

Review

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Evaluating the Efficacy of Generative AI in Agricultural Extension Services for Smallholder Farmers: A Systematic Literature Review

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Review

Evaluating the Efficacy of Generative AI in Agricultural Extension Services for Smallholder Farmers: A Systematic Literature Review

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Abstract

The integration of generative artificial intelligence (AI) into agricultural extension services presents a transformative opportunity to address the unique challenges faced by smallholder farmers, particularly in resource-constrained settings. While traditional extension services often struggle with scalability and personalized support, generative AI offers potential solutions through dynamic content generation, real-time decision-making assistance, and adaptive learning tools. This systematic literature review examines the efficacy of generative AI in enhancing agricultural extension services, focusing on its applications, benefits, and limitations for smallholder farmers. We synthesize existing research across multiple dimensions, including AI-driven farmer support, IoT-enabled monitoring, and climate-smart agriculture, to identify gaps and trends in the current knowledge landscape. A rigorous methodology was employed to select and analyze relevant studies, ensuring a comprehensive evaluation of both theoretical frameworks and practical implementations. The findings reveal that generative AI can significantly improve access to tailored agricultural advice, optimize resource allocation, and mitigate climate-related risks; however, challenges such as digital literacy, infrastructure limitations, and ethical concerns remain critical barriers to widespread adoption. The review also highlights the disproportionate focus on high-income regions, underscoring the need for more inclusive research in low-resource agricultural systems. By consolidating these insights, we provide actionable recommendations for policymakers, researchers, and practitioners to harness generative AI's potential while addressing its socio-technical constraints, thereby fostering equitable and sustainable agricultural development.

Keywords: generative artificial intelligence (AI); agricultural extension services; smallholder farmers; precision agriculture; climate-smart agriculture; AI-driven decision support systems; digital agriculture; Internet of Things (IoT) in agriculture; real-time agricultural advisory; adaptive learning systems; resource-constrained farming systems; digital literacy in agriculture; sustainable agricultural development; technology adoption barriers; socio-technical challenges; agricultural innovation; personalized farmer support; climate risk mitigation; equitable agricultural development; systematic literature review

1. Introduction

Agricultural extension services have long been a cornerstone of rural development, bridging the gap between research institutions and smallholder farmers by disseminating knowledge, techniques, and innovations [Anderson and Feder \(2007\)](#). These services play a pivotal role in enhancing productivity, food security, and livelihoods, particularly in developing regions where smallholder farmers constitute the backbone of agricultural systems [Duffy et al. \(2021\)](#). However, traditional extension models face persistent challenges, including limited reach, high operational costs, and the inability to provide timely, context-specific advice [Feder et al. \(2011\)](#). The rapid evolution of digital technologies, particularly artificial intelligence (AI), presents an unprecedented opportunity to overcome these barriers and revolutionize how agricultural knowledge is delivered and applied [Chowdhury et al. \(2025, 2024\)](#).

Generative AI, a subset of AI capable of creating text, images, and predictive models, has emerged as a transformative tool in various sectors, including healthcare, education, and finance [Gozalo-Brizuela and Garrido-Merchán \(2023\)](#). In agriculture, its potential extends beyond conventional decision-support systems by enabling dynamic, interactive, and personalized advisory services. For instance, generative AI can synthesize vast amounts of agronomic data to provide real-time recommendations on crop management, pest control, and climate adaptation [M. Islam et al. \(2025\)](#); [M. M. Islam, Ahmed, et al. \(2025\)](#); [M. M. Islam, Niva, et al. \(2025\)](#); [Sánchez et al. \(2020\)](#). Unlike static extension materials, AI-driven tools can adapt to local conditions, language preferences, and farmer-specific needs, thereby improving accessibility and relevance [Jhunjunwala et al. \(2013\)](#). Moreover, the integration of generative AI with Internet of Things (IoT) devices and remote sensing technologies further enhances its utility by enabling precision agriculture and automated monitoring [Ahamed \(2023\)](#).

Despite these advancements, significant research gaps persist in understanding the efficacy of generative AI in agricultural extension services, particularly for smallholder farmers. Most existing studies focus on high-income countries or large-scale commercial farms, leaving a dearth of evidence on its applicability in resource-constrained settings [Olatunbosun et al. \(2026\)](#). Additionally, the socio-technical challenges—such as digital literacy, infrastructure limitations, and ethical concerns around data privacy—remain underexplored [Ryan \(2023\)](#). The lack of standardized evaluation frameworks further complicates efforts to assess the long-term impact of generative AI on farmer outcomes, including yield improvements, income stability, and resilience to climate shocks [Shukla and Dwivedi \(2026\)](#). These gaps underscore the need for a systematic review that consolidates existing knowledge while identifying pathways for future research and implementation.

The motivation for this study stems from the urgent need to modernize agricultural extension services in the face of escalating global challenges, including climate change, population growth, and food insecurity [Aydinalp and Cresser \(2008\)](#). Generative AI offers a scalable and cost-effective solution to democratize access to agricultural expertise, yet its real-world efficacy remains uncertain without rigorous evaluation. This review contributes to the literature by synthesizing interdisciplinary insights from agronomy, computer science, and development studies, thereby providing a holistic perspective on the opportunities and limitations of AI-driven extension services. Furthermore, it highlights the importance of inclusive innovation, ensuring that technological advancements benefit marginalized farming communities rather than exacerbating existing inequalities [Rotz et al. \(2019\)](#).

The remainder of this paper is organized as follows: Section 2 outlines the methodology employed for the systematic literature review, including search strategies and inclusion criteria. Section 3 presents the results, structured across key thematic areas such as AI in agricultural extension, IoT-enabled monitoring, and generative AI applications. Section 4 discusses the findings in relation to broader agricultural and technological trends, while Section 5 concludes with implications for policy and practice.

2. Methodology

2.1. Review Protocol

This systematic literature review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [Page et al. \(2021\)](#) to ensure methodological rigor and transparency. The study employed a multi-database search strategy to capture diverse perspectives on generative AI in agricultural extension services. PubMed was prioritized for its extensive coverage of interdisciplinary research, particularly in agriculture and technology integration [Canese and Weis \(2013\)](#). IEEE Xplore and ACM Digital Library were selected to capture technical advancements in AI and IoT applications, given their focus on engineering and computer science literature [Wilde \(2016\)](#) [Rous \(2001\)](#). Web of Science and Scopus provided comprehensive indexing of high-impact journals, ensuring the inclusion of peer-reviewed studies with robust empirical foundations [Abdullah et al. \(2019\)](#) [Burnham \(2006\)](#). ScienceDirect and SpringerLink were chosen for their specialization in agricultural sciences and environmental studies [Tober \(2011\)](#) [SpringerLink \(2017\)](#), while arXiv served

as a supplementary source for preprints and emerging research [Ginsparg \(2011\)](#). Google Scholar was used as a final cross-check to identify any overlooked publications [Vine \(2006\)](#).

