

Artificial Intelligence in Agricultural Extension and Advisory Services: A Scoping Review of Applications, Explainability, Trust and Farmer-Centred Adoption

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Abstract

Background

Artificial intelligence (AI) is increasingly being explored to strengthen agricultural extension and advisory services, yet evidence on its practical applications, explainability, trust, and farmer-centred adoption remains fragmented. This scoping review mapped the available evidence on AI and explainable artificial intelligence (XAI) in agricultural extension, with particular attention to applications, decision-support systems, explainability, adoption determinants, challenges, and future directions.

Methods

A scoping review was conducted following the JBI approach and PRISMA-ScR guidance. Literature published between January 2021, and August 2026 was searched across Scopus, Web of Science Core Collection, ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Frontiers, PubMed, and Google Scholar. Following duplicate removal of title, abstract, and full-text screening, 32 publications met the inclusion criteria. Data were charted and synthesised thematically to present the findings.

Results

The review identified four major evidence domains: AI applications in agricultural extension and advisory services; AI-enabled advisory and decision-support systems; explainability, trust, and determinants of farmer-centred adoption; and implementation challenges and future directions. AI applications included personalised advisory, crop and yield prediction, crop recommendation, pest and disease management, climate and irrigation decision support, and conversational advisory systems. XAI approaches, particularly SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), were increasingly used to improve model interpretability and transparency. However, evidence indicated that technical performance alone does not ensure adoption. Trust, usability, digital literacy, accessibility, contextual relevance, language, infrastructure, and perceived usefulness influence the acceptance and effective use of AI-enabled advisory services. Evidence from smallholder settings remained comparatively limited, with persistent concerns regarding digital divides, data quality, model transparency, contextualisation, and responsible AI governance.

Conclusions

AI and XAI offer substantial opportunities to strengthen agricultural extension through personalised, scalable, and data-driven advisory services. However, future development should move beyond technology-centred performance toward farmer-centred adoption, emphasizing explainability, trust, accessibility, contextual relevance, and responsible implementation. Greater empirical attention to

farmers' experiences and adoption determinants is needed to support equitable and sustainable integration of AI into agricultural extension systems.

1. Background

Agriculture remains fundamental to global food security, rural livelihoods and economic development, but agricultural systems increasingly face pressures from population growth, climate variability, resource constraints and the need for sustainable intensification [1]. These pressures increase the need for timely, context-specific and evidence-informed agricultural decision-making [2, 3]. Agricultural extension and advisory services play a central role by connecting farmers with scientific knowledge, technologies and management practices while supporting learning, problem-solving and technology adoption [4]. However, conventional extension systems continue to face constraints including limited personnel, high farmer-to-extension agent ratios, geographical barriers and difficulties in providing timely and context-specific advice to heterogeneous farming populations [5, 6]. These limitations have increased interest in digital approaches that can extend the reach, responsiveness and personalization of agricultural advisory services [7, 4].

Digital agricultural services increasingly combine information and communication technologies with remote sensing, geographic information systems, Internet of Things technologies, cloud computing, data analytics and artificial intelligence (AI) to support agricultural information exchange and decision-making [4]. AI technologies, including machine learning, natural language processing, computer vision, recommender systems, generative AI and large language models, are increasingly being explored for crop recommendation, disease diagnosis, resource management, knowledge retrieval, farmer query support and advisory communication [8, 9]. In extension and advisory contexts, these technologies have potential to support personalized information delivery, expand advisory coverage, assist extension professionals and facilitate farmer-system interaction. AI is therefore increasingly being considered not only as a technical tool for agricultural production but also as a component of agricultural extension and advisory systems.

However, AI-enabled advisory services raise issues that extend beyond predictive accuracy and technical performance. Agricultural recommendations can influence production practices, resource allocation and livelihood decisions, making the ability of users to understand, evaluate and appropriately act on AI-generated advice important. Concerns therefore include transparency, interpretability, accountability, trust and human oversight, particularly where complex models produce outputs that are difficult for users to understand [10, 11]. These considerations are particularly relevant to agricultural extension, where advisory processes involve communication, interpretation, local knowledge, institutional relationships and behavioural decision-making. AI-enabled extension should consequently be considered a socio-technical process in which technological capabilities interact with farmers, extension professionals, institutions and local knowledge systems.

Explainable artificial intelligence (XAI) has emerged as one approach for improving the interpretability of AI outputs through methods such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), feature-importance techniques and other explanation approaches [10]. In agriculture, XAI has been applied to explain predictions and recommendations in areas including crop recommendation, disease detection, yield prediction and agricultural decision support [11, 12]. Such approaches may support extension professionals and farmers in assessing the basis of AI-generated advice and combining machine-generated information with agronomic knowledge and local experience. However, evidence from broader agricultural AI applications cannot automatically be assumed to represent farmer-facing extension services.

