

International Journal of Agriculture Extension and Social Development

Volume 9; Issue 7; July 2026; Page No. 464-469

Received: 14-05-2026
Accepted: 18-06-2026

Indexed Journal
Peer Reviewed Journal

Artificial intelligence in agricultural extension: Opportunities, challenges and future directions

¹Rohan S Kavalagi, ²Preethi S, ³Bindu S, ⁴Stanzin Yangsdon, ⁵Medipally Vinod, ⁶N Lakshmi Vennela and ⁷Bharthisha SM

¹Ph.D. Scholar, University of Agricultural Sciences, Raichur, Karnataka, India

²M.Sc., Agricultural extension, SRF ICAR ATARI Bengaluru, Karnataka, India

³Ph.D. Scholar, Department of Agricultural Extension, University of Agricultural Sciences GKVK Bangalore, Karnataka, India

⁴Assistant Professor, School of Agricultural Sciences and Technology-Stakna, Leh Campus, University of Ladakh (UoL), Leh Ladakh, India

⁵M.Sc. (Ag. Extension) 1st year, PJTAU, Hyderabad, Telangana, India

⁶M.Sc. Scholar, Department of Agricultural Extension, Acharya NG Ranga Agricultural University, Hyderabad, Telangana, India

⁷Ph.D. Scholar, Department of Agronomy, University of Agricultural Sciences, Dharwad, Karnataka, India

DOI: <https://www.doi.org/10.33545/26180723.2026.v9.i7f.3897>

Corresponding Author: Rohan S Kavalagi

Abstract

Agricultural extension services play a vital role in food security, sustainable farming practices and rural development by bridging the gap between scientific research and agricultural application. However, traditional public extension systems in developing nations are severely constrained by low agent-to-farmer ratios, high operational costs, delay in information dissemination and generic advisory services. This review paper evaluates the emerging role of Artificial Intelligence (AI) as a transformative tool in agricultural extension, focusing on its potential to scale operations, personalize advisories and deliver real-time, data-driven insights to smallholder farmers. We examine core AI technologies including Machine Learning (ML), Computer Vision (CV), Natural Language Processing (NLP), Large Language Models (LLMs) and the Artificial Intelligence of Things (AIoT). The paper details key opportunities offered by AI, such as hyper-localized crop diagnostics, real-time pest and climate warning systems and localized voice-based interfaces that overcome language and literacy barriers. Concurrently, we critically analyze major socio-technical challenges: the rural digital divide, limited localized datasets, risk of algorithmic hallucinations, trust deficits, data privacy issues and institutional resistance. Finally, we propose a strategic roadmap for the future, highlighting the necessity of hybrid “human-in-the-loop” extension models, domain-specific Retrieval-Augmented Generation (RAG) databases, public-private-producer partnerships, capacity building and explainable AI systems. We conclude that AI must serve as an accelerator of human expertise, rather than its replacement, to achieve inclusive and sustainable agricultural transformation.

Keywords: Artificial intelligence, agricultural extension, digital advisory, chatbots, precision agriculture, smallholder farmers

Introduction

Agricultural extension is one of the fundamental pillars of global rural development and food security, acting as a crucial conduit for transferring scientific innovations, agronomic best practices and market information from research centers to farmers (Fabregas *et al.*, 2019) ^[9]. Historically, traditional extension systems have relied on face-to-face visits, physical demonstration plots and training programs led by human extension agents. While these methods have successfully fostered trust and community cohesion, they face systemic limitations. Public extension services, particularly in low- and middle-income countries, suffer from severe resource shortages. The ratio of extension agents to farming households is often extremely low,

exceeding 1:1,000 in many Sub-Saharan African and South Asian nations, compared to the recommended international standard of 1:250.

Consequently, millions of smallholder farmers remain underserved, receiving sporadic, outdated, or generic advice that fails to account for their specific farm microclimates, soil compositions, or crop growth stages.

To address these challenges, the past two decades witnessed the rapid integration of Information and Communication Technologies (ICTs) into agricultural advisory networks. Tools such as Interactive Voice Response (IVR), Short Message Service (SMS) alerts, community radio and basic smartphone applications emerged as “digital extension” channels (Lwoga *et al.*, 2011) ^[15]. Although ICT-enabled

extension succeeded in broadening reach and lowering communication costs, it remains largely static, linear and non-interactive. Traditional digital platforms deliver unidirectional broadcasts (e.g., broad-area weather forecasts

or generic fertilizer packages) that lack the capacity for real-time interaction, localized diagnostic analysis and dynamic adjustments based on shifting farm conditions.