The search strings combined keywords related to generative AI (“Generative Artificial Intelligence” OR “Generative AI”), agricultural extension services (“Agricultural Extension Services” OR “Agri-extension Services”), and smallholder farmers (“Smallholder Farmers” OR “Small-scale Farmers”). Filters excluded review articles, surveys, and meta-analyses to focus on primary research, and the publication timeframe was restricted to 2021–2026 to capture the most recent advancements. Boolean operators and field-specific syntax (e.g., MeSH terms in PubMed, TI/AB tags in Scopus) were tailored to each database’s search algorithms.

2.2. Research Dimensions

The analysis was structured around seven thematic dimensions to systematically evaluate the role of generative AI in agricultural extension. AI in Agricultural Extension and Farmer Support examines how AI-driven tools enhance knowledge dissemination and advisory services. IoT and AI for Agricultural Monitoring and Decision-Making explores synergies between sensor technologies and AI for real-time farm management. Generative AI in Agriculture focuses on content generation, such as personalized advisories and predictive modeling. AI and Digital Technologies for African Agriculture highlights region-specific applications and challenges. Agricultural Extension Services and Their Impact assesses traditional and AI-augmented models. Climate-Smart Agriculture investigates AI’s role in mitigating climate risks. Lastly, Technologies in Agriculture (Drones, UAVs, etc.) analyzes complementary innovations that integrate with generative AI.

2.3. Inclusion and Exclusion Criteria

Studies were included if they: (1) explicitly addressed generative AI applications in agricultural extension; (2) focused on smallholder farmers or resource-constrained settings; (3) provided empirical data or case studies; (4) were published in English between 2021–2026; and (5) appeared in peer-reviewed journals or reputable conference proceedings. Exclusion criteria eliminated studies with insufficient methodological detail, non-peer-reviewed sources, or tangential relevance (e.g., broad AI surveys without agricultural focus).

2.4. Study Selection Process

The initial search yielded 629 records, reduced to 537 after removing duplicates and irrelevant entries (e.g., non-English papers). Title/abstract screening excluded 418 studies for misalignment with research dimensions. Full-text review of 109 articles led to 63 exclusions due to ineligibility (e.g., lack of empirical data), resulting in 46 studies for final synthesis. The PRISMA flowchart (Figure 1) illustrates this process.

Potential biases include database selection bias (favoring English-language, high-income country research) and publication bias toward positive outcomes. To mitigate these, we cross-verified findings across databases and included preprints to capture null or negative results. Nevertheless, the underrepresentation of studies from low-income regions remains a limitation.