[13, 14, 15] have examined AI applications in agriculture, explainable AI, AI adoption and trust, and the emerging role of AI in agricultural extension. These reviews provide important foundations but address different dimensions of the field. Technical reviews of XAI, for example, largely encompass remote sensing, crop classification, disease detection, yield prediction and precision agriculture, whereas extension-focused literature examines advisory systems and communication more broadly. Evidence is therefore dispersed across technological, advisory, behavioural and human-centred perspectives.

A particular gap lies at the intersection of these perspectives. It remains necessary to understand how AI is being applied within agricultural extension and advisory services, how AI-enabled advisory and decision-support systems are being developed and used, and how explainability, transparency and trust are addressed. It is also important to identify the technological, infrastructural, social, institutional and contextual challenges that may shape the development and use of farmer-centred and trustworthy AI-enabled extension. The evidence [13, 14, 15] is methodologically heterogeneous, spanning empirical studies, system-development and evaluation studies, technical contributions, reviews and conceptual work. This makes a scoping review appropriate for mapping the breadth and characteristics of the evidence and identifying patterns and gaps across this rapidly developing field.

Accordingly, this scoping review examines the emerging evidence on artificial intelligence in agricultural extension and advisory services, with particular attention to applications, AI-enabled advisory and decision-support systems, explainability, transparency, trust and farmer-centred implementation. Specifically, the review aims to: (i) examine the applications of AI in agricultural extension and advisory services; (ii) examine the development and use of AI-enabled advisory and decision-support systems for farmers; (iii) assess the role of explainability, transparency and trust in AI-enabled agricultural advisory and decision-making; and (iv) identify the challenges, gaps and future directions for farmer-centred and trustworthy AI-enabled agricultural extension.

2. Methods

2.1 Study Design and Search Strategy

This study employed a scoping review design to map the emerging evidence on artificial intelligence (AI) in agricultural extension and advisory services, with particular attention to AI applications, AI-enabled advisory and decision-support systems, explainability, transparency, trust and farmer-centred implementation. A scoping review was appropriate because the literature spans multiple disciplines and comprises heterogeneous evidence, including empirical studies, system-development and evaluation studies, technical contributions, reviews and conceptual work. The review aimed to characterise the breadth, nature and distribution of the evidence and identify important knowledge gaps rather than estimate a pooled intervention effect.

The review was guided by the methodological framework of the Joanna Briggs Institute (JBI) and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR). The review process comprised literature identification, removal of duplicate articles, screening, full-text eligibility assessment, data charting, evidence mapping and thematic synthesis.

For this review, AI in agricultural extension and advisory services refers to computational approaches, including machine learning, deep learning, natural language processing, computer vision, recommender systems, generative AI, large language models (LLMs) and intelligent decision-support systems, used to generate, interpret, personalise or deliver agricultural information and advice. Explainable artificial intelligence (XAI) refers to approaches that improve the interpretability or understandability of AI predictions, classifications or recommendations. Trust encompasses reported perceptions or assessments relating to transparency, reliability, credibility, accountability and willingness to rely on AI-generated advice. Farmer-centred AI refers to systems that consider users' needs, capabilities, participation, local knowledge, language, accessibility, feedback and decision-making contexts.

The search strategy was developed through preliminary searches of literature and reviews addressing AI in agriculture, agricultural extension, digital advisory services, XAI, trustworthy AI and farmer-centred agricultural technologies. These searches informed the identification of relevant concepts, synonyms and terminology.

The principal search strategy combined three concept groups: (i) AI and related technologies; (ii) agricultural extension, advisory and decision-support contexts; and (iii) farmers and agricultural decision-making. The core search strings were:

"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Natural Language Processing" OR "Generative AI" OR "Large Language Model" OR chatbot OR "Decision Support System" OR "recommender" OR "Explainable Artificial Intelligence" OR "SHAP" OR "LIME" OR "interpretability" OR "explainability" OR "trustworthy AI" AND "Agricultural Extension" OR "Agricultural Advisory" OR "Extension Service" OR "Digital Extension" OR "Digital Advisory" OR "Farmer Advisory" OR "Agricultural Knowledge" OR "Decision Support" AND "farmer" OR "smallholder" OR "agriculture" OR "agricultural" OR "crop" OR "livestock".

Database-specific adaptations were made to accommodate differences in indexing and search syntax. Additional terminology included AI-powered advisory systems, agricultural chatbots, conversational AI, farmer-facing AI, smart agricultural extension, agricultural recommendation systems and human-centred AI. Searches were conducted across Scopus, Web of Science Core Collection, ScienceDirect, IEEE Xplore Digital Library, SpringerLink, MDPI, Frontiers and Google Scholar. Backward reference checking and forward citation tracking were also undertaken to identify potentially eligible publications not retrieved through the database searches.