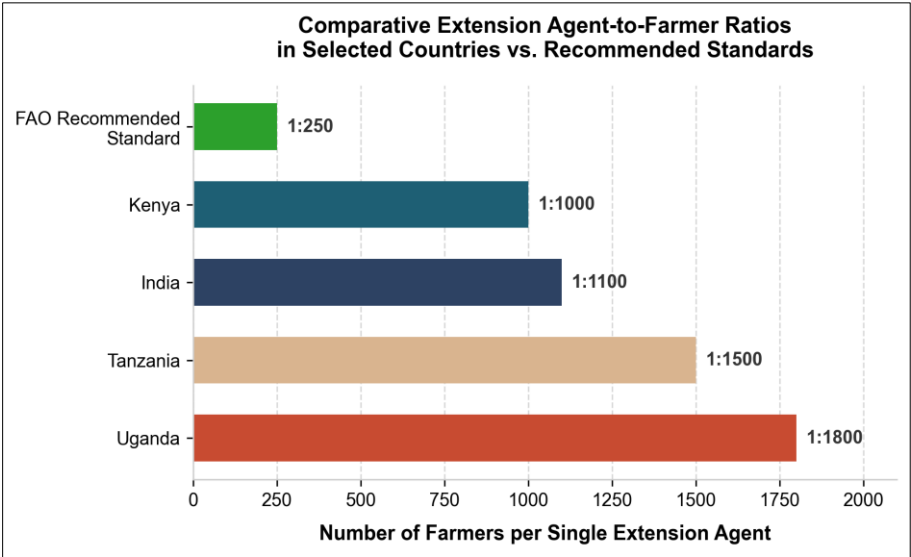


Fig 2: Extension agent-to-farmer ratios in selected developing countries compared to the FAO recommended standard

The emergence of Artificial Intelligence (AI) marks a paradigm shift in agricultural extension. By integrating machine learning, deep learning, computer vision, natural language processing and spatial analytics, AI transforms digital extension from a passive broadcasting medium into an active, intelligent and highly personalized decision-support ecosystem (Singh *et al.*, 2023) ^[18]. AI systems can analyze massive volumes of heterogenous data-ranging from satellite imagery and IoT soil sensors to local weather telemetry and crop diagnostic photos-to formulate site-specific, real-time

agronomic advisories. As global agriculture faces the compounding challenges of climate change, resource depletion and rising food demand, understanding the opportunities, challenges and future directions of AI in agricultural extension is of paramount importance. This review paper synthesizes the state-of-the-art literature, critically reviews real-world case studies, analyzes systemic constraints and presents a strategic framework for designing responsible, inclusive and effective AI-driven extension services.

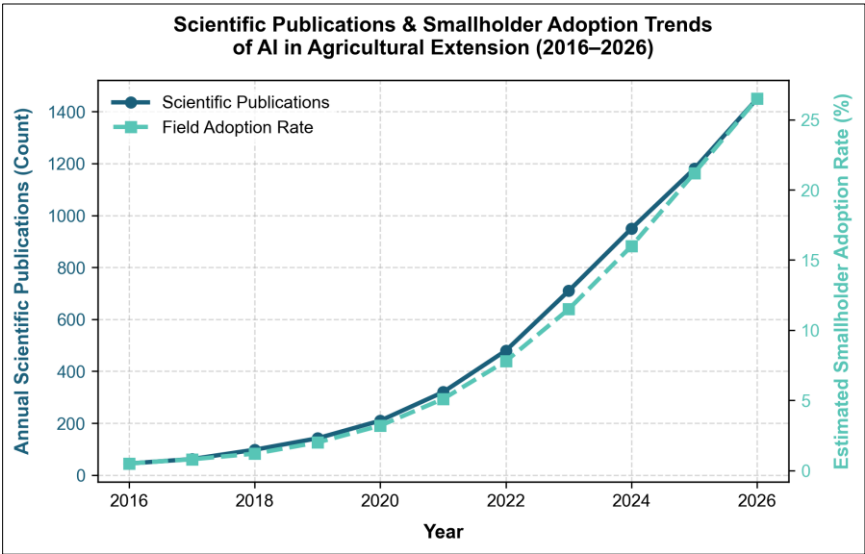


Fig 1: Trends in scientific research and field adoption of AI-driven agricultural extension (2016-2026).

