial intelligence, farming systems, irrigation, adaptive management, machine learning, food security, technology adoption, and crop production. The light green and yellow colored keywords in Figure 8 represent the trending terms. These keywords include machine learning, remote sensing, smart agriculture, farmers' attitude, adoption, climate smart agriculture, smallholder farmers, decision support systems, food security, human resource management, crop yield, agricultural technology, etc. Researchers are consistently exploring novel methods to leverage AI for boosting agricultural productivity, promoting sustainable farming practices, and enhancing climate resilience.

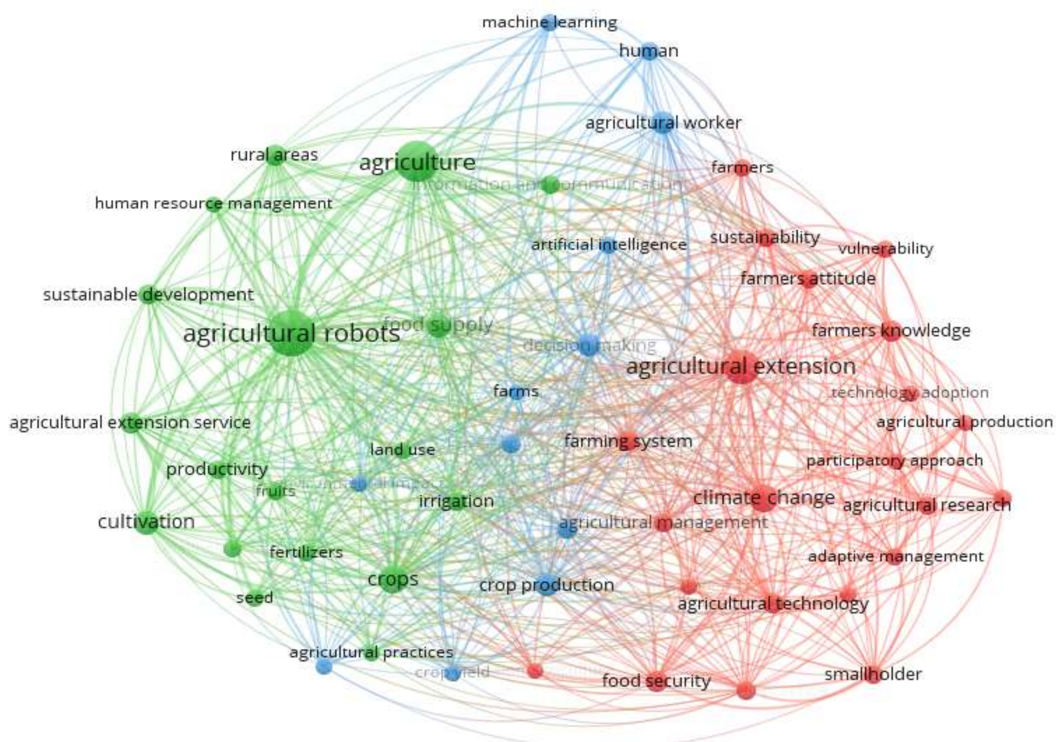

Figure 7. Network Analysis of Co-occurrence Keywords

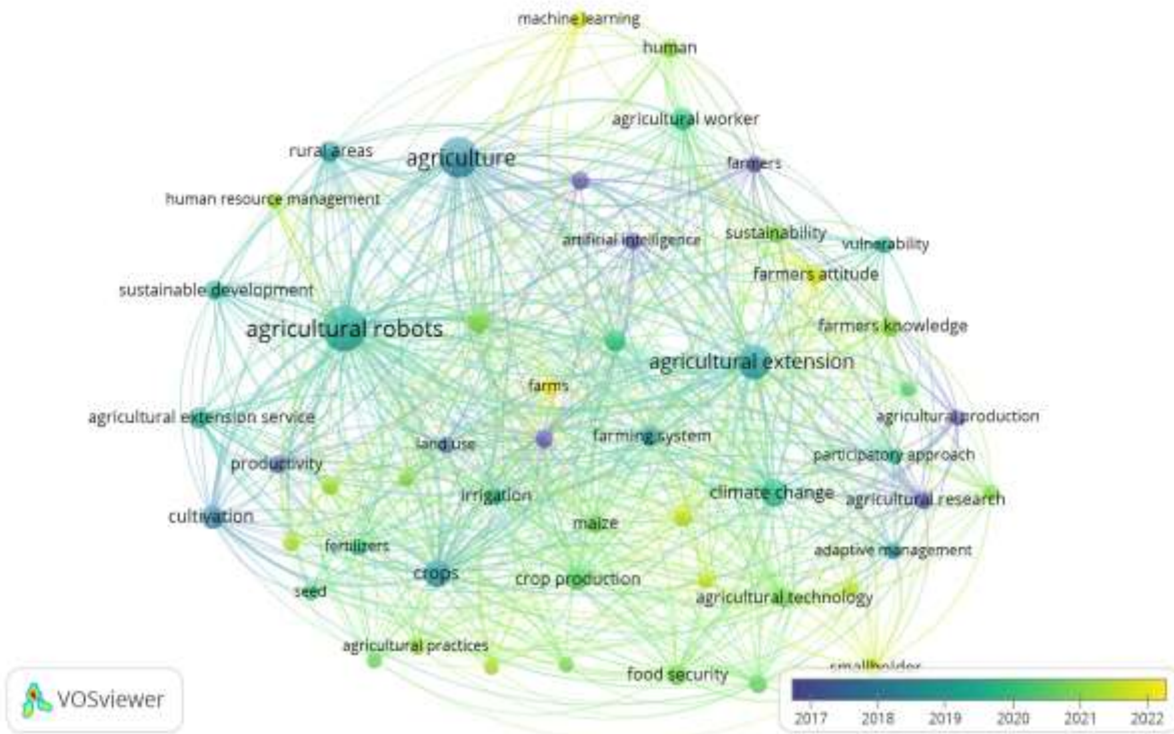

Figure 8. Overlay Visualization of Co-occurrence Keywords

The integration of AI in agricultural extension services is of utmost importance, considering the wide adoption of smart devices and AI technology into our daily activities. According to the International Telecommunication Union (ITU), four out of five people own a phone, and about 70% of these people use the internet (ITU, 2024). This implies that AI-based agricultural extension services can reach remote areas very easily, thus making it accessible to more farmers. The prospects of AI in agricultural extension are overwhelming. However, the majority of the farmers in developing nations lack basic ICT skills, hence the need to train them to properly harness this technology. AI-driven agricultural advisory services powered by mobile platforms, chatbots, and cloud-based systems can extend agricultural extension services to remote and underserved regions. This enhances scalability and ensures that timely, personalized support reaches a broader population of farmers.

5. Conclusion and Recommendations