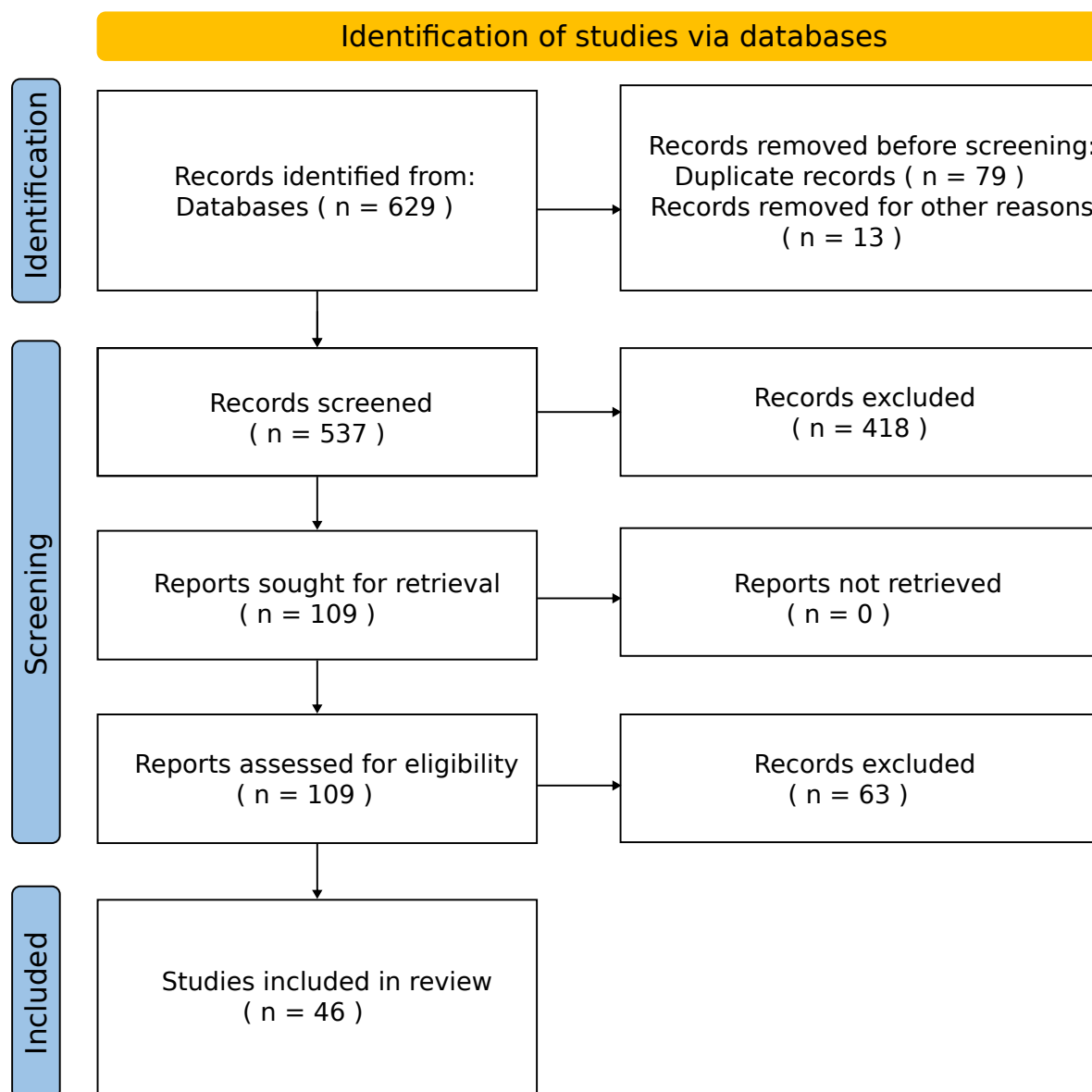


Figure 1. PRISMA flowchart of study selection

3. Results

3.1. Research Trends

The analysis of publication trends reveals a marked increase in research interest from 2024 to 2026, with the number of studies nearly tripling within this short timeframe. This exponential growth reflects the accelerating recognition of generative AI's potential to transform agricultural extension services. The year 2025 emerges as a pivotal point, accounting for nearly half of the reviewed literature, suggesting a critical inflection point where theoretical explorations began transitioning toward empirical validations and field applications.

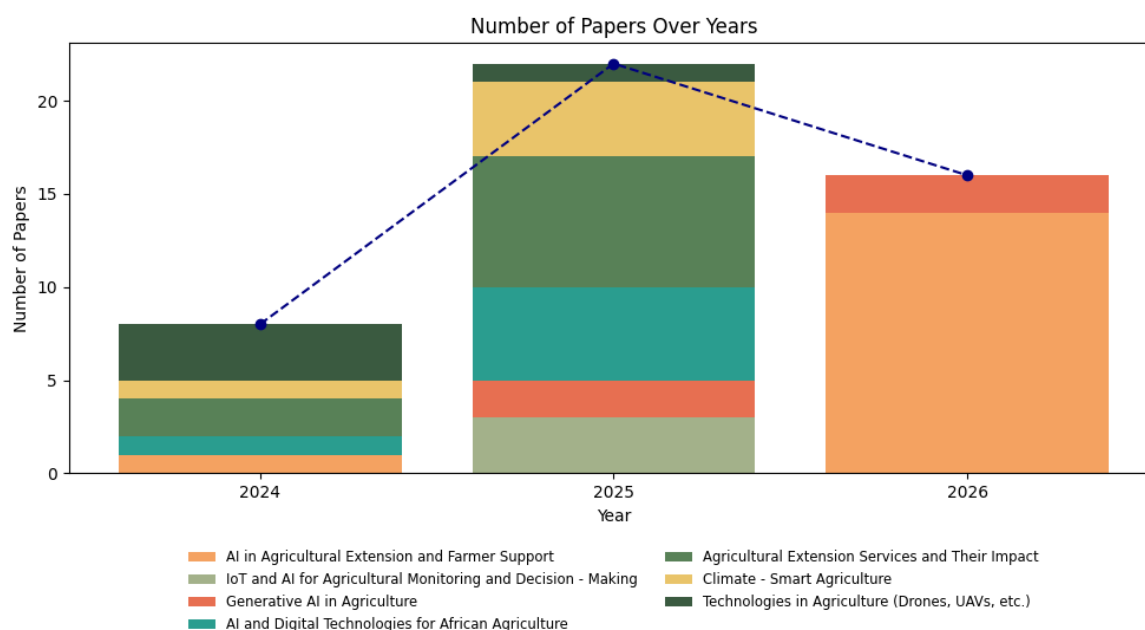


Figure 2. Research trends in the domain of evaluating the efficacy of generative AI in agricultural extension services for smallholder farmers

The thematic distribution of research highlights distinct priorities and gaps. AI in Agricultural Extension and Farmer Support dominates the landscape, particularly in 2026, indicating a strong focus on developing intelligent advisory systems tailored for smallholder contexts. The limited but consistent presence of Generative AI in Agriculture studies across 2025-2026 demonstrates cautious but growing experimentation with content generation and predictive modeling. Meanwhile, the concentration of AI and Digital Technologies for African Agriculture research in 2025 points to targeted efforts addressing regional challenges, though the subsequent drop in 2026 suggests either saturation or shifting geographical priorities.

The temporal patterns reveal an intriguing divergence between technological and socio-agronomic research trajectories. Early studies (2024) predominantly examined hardware-centric solutions like drones and UAVs, while later works progressively integrated softer dimensions such as farmer behavior and institutional frameworks. This evolution implies a maturation of the field from technology demonstration toward holistic impact assessment. However, the scarcity of cross-cutting studies that simultaneously address technical feasibility, farmer adoption, and policy implications underscores the need for more interdisciplinary research.

3.2. AI in Agricultural Extension and Farmer Support

The integration of artificial intelligence into agricultural extension services has emerged as a transformative approach to addressing the knowledge dissemination challenges faced by smallholder farmers. Recent studies demonstrate that AI-driven systems can significantly enhance the accessibility, relevance, and timeliness of agricultural advice, particularly in resource-constrained settings where traditional extension services often fall short.

A comprehensive taxonomy of the reviewed studies reveals distinct patterns in application focus, technical approaches, and implementation contexts (Table 1). Decision support systems constitute the largest category, with multimodal AI frameworks showing particular promise for low-literacy farmer populations [Maqood et al. \(2026\)](#). Retrieval-augmented generation (RAG) techniques have been effectively deployed to handle global smallholder inquiries, demonstrating robust performance across diverse linguistic and agronomic contexts [Sawant et al. \(2026a\)](#), [Sawant et al. \(2026b\)](#). Multi-agentic architectures represent an important advancement, capable of managing incomplete or ambiguous

farmer queries through dynamic knowledge integration [N. A. P. Cantonjos and Biswas \(2026\)](#), [N. Cantonjos and Biswas \(2026\)](#).