2. Core AI Technologies in Agricultural Extension

The implementation of AI in agricultural advisory systems is driven by a suite of distinct yet interconnected digital technologies. These technologies process physical inputs (images, sensor data, text) into actionable, localized insights.

2.1 Machine Learning and Deep Learning for Predictive Analytics

Machine learning (ML) forms the mathematical backbone of AI-driven advisory systems. Supervised learning algorithms, such as Random Forests, Support Vector Machines (SVM)

and Gradient Boosting, are widely utilized to analyze multi-dimensional agricultural data. In extension, ML models are applied to predict crop yields, map soil nutrient distributions and optimize planting schedules based on historical weather records and soil profiles (Barbedo, 2018) ^[2]. Deep learning (DL), utilizing multi-layered artificial neural networks, is particularly effective in handling unstructured spatial and temporal data. Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) are employed to analyze sequential climate variables, providing farmers with advanced warnings regarding drought, heatwaves, or optimal harvest windows.

2.2 Computer Vision for Crop Diagnostics

One of the most immediate and visible applications of AI in agricultural extension is computer vision (CV). Leveraging Convolutional Neural Networks (CNNs), CV algorithms are trained on vast datasets of classified plant images to recognize symptoms of diseases, nutrient deficiencies and pest damage (Hughes & Salathé, 2015) ^[11]. Through mobile applications, a farmer can photograph a symptomatic leaf and receive a diagnostic result along with treatment recommendations within seconds. Applications such as Plantix utilize deep CNN architectures (e.g., ResNet or MobileNet) optimized for mobile deployment, enabling real-time classification of over 500 crop diseases with accuracies exceeding 90%. This instantaneous diagnostic capability effectively places a virtual plant pathologist in the pocket of every farmer, overcoming the acute shortage of field-level agricultural experts.

2.3 Natural Language Processing and Conversational Agents

Traditional digital extension platforms are often constrained

by text-heavy interfaces and language barriers. Natural Language Processing (NLP) and Large Language Models (LLMs) address this limitation by facilitating intuitive, human-like dialogue. Advanced conversational AI chatbots, such as Digital Green’s Farmer.Chat or the Indian government’s Kissan e-Mitra, utilize transformer-based models to interpret complex queries in regional dialects (David & Coley, 2024) ^[7]. These systems employ automatic speech recognition (ASR) and text-to-speech (TTS) engines, allowing illiterate or semi-literate farmers to ask questions via voice messages (e.g., on WhatsApp or Telegram) and receive localized audio responses. Generative AI allows these agents to contextualize answers, drawing upon historical conversation data, regional weather patterns and local agronomic practices to provide highly comprehensive advice.

2.4 Remote Sensing, GIS and the Artificial Intelligence of Things (AIoT)

AIoT refers to the integration of Artificial Intelligence with the Internet of Things. In agriculture, it involves deploying low-cost in-situ soil sensors, weather stations and leaf wetness sensors that continuously stream real-time data to cloud platforms. AI models analyze these data streams in tandem with multispectral satellite imagery (such as Normalized Difference Vegetation Index [NDVI] from Sentinel-2 or Landsat) and Geographic Information Systems (GIS) mapping (Gandhi *et al.*, 2009) ^[10]. This data fusion enables extension agencies to monitor crop health, forecast localized pest outbreaks and map water stress patterns across entire districts. This remote diagnostics approach allows public extension services to allocate their limited physical resources strategically, dispatching human agents to specific hot-spots identified by AI-driven geospatial monitoring.

Table 1: Comparison of core AI technologies in agricultural extension services

Technology	Key Functions	Representative Tools / Platforms	Primary Limitations
Machine Learning & Deep Learning	Yield forecasting, soil nutrient mapping, weather prediction	Random Forest, SVM, LSTM models	Requires large, high-quality historical datasets; lacks explainability.
Computer Vision	Image-based disease diagnosis, pest detection, weed classification	Plantix, LeafSnap, CNN architectures	High susceptibility to lighting/field variation; requires labeled image datasets.
Natural Language Processing / LLMs	Multilingual conversational Q&A, speech-to-text advisory	Farmer.Chat (Digital Green), Kissan e-Mitra	Risk of hallucinations; lack of localized accent support; high computing cost.
Remote Sensing & AIoT	Geospatial crop health monitoring, drought mapping, soil moisture tracking	Sentinel-2, Landsat GIS integration, IoT sensors	High hardware deployment costs; satellite visibility limited by cloud coverage.