Document searches were conducted between March 2026 and 1 September 2026. The search covered publications published between 1 January 2021 and 31 August 2026 and was conducted in English. Searches were not restricted to empirical studies because the review sought to map diverse forms of evidence relevant to AI-enabled agricultural extension and advisory services. The database-specific search strings, search dates and retrieval counts are provided in Supplementary Table 1.

2.2 Eligibility Criteria

Eligibility criteria were developed in accordance with the Population-Concept-Context (PCC) framework recommended for scoping reviews.

Population

Evidence involving farmers, smallholder farmers, agricultural extension professionals, advisory personnel, farm operators and other users or stakeholders involved in agricultural knowledge and decision-making was considered. Studies did not require direct farmer participation where the system or evidence was clearly intended to support agricultural users or extension practice.

Concept

The review focused on the application, development, implementation or evaluation of AI and related technologies for agricultural extension, advisory services, agricultural knowledge delivery or farmer-oriented decision support. Relevant technologies included machine learning, deep learning, natural language processing, computer vision, recommender systems, conversational AI, generative AI, LLMs, intelligent decision-support systems and XAI. Evidence addressing explainability, interpretability, transparency, trust, responsible AI, usability, adoption and human-centred design was included where clearly connected to agricultural advisory or decision-support applications.

Context

The review focused on agricultural extension and advisory services, digital extension, farmer advisory platforms, AI-enabled knowledge delivery, extension-support systems and agricultural decision-support applications with a demonstrable connection to farmer-oriented advice, agricultural decision-making or extension practice. Agricultural AI applications such as crop recommendation, disease diagnosis, soil assessment, yield prediction, irrigation management, pest management, drought prediction, livestock

management and precision agriculture were eligible where they provided or supported an advisory, recommendation or decision-support function.

Publications were eligible if they: (i) applied AI within agricultural extension or advisory services; (ii) developed, implemented or evaluated an AI-enabled farmer advisory or agricultural decision-support system; (iii) examined AI adoption, acceptance, trust, usability or readiness among agricultural users; (iv) investigated explainability, transparency or interpretability with relevance to agricultural advisory or decision-making; or (v) provided a review, framework or research agenda directly informing AI-enabled agricultural extension, advisory services, explainability, trust, responsible AI or farmer-centred adoption.

Eligible evidence included peer-reviewed journal articles, peer-reviewed conference proceedings, relevant scholarly book chapters, substantive scholarly preprints, system-development and evaluation studies, technical or methodological studies, and relevant review or framework publications. These evidence types were distinguished during data charting rather than treated as methodologically equivalent.

Publications were excluded when they focused exclusively on automated farm operations, robotics, autonomous machinery, general remote sensing, crop classification, image processing or precision-agriculture applications without a demonstrable advisory, extension or farmer decision-support component. Theoretical AI studies without an agricultural application or clear relevance to agricultural decision-making were also excluded.

The review was restricted to English-language publications published between 1 January 2021 and 31 August 2026. Editorials, commentaries, opinion pieces, news and magazine articles, patents, book reviews, conference abstracts, posters, presentation slides, workshop summaries, duplicate publications and publications lacking sufficient substantive information for evidence charting were excluded. Grey literature and institutional reports were not included in the final evidence corpus.

2.3 Study Selection

Study selection followed the identification, screening, eligibility and inclusion stages recommended by PRISMA-ScR. A total of 318 records were identified through the selected electronic databases. Following consolidation, 42 duplicate records were removed, leaving 276 records for title and abstract screening.

Three researchers participated in the screening process using the predefined eligibility criteria. A total of 196 records were excluded at the title and abstract stage, leaving 80 publications for full-text assessment. The full texts were assessed for relevance to AI-enabled agricultural extension and advisory services, agricultural decision support, explainability, transparency, trust, adoption and farmer-centred AI applications. Disagreements were resolved through discussion and consensus.

Following the full-text assessment, 48 publications were excluded and 32 publications met the inclusion criteria. The final evidence base comprised heterogeneous publications, including empirical studies, AI system-development and evaluation studies, technical and explainability studies, and review or framework publications. Some publications provided direct evidence on AI applications in agricultural

extension and advisory services, whereas others provided supporting evidence on explainability, transparency, trust, responsible AI, AI-enabled decision support or farmer-centred implementation. Each publication was counted once in the final evidence base, although individual publications could contribute to more than one thematic area. The complete selection process is presented in the PRISMA-ScR flow diagram (Fig. 1).

Duplicate records removed

Records removed (n = 42)

Figure 1: PRISMA Flow chart for the review

2.4 Data Charting and Evidence Synthesis

Data were charted from the 32 included publications using a structured framework developed in accordance with the four review objectives. Extracted information included publication characteristics, geographical context, evidence type, study design, population or users, agricultural domain, AI technology, advisory or decision-support function, extension relevance, explainability and transparency, trust and adoption considerations, farmer-centred features, reported challenges, major findings and evidence gaps.