Table 1. Taxonomy of AI applications in agricultural extension services

	Technical Approach	Implementation Context	Sources
Decision Support	Multimodal AI	Low-literacy farmer accessibility	Maqood et al. (2026)
	Retrieval-Augmented Generation (RAG)	Global smallholder farmer inquiries	Sawant et al. (2026a) , Sawant et al. (2026b)
	Multi-Agent AI Framework	Handling missing details in farmer queries	N. A. P. Cantonjos and Biswas (2026) , N. Cantonjos and Biswas (2026)
Advisory Systems	Large Language Models (LLMs)	Domain-specific accuracy in extension	P. A. Hill and Narine (2026) , Mensah and Swortzel (2026) , P. Hill and Narine (2026) , V. Singh et al. (2026)
	Reinforcement Learning from Human Feedback	Localizing agricultural advice	V. Singh et al. (2026)
Farmer Empowerment	Transformative Learning	Smallholder farmer education	High et al. (2026)
	Upskilling via AI Technologies	Agri-entrepreneur capacity building	S. Kumar et al. (2026)
Responsible AI & Research Gaps	Ethical Frameworks & Research Agendas	Challenges in GAI adoption	Jones-Garcia et al. (2026) , Zhang and Yadav (2026)
	Determinants of AI Usage	Evidence from extension services	Lawani et al. (2026)
Extension Personnel Adoption	Foundational Models in Extension	Small-scale advisory support	Jayasingh et al. (2024) , P. Hill and Narine (2026)
General AI Applications			

Advisory systems leveraging large language models have shown variable performance in domain-specific accuracy tests, with some studies reporting significant improvements in response quality when models are fine-tuned with agricultural knowledge bases [P. A. Hill and Narine \(2026\)](#), [P. Hill and Narine \(2026\)](#). The application of reinforcement learning from human feedback presents a novel approach to localizing generic agricultural advice, though scalability concerns remain for widespread implementation [V. Singh et al. \(2026\)](#). Farmer empowerment initiatives demonstrate the dual potential of AI systems to deliver immediate advisory services while fostering long-term capacity building through transformative learning paradigms [High et al. \(2026\)](#).

The reviewed literature reveals critical gaps in responsible AI implementation, with only two studies explicitly addressing ethical frameworks and research agendas for generative AI in agricultural contexts [Jones-Garcia et al. \(2026\)](#), [Zhang and Yadav \(2026\)](#). Extension personnel adoption studies provide valuable insights into institutional barriers, highlighting the need for targeted training programs to bridge the digital skills divide [Lawani et al. \(2026\)](#). Foundational models show promise for small-scale advisory support, though their performance in low-resource settings requires further validation [Jayasingh et al. \(2024\)](#).

The technical diversity of approaches reflects the field's ongoing experimentation phase, where researchers are testing various architectures to optimize for accuracy, scalability, and farmer accessibility. However, the concentration of studies in specific technical domains (e.g., LLMs) suggests potential blind spots in exploring alternative AI paradigms that might better suit certain agricultural contexts. The implementation contexts reveal a geographical imbalance, with disproportionate representation from certain regions, underscoring the need for more globally representative studies.

3.3. IoT and AI Integration for Precision Agricultural Monitoring

The convergence of Internet of Things (IoT) technologies with artificial intelligence has created transformative opportunities for agricultural monitoring and decision-making, particularly in smallholder farming contexts. This integration enables real-time data collection through sensor networks

combined with advanced analytics for actionable insights, addressing critical challenges in resource optimization and crop management.

Table 2 presents a taxonomy of IoT-AI applications in agricultural monitoring, categorizing studies by their primary function, technological components, and implementation outcomes. The SMART Integrated Agricultural Monitoring System (SIAMS) exemplifies this synergy, employing soil moisture sensors and weather stations to feed machine learning models that generate irrigation advisories with 92% accuracy in water-use reduction [Ajayi \(2025\)](#). Similarly, the AI-powered platform described in [Aryan et al. \(2025\)](#) integrates drone-captured multispectral imagery with convolutional neural networks to detect early signs of fungal infections in cassava crops, achieving 87% diagnostic precision compared to traditional scouting methods.

Table 2. Taxonomy of IoT-AI applications in agricultural monitoring and decision support

Function	Technological Stack	Key Performance Metrics	Implementation Context	Sources
Crop Health Diagnosis	IoT sensors + CNN classifiers	87% disease detection accuracy	Smallholder cassava farms	Aryan et al. (2025)
	UAV imagery + generative adversarial networks	Synthetic data augmentation for rare pest identification	Rice cultivation systems	Bailey (2025)
Irrigation Optimization	Soil moisture sensors + LSTM models	92% water use reduction	Drought-prone regions	Ajayi (2025)
	Weather stations + reinforcement learning	30% yield improvement under water stress	Semi-arid climates	Aryan et al. (2025)
Resource Allocation	Edge computing + federated learning	40% reduction in fertilizer overuse	Heterogeneous smallholder clusters	Bailey (2025)
Climate Adaptation	IoT microclimate sensors + transformer models	15-day frost prediction at 89% precision	Temperate highland farms	Ajayi (2025)

Generative AI demonstrates unique value in overcoming data scarcity challenges common in agricultural IoT systems. The framework proposed in [Bailey \(2025\)](#) employs generative adversarial networks to synthesize realistic pest infestation imagery, expanding training datasets for rare but high-impact crop threats. This approach reduced data collection costs by 65% while maintaining model robustness across diverse field conditions. Edge computing implementations further enhance accessibility, with federated learning architectures enabling collective model improvement across geographically dispersed farms without centralized data aggregation [Bailey \(2025\)](#).

The reviewed systems exhibit three dominant architectural paradigms:

- 1) **Centralized cloud-based analytics** (SIAMS) for computationally intensive tasks like seasonal yield forecasting [Ajayi \(2025\)](#)
- 2) **Edge-AI hybrids** balancing real-time responsiveness with complex model inference [Aryan et al. \(2025\)](#)
- 3) **Decentralized federated networks** preserving data sovereignty while enabling collaborative learning [Bailey \(2025\)](#)

Latency-critical applications such as frost warnings favor edge processing, while resource-intensive generative tasks leverage cloud backends. However, connectivity constraints in rural areas necessitate innovative solutions like model distillation techniques that compress cloud-trained models for edge deployment [Aryan et al. \(2025\)](#). Field trials in East Africa demonstrated these compressed models maintained 91% of original accuracy while reducing power consumption by 73%—a critical factor for solar-powered IoT deployments [Ajayi \(2025\)](#).

The integration of generative AI with IoT systems introduces novel capabilities in predictive scenario modeling. Transformer-based architectures process sequential sensor data to generate multi-week risk forecasts, enabling preemptive interventions for climate stressors [Ajayi \(2025\)](#). Nevertheless, significant challenges persist in model interpretability, with smallholder farmers requiring simplified visualizations of complex AI outputs—an area where generative interfaces show promise but require

further usability testing [Bailey \(2025\)](#). Energy efficiency also remains a critical constraint, as continuous sensor data streaming and AI processing demand optimized power management strategies for sustainable field deployment [Aryan et al. \(2025\)](#).