In summary, the bibliometric analysis highlights the rapid development of AI applications in agricultural extension services while identifying knowledge gaps and collaboration needs. There has been a notable increase in publications on the application of AI in agricultural extension, particularly since 2019. This surge reflects the rising interest in digital agriculture, advancements in AI technologies, and the integration of big data into the agricultural sector. Similarly, there has been a corresponding increase in citations from 2016 onwards, reflecting the researchers' high interest in applying AI in agricultural extension services. The research output covers the use of mobile and web-based applications for crop and animal disease diagnosis and management; the use of LLMs for seeking agricultural advisory services; robots in harvesting, crop monitoring, weeding, spraying and irrigation, seeding and planting, and autonomous tractors; thus bringing the best farming practices to the farmers.

The co-authorship network represents a high level of collaboration among the participating countries with a global coverage. However, more collaboration between the developed and developing nations is required to tap into the rich technological advancements in building local solutions. The bibliographic coupling network also reveals a global access to research on AI in agricultural extension. Keyword analysis highlights a strong emphasis on technological innovation in AI-driven agricultural extension, with an emerging focus on areas such as machine learning, farmers' knowledge, adoption, agricultural practices, and climate smart agriculture. Future studies should focus on local content development and scalable solutions to ensure that AI-based systems effectively address the diverse needs of farmers and extension workers across different agricultural environments.

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