The included publications were classified according to their primary contribution as empirical, system-development and evaluation, technical or methodological, explainability or trust, and review or framework evidence. This classification was used to distinguish the nature of the evidence rather than to imply methodological equivalence.

The synthesis also distinguished between direct evidence, referring to publications explicitly examining or implementing AI within agricultural extension, advisory services or farmer-oriented decision-support systems, and supporting evidence, referring to publications addressing relevant dimensions such as explainability, transparency, trust, adoption, responsible AI or human-centred design with clear relevance to the review.

Given the heterogeneity of the evidence, quantitative meta-analysis was not undertaken. Instead, findings were synthesised through descriptive evidence mapping and thematic synthesis. Publication characteristics, technologies, advisory functions, user groups and implementation contexts were mapped, followed by comparison of findings across the four review objectives.

The thematic synthesis was organised around four predefined themes corresponding to the review objectives: (i) AI Applications in Agricultural Extension and Advisory Services; (ii) AI-Enabled Advisory and Decision-Support Systems; (iii) Explainability, Transparency and Trust in Agricultural AI; and (iv) Challenges, Gaps and Future Directions for Farmer-Centred AI Extension. Findings were compared across geographical contexts, user groups, AI technologies and evidence types to identify recurring

patterns, areas of limited evidence and research gaps. The synthesis focused on mapping the evidence base rather than ranking technologies or estimating comparative effectiveness.

3. Results

3.1 Selection of Sources of Evidence

The search identified 318 records across the selected electronic databases and scholarly search platforms. Following removal of 42 duplicates, 276 unique records remained for title and abstract screening. Of these, 196 were excluded because they did not meet the predefined scope and eligibility criteria.

A total of 80 publications underwent full-text assessments, of which 48 were excluded. The remaining 32 publications which met the eligibility criteria constituted the final evidence base for data charting, evidence mapping and thematic synthesis. The complete selection process is presented in the PRISMA-ScR flow diagram (Fig. 1).

3.2 Characteristics of Included Publications

The 32 included publications represented a heterogeneous evidence base spanning empirical research, AI system-development and evaluation studies, technical and methodological contributions, explainability and trust studies, and review or framework publications. The evidence covered a range of geographical contexts and agricultural settings, with farmers, smallholder farmers, extension professionals and other agricultural users represented across the literature.

The publications examined diverse AI approaches, including machine learning, explainable AI, conversational AI, chatbots, generative AI, large language models, recommender systems and intelligent decision-support systems. Reported applications included agricultural information delivery, crop and input recommendations, crop-health assessment, irrigation and resource management, farmer query support and personalised advisory services.

The evidence also varied in its treatment of human-centred dimensions. Some publications focused primarily on technical system development or model performance, whereas others examined explainability, transparency, trust, adoption, usability, human oversight and responsible AI. This heterogeneity reflects the interdisciplinary and rapidly developing nature of AI-enabled agricultural extension research. Detailed characteristics and evidence contributions of the included publications are presented in Supplementary Table 2.

3.3 Thematic Overview of the Evidence

The 32 included publications were organised into four thematic areas corresponding to the review objectives (Supplementary Table 3). The themes were analytically distinct but not mutually exclusive, and individual publications could contribute evidence to more than one theme.

3.4 Emergent Patterns and Summary Observations

Several cross-cutting patterns emerged across the four thematic areas. First, the evidence indicates progression from AI-assisted information and extension support towards interactive, personalised and increasingly generative advisory systems. Applications now include machine-learning-based decision support, conversational AI, large language models and integrated intelligent advisory platforms.

Second, increasing attention is being given to the personalisation and contextualisation of agricultural advice. Systems are being developed to incorporate agricultural, environmental, user and location-specific information to support more targeted recommendations. However, much of the evidence remains focused on system development, technical performance, user engagement and advisory functionality rather than sustained farmer-level outcomes.

Third, explainability, transparency and trust are emerging as important dimensions of agricultural AI. Technical XAI approaches such as SHAP and LIME are increasingly used to interpret model outputs, but evidence on whether such explanations are understandable and actionable for farmers and extension professionals remains limited. Human oversight and expert involvement also recur across the evidence as mechanisms for supporting responsible use.

Finally, the literature identifies persistent socio-technical barriers, including digital and AI literacy, connectivity and infrastructure, data availability and quality, affordability, localisation, language, institutional capacity, trust and governance. Collectively, these findings indicate rapid technological development alongside comparatively limited evidence on sustained, farmer-centred implementation and outcomes.

3.5 Theme 1: AI Applications in Agricultural Extension and Advisory Services

The included publications reported a range of AI applications in agricultural extension and advisory services, including AI-assisted extension activities, agricultural information delivery, farmer decision support, mobile advisory platforms and generative-AI tools.