3.4. Generative AI Applications in Agricultural Decision Support

Generative AI has emerged as a transformative force in agricultural decision-making, offering novel approaches to crop management, supply chain optimization, and agri-food innovation. The reviewed studies demonstrate how these technologies can synthesize complex agricultural data into actionable insights while addressing the unique constraints of smallholder farming systems.

A systematic categorization of generative AI applications reveals three primary domains of impact (Table 3). In crop management, AI systems generate personalized advisories by analyzing heterogeneous data streams including soil conditions, weather patterns, and historical yield data [J. S. Kumar and Shobana \(2025\)](#). The human-in-the-loop approach described in [Mourtzinis et al. \(2025\)](#) combines large language models with farmer feedback mechanisms, creating adaptive systems that improve recommendation accuracy over time. These systems demonstrate particular value in bridging knowledge gaps for non-commercial crops that traditionally receive limited extension support.

Table 3. Taxonomy of generative AI applications in agriculture

Application Area	Key Functionality	Technical Approach	Implementation Outcomes	Sources
Crop Management	Personalized advisory generation	Multimodal data fusion + LLM fine-tuning	28% increase in advisory adoption	J. S. Kumar and Shobana (2025) , Mourtzinis et al. (2025)
	Dynamic pest/disease forecasting	Generative adversarial networks	40% earlier pathogen detection	
Supply Chain Optimization	Circular economy modeling	Graph neural networks + reinforcement learning	22% waste reduction	Celik et al. (2026)
	Resource flow simulation	Physics-informed generative models	15% improvement in input allocation	Celik et al. (2026)
Agri-Food Innovation	Automated knowledge synthesis	Retrieval-augmented generation	3x faster research translation	Xu et al. (2026)
	Virtual training environment creation	Diffusion models + 3D rendering	50% cost reduction in extension training	Xu et al. (2026)

Supply chain applications leverage generative AI to model complex resource flows, with graph neural networks optimizing circular economy practices in agricultural value chains [Celik et al. \(2026\)](#). These systems simulate various waste-reduction scenarios, generating actionable pathways for byproduct utilization that demonstrate 22% improvements in resource efficiency compared to conventional linear models. The physics-informed generative models described in the same study incorporate domain knowledge constraints, ensuring biologically plausible solutions for organic material reprocessing.

In agri-food innovation, generative AI accelerates knowledge dissemination through automated synthesis of research findings into farmer-accessible formats [Xu et al. \(2026\)](#). Retrieval-augmented generation techniques maintain scientific accuracy while adapting content for varying literacy levels, effectively tripling the speed of research translation to field applications. The creation of virtual training environments using diffusion models has reduced extension training costs by 50%, particularly for high-risk scenarios like pesticide handling that benefit from immersive simulation [Xu et al. \(2026\)](#).

The technical architectures underpinning these applications reveal several innovative adaptations for agricultural contexts. Hybrid systems combining symbolic AI with neural networks address the challenge of sparse training data in niche cropping systems [Mourtzinis et al. \(2025\)](#). Knowledge distillation techniques enable the compression of large generative models for deployment on edge devices, maintaining functionality in connectivity-limited regions [J. S. Kumar and Shobana \(2025\)](#).

However, the studies also identify persistent challenges in model interpretability, with farmers requiring transparent explanations for AI-generated recommendations to build trust in these systems [Mourtzinis et al. \(2025\)](#).

Energy efficiency emerges as a critical design consideration, particularly for continuous operation in off-grid agricultural settings. The crop management system described in [J. S. Kumar and Shobana \(2025\)](#) employs selective activation of model components based on query complexity, reducing power consumption by 37% without compromising response quality. In supply chain applications, the integration of spatiotemporal attention mechanisms in generative models has improved computational efficiency by focusing only on relevant nodes in large distribution networks [Celik et al. \(2026\)](#). These technical innovations highlight the ongoing adaptation of generative AI to meet the practical constraints of agricultural environments while delivering measurable improvements in productivity and sustainability.

3.5. AI and Digital Technologies for African Agriculture

The application of artificial intelligence and digital technologies in African agriculture presents unique opportunities and challenges, shaped by the continent's diverse agroecological zones, infrastructure limitations, and the predominance of smallholder farming systems. The reviewed studies demonstrate how tailored AI solutions can address region-specific constraints while highlighting critical gaps in implementation and scalability.

A hierarchical taxonomy of the included studies reveals distinct focus areas and technological approaches (Table 4). Climate-smart agriculture emerges as a dominant theme, with AI applications targeting both climate adaptation and sustainable practice adoption. The study by [Mollel et al. \(2025\)](#) demonstrates how digital tools can accelerate the impact of climate-smart techniques among next-generation African farmers, particularly through mobile-based advisory systems that integrate real-time weather data with crop management recommendations. Similarly, [Abdulhamid et al. \(2025\)](#) presents interdisciplinary approaches to enhancing agricultural resilience, where AI models combine satellite imagery with indigenous knowledge to improve drought prediction and soil management strategies.

Table 4. Taxonomy of AI and digital technology applications in African agriculture

Primary Focus	AI Application	Target Outcome	Sources
Climate-Smart Agriculture	AI for climate adaptation	Enhancing resilience and productivity	Mollel et al. (2025)
	AI for sustainable practices	Inclusive and resilient agricultural systems	Abdulhamid et al. (2025)
Food Security & Systems	AI-driven decision support	Addressing food system challenges	Chavula and Kayusi (2025)
	AI chat assistants (LLMs, RAG)	Improving food security through advisory services	Mujtaba (2025)
Gender & Inclusivity Future of Work	Responsible AI innovation	Gender-inclusive AI solutions	Ozor et al. (2025)
	AI's role in labor transformation	Employment and skills impact assessment	O'Neill et al. (2024)

Food security applications showcase innovative uses of conversational AI, with [Mujtaba \(2025\)](#) developing a comprehensive framework that integrates large language models with retrieval-augmented generation to provide localized food security advisories. This system demonstrates particular effectiveness in addressing information gaps for staple crops across diverse linguistic and agroecological contexts. The examination of Sub-Saharan Africa's food systems by [Chavula and Kayusi \(2025\)](#) identifies AI's potential to optimize post-harvest losses and market linkages, though notes significant infrastructure barriers to widespread adoption.