3. Opportunities of AI Integration in Agricultural Extension

The deployment of AI technologies within extension frameworks offers unprecedented opportunities to overcome the core limitations of scale, speed and personalization that have historically constrained agricultural development.

3.1 Hyper-Personalized and Site-Specific Advisories

Traditional agricultural advisories are typically formulated at a macro level (e.g., provincial or district recommendations), which ignore the microclimatic variations between neighboring farms. AI-driven extension models resolve this by generating hyper-personalized advice tailored to the precise GPS coordinates of a farm (Fabregas *et al.*, 2019) ^[9]. By integrating real-time weather forecasts, high-resolution

soil maps, historical crop rotations and local planting dates, AI algorithms can calculate custom fertilizer blend requirements, optimize irrigation schedules and suggest precise sowing depths. This tailored approach enhances resource-use efficiency, lowers production costs and minimizes environmental run-off by preventing over-application of chemicals.

3.2 Mass Scalability and Low Marginal Costs

One of the most critical challenges of public extension is its inability to scale. Physical extension visits are labor-intensive, logistically expensive and slow. In contrast, AI chatbots and mobile diagnostic apps operate as digital public goods with near-zero marginal cost per additional user (Singh *et al.*, 2023) ^[18]. An AI advisory agent can simultaneously

process thousands of queries from diverse regions, offering continuous, 24/7 support. This scalability enables public extension services to extend their reach to millions of smallholders, including marginalized farmers in remote regions who have historically been excluded from face-to-face extension networks due to travel constraints.

3.3 Dynamic, Real-Time Risk Mitigation

Agriculture is highly sensitive to environmental dynamics; a sudden pest infestation or unseasonal rain can devastate seasonal yields. Traditional extension dissemination is slow, often taking weeks for recommendations to cascade from research labs to block offices and finally to farmers. AI-driven predictive systems mitigate this risk by issuing real-time alerts. By continuously running forecasting models that combine weather forecasts, crop growth models and historic pest migration patterns, AI systems can automatically trigger SMS or voice-call warnings to farmers when conditions are ripe for specific diseases (e.g., fall armyworm or potato late blight) (Barbedo, 2018) ^[2]. Farmers can then take immediate, targeted preventive actions, protecting their crops before severe damage occurs.

3.4 Democratic Knowledge Access and Language Inclusivity

The digital divide is not merely infrastructural but also cognitive and linguistic. Most agronomic research and official extension manuals are written in national languages and structured in complex academic text, creating a barrier for rural farmers who speak local dialects or have limited literacy. NLP and voice-enabled LLMs democratize access to this knowledge. By integrating multilingual translation pipelines (e.g., using models like NLLB or Whisper), AI chatbots can translate complex scientific guidance into local oral dialects, delivering it through natural, spoken dialogue (David & Coley, 2024) ^[7]. This voice-first approach empowers female farmers, elderly farmers and historically disadvantaged groups who typically have lower literacy rates, ensuring equitable access to vital agricultural intelligence.

4. Challenges and Constraints to Adoption

While the potential of AI in agricultural extension is immense, its implementation is hindered by complex socio-technical, data-related and institutional challenges that must be addressed to prevent unintended negative consequences.

4.1 The Rural Digital Divide and Infrastructure Deficits

The most fundamental constraint to AI-driven extension is the digital divide. Deep learning, real-time sensor processing and generative AI models require robust digital infrastructure, including high-speed internet connectivity (3G/4G/5G), widespread smartphone ownership and reliable electricity grids (AESAs, 2023) ^[1]. However, rural areas in developing nations frequently suffer from poor network coverage, high mobile data costs and frequent power outages. Smallholder farmers often use basic feature phones rather than smartphones, preventing them from accessing image-based diagnostic apps or interactive web-based chat interfaces. Without intentional public intervention, the deployment of AI-based extension tools may disproportionately benefit resource-rich farmers, widening the socioeconomic gap between wealthy and small-scale farmers.

4.2 Data Constraints: Scarcity, Quality and Bias

AI models are entirely dependent on the quality and volume of their training data. In smallholder farming systems, high-quality, long-term and georeferenced data is scarce. Agricultural databases in developing countries are often fragmented, unstandardized, or digitized manually with high error rates (IFPRI, 2023). Furthermore, standard machine learning models exhibit strong regional biases because they are trained on datasets from developed nations. A model trained on commercial, mechanized monoculture crop images in North America will perform poorly when applied to diverse, intercropped smallholder farms in East Africa or South Asia. Similarly, orphan crops (e.g., cassava, sorghum, yams), which are critical for local food security, suffer from a massive lack of labeled training data, leading to inaccurate diagnostics and recommendations.