Among extension professionals, [20], in a study of 131 agricultural extension professionals in Nigeria, reported that respondents identified real-time farm and landscape information (97.7%) and reliable farm data (75.6%) as major opportunities associated with AI-based digital technologies. Improved communication (88.5%) and access to updated technical information (64.1%) were also reported as important benefits. [34] similarly reported awareness and use of AI-related technologies among agricultural extension professionals in India, with infrastructure and capacity identified among the reported constraints to utilisation.

[25], using data from 240 agricultural extension agents in Benin, examined generative-AI use in extension practice. Generative-AI use was positively associated with advisory performance, assessed using

indicators including the number of farmers trained, speed, precision and relevance of advice.

AI applications involving direct farmer engagement were also reported. [32], in a study of 200 rural farmers in Abuja, found that respondents associated AI use particularly with support for farming decisions and weather planning. [31] reported the use of AI-powered mobile extension platforms for agricultural information dissemination, farmer–extension interaction and advisory services among farmers in Southeast Nigeria.

The included literature also reported customised generative-AI applications for specific agricultural extension contexts. [27] evaluated Utah PeachBot, a customised GPT developed to support Extension agents assisting small-scale peach producers. The study reported high reliability for general peach-production queries, while also identifying limitations relating to regional specificity and practical applicability.

The reported outcomes primarily concerned awareness and utilisation, perceived benefits, information access, communication, advisory performance and system functionality, with fewer publications reporting sustained farmer-level outcomes.

3.6 Theme 2: AI-Enabled Advisory and Decision-Support Systems

The included publications reported a range of AI-enabled advisory and decision-support systems, including generative-AI chatbots, large language model (LLM)-based assistants, mobile advisory platforms and systems integrating AI models with agricultural databases, crop models, remote-sensing information and other contextual data.

Generative AI was used in several publications to provide conversational and personalised agricultural advisory. [38] reported the deployment of Farmer.Chat across four countries to provide agricultural information to smallholder farmers. At the time reported in the study, the system had engaged more than 15,000 farmers and responded to more than 300,000 queries. Evaluation covered response quality, user engagement, trust and reported changes in farming practices. [36] examined the Ama Krushi chatbot in Odisha, which used natural language processing to provide agricultural information in Odia and Sambalpuri.

The included publications also reported systems designed to incorporate domain-specific and contextual agricultural information. [23] described a generative-AI architecture for rice systems that integrates crop-specific knowledge, knowledge graphs, crop simulation models and remote-sensing information to support farm-level advisory. The study also addressed the use of contextual agricultural information in generating recommendations.

Other studies developed integrated AI-based decision-support systems. [18] developed an AI-powered decision-support system combining chatbot functionality, machine learning and data analytics to provide personalised agricultural information. [40] described an agentic AI-based decision-support framework

incorporating soil classification, soil-parameter estimation, crop recommendation and fertiliser recommendation.

Human-AI interaction within agricultural advisory was also examined. [26] examined farmer.chat from an agricultural extension perspective and reported its use for providing personalised agricultural knowledge to smallholder farmers. [25], using data from 240 agricultural extension agents in Benin, reported an association between generative-AI use and advisory performance, measured using indicators including the number of farmers trained, speed, precision and relevance of advice.

Across the included articles, AI-enabled advisory systems incorporated functions such as conversational question answering, personalised information delivery, crop recommendation, fertiliser recommendation, soil assessment and integration of multiple agricultural information sources. The reported evidence covered system development, deployment, user engagement, advisory performance and technical functionality, with several studies involving generative AI and conversational systems.

3.7 Theme 3: Explainability, Transparency and Trust in Agricultural AI

The included publications reported increasing use of explainable artificial intelligence (XAI) and related approaches to improve the interpretability and transparency of agricultural AI systems. The methods reported included SHAP, LIME, Grad-CAM, rule-based approaches and other intrinsic and post-hoc explanation techniques.

[14] reviewed XAI applications across agricultural domains including crop-weed discrimination, disease detection, yield forecasting, precision agriculture and soil assessment, identifying approaches such as SHAP, LIME and Grad-CAM. [11] developed XAI-CROP, which used soil and weather variables to generate crop recommendations and provide explanations of factors contributing to individual predictions. [16] applied LIME to crop recommendation and examined the contribution of variables including nitrogen, humidity and rainfall to individual recommendations.

[41] proposed a federated XAI framework combining SHAP, LIME and Grad-CAM with Internet of Things (IoT), federated learning and multimodal agricultural data. [43] applied SHAP and LIME to irrigation-demand prediction using meteorological, soil, crop-management and remote-sensing variables. These studies reported the generation of global or local explanations for agricultural predictions and recommendations.