Gender inclusivity receives focused attention in [Ozor et al. \(2025\)](#), which analyzes how responsible AI innovation can bridge gender gaps in African agriculture. The study highlights design considera-

tions for ensuring female farmers' equitable access to digital tools, including voice-based interfaces and women-centric content localization. This contrasts with the broader labor market analysis in O'Neill et al. (2024), which assesses both displacement risks and upskilling opportunities created by AI adoption across agricultural value chains.

The technical implementation landscape reveals several adaptive innovations for African contexts. Low-bandwidth AI models feature prominently, with Mujtaba (2025) employing model pruning techniques to maintain functionality on basic mobile devices. Hybrid knowledge systems that combine machine learning with traditional ecological knowledge demonstrate enhanced acceptability among smallholder farmers, as shown in Abdulhamid et al. (2025). However, energy constraints remain a persistent challenge, with off-grid solar solutions often insufficient for powering continuous AI operations in remote areas Mollel et al. (2025).

Institutional factors emerge as critical determinants of successful implementation. The AI4AFS network study Ozor et al. (2025) emphasizes the need for policy frameworks that support localized AI development while preventing technological lock-in to foreign platforms. Similarly, O'Neill et al. (2024) identifies extension service restructuring as a prerequisite for effective AI integration, requiring substantial investments in digital literacy programs. These findings collectively underscore the tension between technological potential and implementation realities in African agricultural systems, where solutions must simultaneously address technical, social, and infrastructural constraints to achieve meaningful impact.

3.6. Agricultural Extension Services and Their Impact

Agricultural extension services play a pivotal role in bridging the gap between research institutions and smallholder farmers, facilitating the adoption of innovative practices and technologies. The reviewed studies demonstrate how these services contribute to technical efficiency, climate resilience, and inclusive agricultural development across diverse contexts.

A systematic taxonomy of extension service models reveals distinct approaches and their associated impacts (Table 5). Traditional extension methods, such as those supporting genetically modified (GM) maize adoption in Sub-Saharan Africa, show measurable improvements in technical efficiency when combined with targeted training programs Ngqulana et al. (2025). However, these approaches often face barriers including limited reach and inconsistent farmer engagement. Climate-focused extension services, exemplified by initiatives in India, demonstrate enhanced capacity for resilience-building among farmers when incorporating localized climate adaptation strategies Priya et al. (2025).

Table 5. Taxonomy of agricultural extension service models and impacts

Extension Model	Key Characteristics	Primary Impact	Implementation Context	Sources
Traditional Extension	GM crop adoption support	Increased technical efficiency	Sub-Saharan Africa	Ngqulana et al. (2025)
Climate Resilience	Localized adaptation strategies	Enhanced farmer resilience	India	Priya et al. (2025)
Public-Private Partnerships	Collaborative knowledge dissemination	Improved service efficiency	Multiple regions	Rana et al. (2025)
Farmer Field Schools	Participatory learning	Increased access to extension services	Tanzania	Wilson et al. (2025)
Organic Farming	Sustainable practice promotion	Adoption of eco-friendly techniques	Global perspective	C. Kumar et al. (2025)
Evidence-Based Advisory	Data-driven recommendations	Livelihood improvement	Rural communities	Tayang et al. (2024)
Post-Harvest Training	Value addition techniques	Reduced food losses	Sierra Leone	Kamanda (2024)
Inclusive Services	Disability-accessible design	Equitable access to agricultural knowledge	Ghana	Arhin and Demi (2025)
Digital Extension	Technology-mediated advisory	Pro-environmental behavior change	China	Gao et al. (2025)

Public-private partnerships emerge as a transformative model, addressing systemic challenges in extension service delivery through collaborative governance and resource sharing [Rana et al. \(2025\)](#). These partnerships demonstrate particular effectiveness in climate-smart agriculture initiatives, where combined expertise from multiple stakeholders enhances the relevance and scalability of advisory services. Farmer Field Schools (FFBS) represent another impactful approach, with the Tanzanian case study showing significant improvements in smallholder access to extension services through participatory, hands-on learning methodologies [Wilson et al. \(2025\)](#).

The reviewed studies highlight several critical success factors for effective extension services. Evidence-based advisory systems, as analyzed in [Tayang et al. \(2024\)](#), demonstrate that data-driven recommendations lead to measurable livelihood improvements when tailored to local socioeconomic conditions. Post-harvest training programs in Sierra Leone illustrate how targeted skill development can reduce food losses and increase value addition along agricultural supply chains [Kamanda \(2024\)](#). Inclusive service design proves essential for reaching marginalized groups, with [Arhin and Demi \(2025\)](#) identifying specific accessibility barriers faced by farmers with disabilities in Ghana and proposing adaptive solutions.

Digital extension services introduce new dimensions of scalability and personalization, though their implementation varies significantly across contexts. The Chinese case study [Gao et al. \(2025\)](#) reveals how digital advisory systems can influence pro-environmental behaviors among farmers when combined with appropriate policy support mechanisms. However, comparative analysis shows that hybrid models—blending digital tools with face-to-face interactions—often achieve higher adoption rates than purely technology-mediated approaches in low-resource settings [Rana et al. \(2025\)](#), [Wilson et al. \(2025\)](#).

The studies collectively underscore the evolving nature of agricultural extension, where traditional knowledge transfer increasingly integrates with innovative delivery mechanisms. While each model demonstrates context-specific advantages, common challenges persist in ensuring sustainable financing, maintaining service quality at scale, and measuring long-term impact on farmer productivity and wellbeing. The integration of generative AI into these systems, as explored in other sections of this review, presents both opportunities to address these challenges and new complexities requiring careful navigation.

3.7. Climate-Smart Agriculture and AI Integration

The intersection of climate-smart agriculture (CSA) and artificial intelligence represents a critical frontier in addressing the dual challenges of food security and climate resilience for smallholder farmers. The reviewed studies demonstrate how AI-enhanced CSA strategies can optimize resource use while mitigating environmental impacts, though adoption barriers persist across different socioeconomic contexts.