4.3 AI Reliability, Hallucinations and Safety Risks

Generative AI and Large Language Models are prone to “hallucinations”—generating confident but factually incorrect statements. In agriculture, an AI hallucination can lead to catastrophic consequences. If a chatbot recommends a toxic chemical dosage, misidentifies a benign insect as a major threat, or proposes an incorrect planting window, it can result in total crop failure, financial ruin, or physical harm to the farmer (IFPRI, 2023). Unlike other digital sectors where chatbot errors are low-stakes, agricultural advice carries high physical and economic risks. Grounding LLMs to prevent hallucinations and ensuring strict verification of AI-generated advice remains a critical technical challenge.

4.4 Trust Deficit and Cultural Barriers

Farmers operate under high economic uncertainty and risk. Consequently, their adoption of new technologies relies heavily on trust, social proof and face-to-face relationships built over years with local human extension workers. AI-driven recommendations, which often arrive as automated text messages or machine-voiced calls, lack the empathy, personal touch and local contextual understanding of human agents (AESAs, 2023) ^[1]. Farmers are naturally skeptical of black-box algorithms that provide no explanation for their advice. If an AI tool suggests a counter-intuitive practice (e.g., reducing fertilizer application or changing planting dates), farmers are unlikely to comply unless the advice is validated by trusted community members or local extension agents.

4.5 Ethics, Privacy and Data Sovereignty

AI systems require extensive collection of farmer data, including exact farm coordinates, soil profiles, yields, financial histories and demographic information. The collection and storage of these data raise serious ethical questions regarding data ownership, privacy and sovereignty. In the absence of strong national data protection regulations in rural regions, smallholders are vulnerable to data exploitation by private agri-businesses (CropIn, 2024) ^[6]. Corporate entities could potentially use localized yield forecasts to manipulate market prices, upsell expensive proprietary seeds/fertilizers, or monopolize local agricultural supply chains. Ensuring that farmer data is handled transparently, protected from breaches and used solely for their benefit is a major governance hurdle.

Table 2: Matrix of opportunities vs. challenges in AI extension integration

Integration Dimension	Key Opportunities	Challenges and Barriers
Scalability	Mass reach with near-zero marginal cost; 24/7 continuous advisory.	Rural digital divide; high cost of smartphones and mobile data packages.
Personalization	Hyper-local advice based on exact GPS, soil and local crop growth stage.	Extreme data scarcity; lack of standardized regional agricultural registries.
Inclusivity	Speech-to-text/voice interfaces that bypass digital and literacy barriers.	Skewed training data; high risk of gender, region and orphan-crop biases.
Trust & Adoption	Dynamic, real-time alerts for pest outbreaks and meteorological risks.	Farmers' preference for human relationships; trust deficit in black-box advice.
Data Governance	Aggregated, anonymized regional trends to inform public policymaking.	Ethical data exploitation risks; absence of strict data sovereignty laws.

5. Future Directions and Policy Recommendations

To successfully leverage the power of AI while mitigating its risks, agricultural extension must transition from isolated digital experiments to integrated, ethical and stakeholder-driven systems.

5.1 Implementing Hybrid “Human-in-the-Loop” Extension Models

The future of agricultural advisory is not a choice between human agents or AI, but rather their integration. We advocate for a hybrid extension model where AI serves as a force-multiplier for human extension workers (Microsoft, 2024)^[16]. In this model, AI-powered diagnostic and predictive tools are used by traditional extension agents to rapidly assess farm conditions, screen crop diseases and synthesize weather forecasts. The human agent then filters and contextualizes this advice, translating it to the farmer within the context of their personal relationship and local customs. This triage approach allows extension agents to focus their physical visits on complex cases, maximizing institutional efficiency while maintaining vital community trust.

5.2 Development of Localized, Domain-Specific LLMs and RAG Databases

To eliminate AI hallucinations and ensure accuracy, the agricultural research community must develop open-access, localized Retrieval-Augmented Generation (RAG) frameworks. Rather than relying on generic, commercial LLMs trained on internet data, agricultural AI systems must be strictly grounded in validated local data sources, including peer-reviewed agronomic journals, national university research repositories and official government extension manuals (CGAP, 2024). These models should be fine-tuned to recognize regional dialects, crop varieties and local farming practices, ensuring that advice is technically sound and socio-culturally appropriate.