Evidence relating to transparency and user perceptions was also reported. [42], studying farm operators in Serbia, reported associations between perceived AI transparency, climate awareness and decision confidence, as well as between transparency and perceived farm resilience. The study was conducted in an agritourism and climate-adaptation context.

[24] examined trust in agricultural AI and identified transparency and explainability alongside accountability, fairness, data ownership, privacy and security as relevant dimensions of trustworthy AI.

[19], in a systematic review of 38 studies, reported low trust and the digital divide among recurring issues in agricultural AI applications. The review also identified explainability, reliability, technical skills, data governance and technology costs among factors associated with AI adoption and trust.

The included publications further addressed trust and responsible use in generative AI. [29] identified contextual and gender-related blind spots, stakeholder engagement and human reasoning as issues in responsible generative AI for agricultural extension. [39] reported the use of more than 25,000 expert-reviewed question-and-answer pairs in Farmer.Chat through reinforcement learning from human feedback, with reported improvements in the quality, tone, contextual relevance and cultural fit of agricultural advice. [21] examined trustworthy AI for precision agriculture, linking the approach to data sourcing, model validation and actionable outputs.

The included publications covered three related areas: technical methods for explaining agricultural AI predictions and recommendations; studies examining transparency and trust; and approaches incorporating expert feedback, data governance and other responsible-AI considerations. Most XAI studies focused on model or system-level interpretability, while fewer directly evaluated users' understanding or subsequent use of AI-generated explanations.

3.8 Theme 4: Challenges, Gaps and Future Directions for Farmer-Centred AI Extension

The included publications reported challenges to AI-enabled agricultural extension and advisory services across infrastructural, technical, institutional, socio-economic and contextual dimensions. Recurring issues included limited digital infrastructure and skills, technology costs, data availability and quality, localisation, trust, institutional capacity and contextual adaptation.

[32] identified internet access, digital literacy and device costs among barriers affecting the use of AI-related technologies among rural farmers in Abuja. [20] similarly reported inadequate technical skills and lengthy adoption processes among challenges associated with AI-based digital technologies in agricultural extension. [34] also reported infrastructure and capacity-related constraints affecting the utilisation of AI-related technologies among agricultural extension professionals in India.

[44] examined challenges to AI-enabled digital technology adoption in farming and identified 13 challenges, including limited knowledge and skills, psychological barriers, inadequate baseline data, high costs, technology-management culture, soil and farmland standardisation and limited intermediary support. The study also reported the role of extension hubs and hands-on training in addressing adoption-related constraints.

Challenges relating to localisation and contextual adaptation were also reported. [37] examined generative-AI and chatbot-based agricultural advisory systems and addressed the importance of agricultural and regional contextualisation. [33] identified infrastructure, data availability, skills, ethics,

stakeholder trust and policy among issues affecting AI integration in agriculture. [17] similarly examined socio-economic, infrastructural and justice-related factors associated with AI adoption in agriculture.

The literature also reported gaps in evidence concerning farmer-level outcomes and user engagement. Several publications focused primarily on technical performance, system functionality, awareness, perceived usefulness, adoption or advisory performance. Fewer studies examined sustained changes in farmer knowledge, behaviour, productivity or profitability. Limited evidence was also reported on farmers' and extension professionals' interpretation and verification of AI-generated recommendations and on their involvement in the design and development of AI-enabled advisory systems.

Across the included publications, the reported challenges therefore encompassed access to infrastructure and skills, affordability, data limitations, contextual and regional adaptation, institutional capacity, trust, ethical considerations and user participation. The evidence also showed variation in the extent to which AI systems incorporated local agricultural knowledge, user needs and extension-system requirements.

4. Discussion

4.1 Major Findings

This scoping review mapped 32 publications on artificial intelligence in agricultural extension and advisory services. The evidence covers AI-supported extension activities, conversational and generative-AI advisory, intelligent decision-support systems, and explainable and trustworthy AI. The literature is heterogeneous, comprising empirical studies, system-development and evaluation studies, technical contributions, reviews and conceptual work. Across these categories, considerable attention has been given to AI functionality, advisory performance, system development and user engagement, whereas evidence on sustained farmer-level outcomes remains comparatively limited [20, 38, 25, 19].

A major development is the movement from AI applications supporting extension personnel towards systems that interact directly with farmers and provide personalised agricultural advice. Farmer.Chat, for example, demonstrates the use of generative AI for farmer-facing advisory at scale, while Ama Krushi illustrates the use of conversational AI for local-language agricultural information delivery [38, 36]. More recent work integrates generative AI with crop-specific knowledge, knowledge graphs, crop simulation and remote-sensing information to support context-specific farm-level advisory [23]. These developments indicate increasing technical sophistication, although evidence demonstrating sustained effects on farmer knowledge, practices, productivity and livelihoods remains limited.