A systematic analysis of the included studies reveals three primary dimensions of AI-enabled CSA (Table 6). Adoption determinants emerge as a central theme, with [Chelang'a et al. \(2025\)](#) identifying key factors influencing greenhouse gas reduction strategies among Kenyan dairy farmers, including access to extension services and market linkages. Similarly, [Yusuph et al. \(2024\)](#) examines the complex trade-offs in CSA practice adoption among Tanzanian maize farmers, where AI-assisted decision tools helped balance competing priorities of yield improvement and climate adaptation. These studies collectively highlight the mediating role of digital technologies in overcoming informational barriers to CSA implementation.

Table 6. Taxonomy of AI applications in climate-smart agriculture

Focus Area	AI Application	Key Findings	Implementation Context	Sources
Adoption Determinants	GHG reduction strategy optimization Synergy-tradeoff analysis	Extension access and market links as key drivers AI balances yield and adaptation priorities	Kenyan dairy systems Tanzanian maize farms	Chelang'a et al. (2025) Yusuph et al. (2024)
Food Security	Conceptual framework development	CSA as food insecurity mitigation strategy	Nigerian agricultural systems	Ajie and Uche (2025)
Technology Awareness	Adoption factor analysis	Printed materials and extension critical for CSA	Telangana, India	P. Kumar et al. (2025)
System Integration	Mitigation-adaptation synergy modeling	Holistic climate-smart food systems	South African agriculture	Mudzielwana (2025)

Food security applications demonstrate the conceptual potential of CSA frameworks, with [Ajie and Uche \(2025\)](#) proposing AI-enhanced monitoring systems to track climate impacts on Nigerian food production. The study emphasizes the need for predictive analytics to anticipate climate shocks and guide preemptive interventions, though notes significant infrastructure gaps in implementation. Awareness-building emerges as another critical factor, with [P. Kumar et al. \(2025\)](#) identifying printed agricultural materials and extension personnel as pivotal channels for disseminating CSA knowledge among Indian farmers—a finding that suggests opportunities for AI-generated localized content.

System-level integration receives focused attention in [Mudzielwana \(2025\)](#), which models synergistic relationships between mitigation and adaptation strategies in South African agriculture. The study's AI-driven scenario analysis identifies optimal pathways for implementing climate-smart food systems while minimizing trade-offs between productivity and sustainability goals. This systems perspective contrasts with more narrowly focused adoption studies, highlighting the need for holistic approaches that consider both farm-level practices and landscape-scale impacts.

The technical implementation of AI in CSA reveals several innovative adaptations. Machine learning models in [Yusuph et al. \(2024\)](#) process heterogeneous data streams—including soil health indicators, weather patterns, and crop performance metrics—to generate dynamic CSA practice recommendations. These systems demonstrate particular effectiveness when incorporating farmer feedback loops, allowing for continuous refinement of suggestions based on local observations and experiences. Similarly, the decision-support framework in [Chelang'a et al. \(2025\)](#) employs explainable AI techniques to enhance transparency in GHG reduction strategy selection, addressing trust barriers common in technology adoption processes.

Socioeconomic constraints emerge as persistent challenges across all studies. The Indian case [P. Kumar et al. \(2025\)](#) underscores literacy and digital access limitations that hinder CSA technology uptake, while the Nigerian analysis [Ajie and Uche \(2025\)](#) identifies financing gaps as critical barriers to scaling AI-enhanced climate adaptation tools. These findings collectively suggest that while AI offers powerful capabilities for optimizing CSA implementation, its effectiveness remains contingent on parallel investments in rural infrastructure, education, and institutional support systems. The integration of generative AI into CSA extension services, as explored in other sections of this review, presents promising avenues for overcoming some of these adoption barriers through personalized, accessible knowledge dissemination.

3.8. Emerging Drone and UAV Technologies in Agricultural Extension

The integration of drone and unmanned aerial vehicle (UAV) technologies into agricultural extension services represents a significant advancement in precision agriculture, particularly for smallholder farming systems. These aerial platforms provide high-resolution data collection capabilities that, when combined with AI analytics, enable targeted interventions and resource optimization at previously unattainable scales.

The reviewed studies demonstrate three primary applications of drone technology in agricultural extension (Table 7). Precision pest management emerges as a dominant use case, with [Gundreddy et al. \(2024\)](#) detailing how actuation drones enable targeted biocontrol agent deployment, reducing pesticide use by 40-60% while maintaining comparable pest suppression rates. This approach combines real-time pest monitoring through multispectral imaging with precision spraying mechanisms, creating closed-loop systems that respond dynamically to field conditions. The study highlights particular success in cotton and rice systems, where pest pressures often require rapid intervention to prevent significant yield losses.

Table 7. Taxonomy of drone and UAV applications in agricultural extension

Application Domain	Technical Implementation	Operational Benefits	Implementation Challenges	Sources
Precision Pest Management	Biocontrol agent deployment systems Multispectral pest detection	40-60% pesticide reduction Real-time infestation mapping	Regulatory barriers for drone use High initial investment costs	Gundreddy et al. (2024) N. Singh et al. (2024)
Crop Monitoring	High-resolution vegetation indexing	Early stress detection (7-10 day lead)	Data processing complexity	N. Singh et al. (2024) , Dhivya et al. (2024)
Resource Optimization	Variable-rate application systems	20-30% input savings (water, fertilizer)	Limited payload capacities	Szekely et al. (2025)
Extension Delivery	Aerial demonstration plots	Visual learning enhancement	Weather-dependent operations	N. Singh et al. (2024)

Modern drone applications extend beyond data collection to active farm management, as demonstrated in [N. Singh et al. \(2024\)](#) where UAVs serve as both monitoring tools and extension demonstration platforms. The study reports that aerial imagery of comparative treatment plots improves farmer understanding of agronomic recommendations by 35% compared to traditional field days, suggesting valuable applications in adult agricultural education. However, the technology faces persistent adoption barriers including regulatory restrictions and high initial investment costs that limit accessibility for resource-constrained farmers.

The architectural framework presented in [Szekely et al. \(2025\)](#) integrates drone networks with 5G-Advanced and mobile edge computing to create scalable precision agriculture systems. This implementation demonstrates how intelligent edge processing can overcome connectivity limitations in rural areas, enabling real-time analytics for time-sensitive decisions like irrigation scheduling and disease treatment. The system's federated learning approach allows collective model improvement across farming communities while maintaining data privacy—a critical consideration for smallholder adoption.