4.2 AI, Extension and the Human-AI Relationship

The findings suggest that AI is more appropriately understood as a component of agricultural extension than as a direct substitute for extension professionals. Studies involving extension agents report applications for information access, communication and advisory performance, while farmer-facing

studies continue to report the relevance of extension personnel within the advisory process [20, 25, 32]. Farmer-facing evidence also shows that perceptions of AI do not necessarily imply reduced reliance on extension agents; in Abuja, for example, farmers expressed stronger agreement that AI supported farming decisions and weather planning than that it reduced dependence on extension agents [32].

Supporting evidence from digital extension reinforces the importance of institutional and human capacity. Although not included in the AI evidence corpus, [45] found that 82% of agricultural extension educators in Kwara State were aware of digital tools and 77% demonstrated high knowledge and favourable attitudes, while only 48.2% reported high usage. Poor orientation, internet connectivity costs and equipment costs were reported as major constraints, with digital literacy significantly associated with willingness to adopt digital extension tools ($r = 0.72$, $p < 0.05$). These findings provide relevant contextual evidence that the transition from awareness to effective technology use depends on institutional and user capacity, not technological availability alone.

4.3 Explainability, Transparency and Trust

Explainability emerged as an important but distinct component of trustworthy agricultural AI. The included literature demonstrates substantial technical development in the use of SHAP, LIME, Grad-CAM and related methods to explain agricultural predictions and recommendations [14, 11, 16, 41, 43]. However, technical interpretability does not by itself establish that farmers or extension professionals understand or appropriately act on those explanations.

This distinction is consistent with [24], who identify transparency and explainability alongside accountability, fairness, data ownership, privacy and security as important dimensions of trust in agricultural AI. Similarly, [19], reviewing 38 agricultural AI/ML studies, identified low trust and the digital divide as prominent themes and reported interconnected concerns involving data governance, technical skills, explainability, reliability and technology costs.

For agricultural extension, these findings broaden the meaning of trustworthy AI beyond model interpretability. An advisory system may generate technically explainable outputs while remaining difficult for users to evaluate if the underlying data, limitations, uncertainty or provenance are unclear. The evidence therefore supports consideration of explainability together with transparency, data governance, human oversight and mechanisms for users to question or verify AI-generated advice [24, 29, 21].

4.4 Farmer-Centred AI Extension

The review indicates that barriers to farmer-centred AI extension are multidimensional. Across the included literature, recurring issues include digital infrastructure, technical skills, affordability, data availability, localisation, trust, institutional capacity and contextual adaptation [20, 32, 44, 33]. These findings are consistent with the broader agricultural AI literature, where technology costs, digital skills, explainability, reliability and data governance are reported as interconnected conditions affecting trust and adoption [19].

The review also identifies a gap between technological demonstration and farmer-centred evaluation. Several included studies assess model performance, system functionality, advisory quality, awareness, adoption or user engagement, whereas fewer examine sustained changes in farmer knowledge, behaviour, productivity or profitability [18, 38, 40, 44]. Similarly, evidence on how farmers interpret, verify and act upon AI-generated recommendations remains limited. This distinction is important because the successful deployment of an AI advisory system requires more than generating technically plausible recommendations; the advice must also be usable within the knowledge, language, connectivity and decision-making contexts of intended users.

4.5 Research Gaps and Future Directions

Four priorities emerge from the evidence mapped in this review. First, longitudinal studies are needed to examine whether AI-enabled advisory produces sustained changes in farmer knowledge, decision-making, management practices, productivity and profitability. Second, XAI research should move beyond model-level explanations towards user-centred evaluation of whether explanations are understandable and actionable for farmers and extension professionals [14, 16]. Third, greater attention is required to local languages, low-connectivity environments, contextual agricultural knowledge and participatory design, particularly in smallholder settings [36, 44, 29]. Fourth, comparative evaluation of human-only, AI-enabled and human-AI advisory arrangements would help clarify how AI can be integrated into existing extension systems while maintaining professional judgement and accountability.

The evidence indicates that the central research challenge is shifting from demonstrating whether AI can generate agricultural information or recommendations towards establishing whether AI-enabled advisory systems can provide contextually appropriate, understandable, trusted and beneficial support within real-world agricultural extension systems.

5. Conclusions

AI is increasingly being integrated into agricultural extension through intelligent decision-support systems, chatbots, generative AI and personalised advisory platforms. However, the evidence remains concentrated on technical development, system functionality and user engagement, with limited evidence of sustained effects on farmer knowledge, behaviour, productivity and livelihoods.

Future research should prioritise human-AI advisory models, locally validated and explainable systems, and longitudinal, participatory evaluation of farmer-level outcomes. The key gap is shifting from whether AI can generate agricultural advice to whether it can provide understandable, trusted, contextually appropriate and beneficial support within real-world extension systems.