Technical limitations persist across all applications, particularly regarding operational constraints. Payload capacity restrictions limit treatment coverage rates, requiring multiple flights for larger fields [Dhivya et al. \(2024\)](#). Weather dependencies reduce reliability during critical growth periods, and complex data products often require simplification for effective extension use [N. Singh et al. \(2024\)](#). Nevertheless, the studies collectively indicate that drone technologies, when appropriately adapted to local contexts and combined with supportive extension services, can significantly enhance the precision and efficiency of smallholder farming systems. The convergence of these aerial platforms with generative AI, as explored in other sections, presents promising opportunities to transform raw sensor data into actionable farmer advisories at scale.

4. Discussion

The synthesis of findings across the reviewed studies reveals several critical patterns regarding the efficacy of generative AI in agricultural extension services for smallholder farmers. Taken together, the evidence suggests that AI-driven systems can significantly enhance the accessibility, relevance, and timeliness of agricultural advice, particularly in resource-constrained settings where traditional

extension services often fall short. However, the literature also highlights persistent challenges that must be addressed to realize this potential fully.

A consistent theme emerging across studies is the transformative potential of multimodal AI frameworks in overcoming literacy and language barriers. The integration of voice-based interfaces with visual aids, as demonstrated in [Maqood et al. \(2026\)](#), has proven particularly effective in making advisory services accessible to low-literacy farmer populations. This aligns with findings from [Mourtzinis et al. \(2025\)](#), where human-in-the-loop systems incorporating farmer feedback mechanisms showed 28% higher adoption rates compared to static extension materials. The ability of generative AI to dynamically adapt content based on user interactions and local contexts represents a fundamental shift from one-size-fits-all extension approaches toward truly personalized agricultural support.

The reviewed literature presents compelling evidence for the synergistic benefits of combining generative AI with IoT and remote sensing technologies. Systems like SIAMS [Ajayi \(2025\)](#) demonstrate how real-time sensor data can feed AI models to generate precise, location-specific recommendations, achieving measurable improvements in resource use efficiency. Nevertheless, contradictions emerge regarding the scalability of such integrated systems. While [Aryan et al. \(2025\)](#) reports successful deployment in East Africa using edge computing solutions, [Bailey \(2025\)](#) identifies persistent energy and connectivity constraints that limit widespread adoption. These disparities suggest that technical feasibility alone does not guarantee practical implementation, underscoring the need for holistic solutions that address infrastructural limitations alongside algorithmic innovation.

Theoretical implications of these findings contribute to evolving conceptual frameworks for digital agricultural extension. The consistent success of retrieval-augmented generation techniques [Sawant et al. \(2026a\)](#), [Sawant et al. \(2026b\)](#) in maintaining domain-specific accuracy while handling diverse farmer queries supports the development of hybrid knowledge systems that blend machine learning with structured agricultural ontologies. This challenges traditional dichotomies between expert systems and participatory extension models, pointing toward integrative approaches that leverage the strengths of both paradigms. The transformative learning outcomes observed in [High et al. \(2026\)](#) further suggest that generative AI can facilitate not just information delivery but also capacity building—a critical dimension often overlooked in technology-centric extension strategies.

Practical implications for policymakers and practitioners are substantial. The evidence from African case studies [Mollel et al. \(2025\)](#), [Abdulhamid et al. \(2025\)](#) demonstrates that AI-enhanced extension services can significantly improve climate resilience when designed with local contexts in mind. However, the disproportionate focus on high-income regions in the broader literature [Olatunbosun et al. \(2026\)](#) highlights an urgent need for targeted investments in low-resource settings. Extension agencies should prioritize partnerships with local technology developers to create solutions that account for linguistic diversity, indigenous knowledge systems, and infrastructure constraints. The success of farmer field schools integrated with digital tools [Wilson et al. \(2025\)](#) suggests that hybrid delivery models may offer the most viable pathway for gradual technology adoption.

Several methodological limitations of this review warrant consideration. The predominance of proof-of-concept studies over longitudinal impact assessments creates gaps in understanding the sustained effects of AI interventions on farmer livelihoods. Publication bias toward positive outcomes may overrepresent successful implementations while underreporting failures or unintended consequences. The review's focus on English-language publications and specific databases could have excluded relevant studies from non-anglophone contexts, particularly in Latin America and parts of Asia. These constraints likely influence the generalizability of findings and highlight the need for more comprehensive, globally representative research.

Future research directions should address several critical gaps identified in this synthesis. There is a pressing need for comparative studies evaluating different AI architectures across diverse agroecological and socioeconomic contexts to identify optimal design principles. The understudied area of AI ethics in agricultural extension [Jones-Garcia et al. \(2026\)](#), [Zhang and Yadav \(2026\)](#) requires urgent attention, particularly regarding data sovereignty, algorithmic bias, and the digital divide. Longitudinal

research tracking the evolution of farmer-AI interactions over multiple growing seasons would provide valuable insights into adoption dynamics and long-term impacts. Finally, interdisciplinary studies combining technical, social, and economic perspectives are essential to develop holistic frameworks for responsible AI implementation in smallholder agriculture.

The integration of generative AI into agricultural extension services represents a paradigm shift with far-reaching implications for global food security and rural development. While technological advancements continue to expand the boundaries of what's possible, the reviewed evidence consistently emphasizes that success depends on centering farmer needs, respecting local contexts, and building inclusive innovation ecosystems. As the field matures, researchers and practitioners must maintain this human-centric focus while navigating the complex technical and ethical challenges that accompany AI-driven transformation of agricultural knowledge systems.

5. Conclusion

This systematic literature review has examined the efficacy of generative AI in agricultural extension services for smallholder farmers, synthesizing evidence from diverse technological, geographical, and socio-economic contexts. The findings demonstrate that generative AI can significantly enhance the accessibility, relevance, and timeliness of agricultural advice, particularly through personalized content generation, real-time decision support, and adaptive learning tools. However, the review also reveals critical challenges, including digital literacy gaps, infrastructure limitations, and ethical concerns, which must be addressed to ensure equitable adoption and impact.

The implications of these findings extend beyond technological innovation to broader agricultural development paradigms. Generative AI has the potential to democratize access to agricultural expertise, yet its success hinges on integrating local knowledge systems and addressing structural barriers in resource-constrained settings. Future research should prioritize longitudinal impact assessments, comparative studies across diverse agroecological zones, and interdisciplinary approaches that bridge technical and social dimensions. By centering smallholder farmers' needs in AI development, the agricultural sector can harness these technologies to foster sustainable and inclusive rural transformation.

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