Declarations

Ethical approval

Not applicable. This study involved the synthesis of evidence from previously published literature and did not involve human participants, personal data collection, or direct interaction with research participants.

Consent for publication

Not applicable. This study did not involve individual-level participant data or identifiable personal information.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Makinde OO conceived and designed the review, developed the review framework and search strategy, and contributed to literature screening and data extraction. Ola LA, Ojo KO, and Ayegbusi OO contributed to literature screening and data extraction, synthesised the evidence, and contributed to drafting the manuscript. Shitu AG contributed to the review process and manuscript development. Yusuf OJ critically reviewed the manuscript and contributed to refinement of the review methodology. All authors read and approved the final manuscript.

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Availability of data and materials

All data generated and analysed during this scoping review are derived from publicly available published literature. The study's search strategy, screening process, and extracted evidence are presented in the manuscript and supplementary materials. Additional information concerning the review process may be obtained from the corresponding author on reasonable request.

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Figures

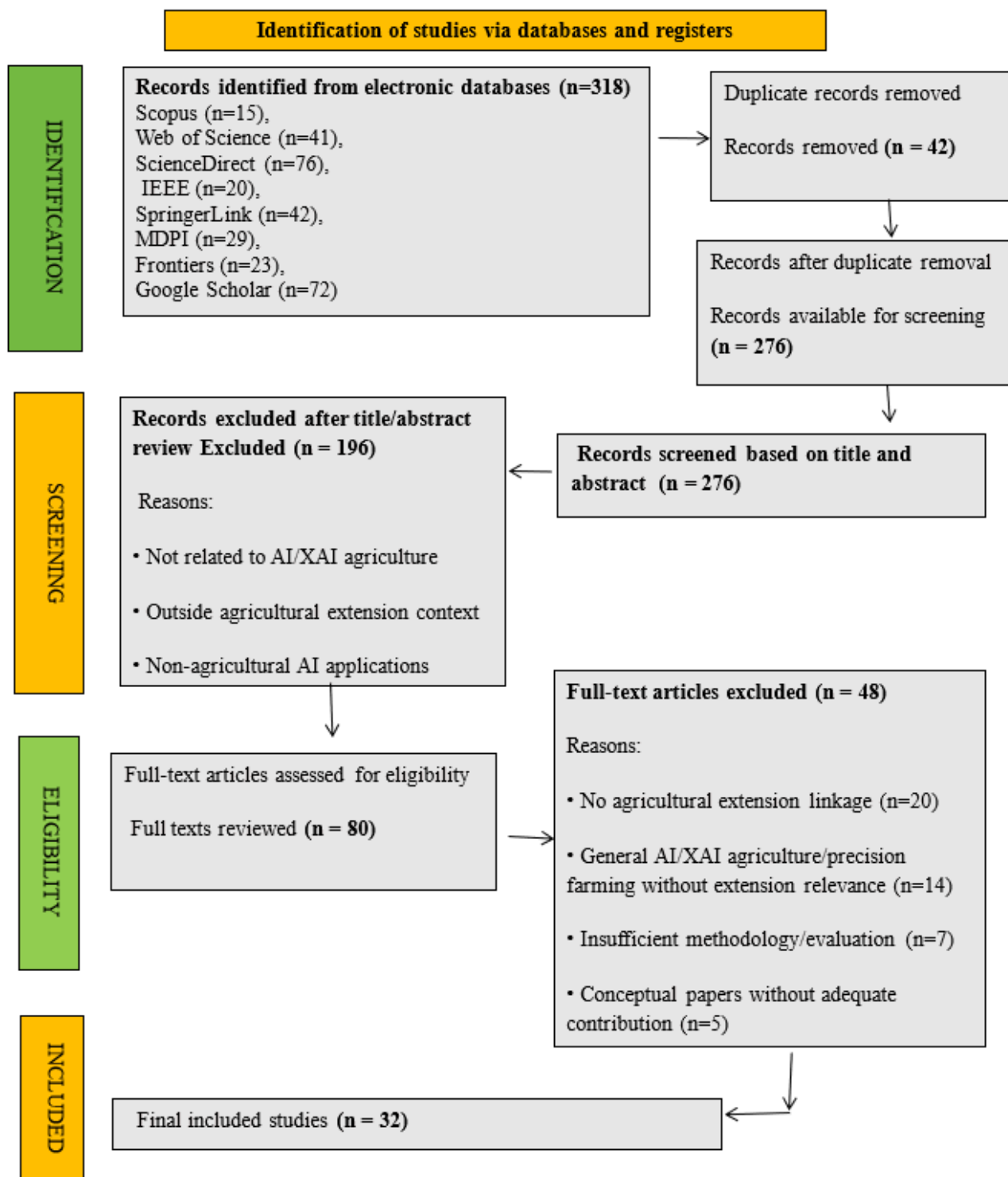


Figure 1

PRISMA Flow chart for the review

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