5.3 Strengthening Public-Private-Producer Partnerships (4Ps)

Developing and maintaining robust AI systems is capital-intensive and requires diverse competencies. Governments must foster collaborative ecosystems that bring together public research institutes (data and scientific validation), private agri-tech startups (technical architecture and scaling) and producer organizations (farmer feedback and adoption panels). Public-Private-Producer Partnerships (4Ps) can co-design open-source, regional digital public infrastructure—such as shared crop disease image libraries, localized weather databases and translation engines—ensuring that even small,

local tech firms can develop low-cost, tailored advisory tools for niche farming communities (Digital Green, 2024)^[8].

5.4 Capacity Building and Digital Literacy Initiatives

Investing in technology without investing in human capability is futile. Governments and educational institutions must initiate comprehensive training programs to build digital literacy among rural farmers, with a specific focus on women and youth. Furthermore, agricultural university curricula must be modernized to include coursework on digital agriculture, agricultural data science and AI ethics. Current extension officers must receive continuous professional training to operate digital diagnostic devices, interpret predictive AI charts and instruct farmers on using voice-based chatbots effectively.

5.5 Advancing Explainable AI (XAI) for Transparency

To overcome the trust deficit, researchers must design Explainable AI (XAI) interfaces that make the model's reasoning transparent to extension agents and farmers. For example, instead of simply displaying a disease diagnosis, a computer vision app should highlight the specific visual features of the leaf (e.g., spots, discoloration) that led to the classification and present confidence percentages in simple, intuitive formats (e.g., color-coded meters). When an AI model suggests a crop rotation shift, it should provide a clear, logical explanation.

6. Conclusion

The integration of Artificial Intelligence in agricultural extension represents a significant technological leap in rural development, offering powerful opportunities to scale hyper-personalized, real-time and inclusive advisory services to millions of smallholder farmers. By transforming passive information broadcasting into dynamic, interactive and voice-accessible dialogue, AI can bridge long-standing literacy, language and geographic divides. However, the technology is not a panacea. Its success is heavily bounded by the realities of the rural digital divide, data scarcity, safety concerns regarding algorithmic hallucinations and the fundamental role of human trust in agricultural decision-making. Addressing these challenges requires a deliberate shift from tech-centric, top-down approaches to collaborative, human-centered designs. The future of agricultural advisory lies in hybrid models that empower human extension agents with AI tools, backed by localized domain-specific databases, public-private-producer partnerships and explainable AI interfaces. By prioritizing equity, ethical data governance and localized

research, AI can serve as a powerful catalyst to achieve sustainable, resilient and food-secure agricultural systems worldwide.

References

1. Agricultural Extension in South Asia Network. Digitalizing agricultural extension: Opportunities, challenges and the way forward. Agricultural Extension in South Asia Network Policy Brief. 2023;14(3):1-8.
2. Barbedo JGA. Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering. 2018;172:84-91.
3. Benos L, Tagarakis AC, Gitis G, Kateris D, Bochtis D. Machine learning in agriculture: A comprehensive review. Agronomy. 2021;11(2):375-395.
4. Consultative Group to Assist the Poor. Grounding large language models for smallholder advisory: Retrieval-augmented generation in practice. Consultative Group to Assist the Poor Technical Report. 2024;4(2):54-68.
5. Cole G, Fernando A. Mobile technologies and agricultural extension: Evidence from India. American Economic Journal: Applied Economics. 2021;13(3):289-317.
6. CropIn. Data sovereignty and ethical AI in smallholder agriculture. CropIn Agri-Tech Whitepaper Series. 2024;8(1):34-42.
7. David M, Coley J. Kissan GPT and conversational AI for smallholder farming. Journal of Agricultural Extension. 2024;28(1):45-56.
8. Digital Green. Farmer.Chat: Hyperlocal generative AI for smallholder agricultural extension. Digital Green Trust Whitepaper. 2024;3(1):12-21.
9. Fabregas R, Kremer M, Robinson J. Digital technology and agricultural extension in developing countries. Science. 2019;366(6472):eaay3038.
10. Gandhi R, Veeraraghavan R, Toyama K, Ramprasad V. Digital Green: Social video for agricultural extension. Information Technology for Development. 2009;15(3):151-167.
11. Hughes D, Salathé M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv. 2015;arXiv:1511.08060.
12. International Food Policy Research Institute. Artificial intelligence in agriculture: Assessing the risks and benefits for smallholder farmers. IFPRI Discussion Paper 2185. Washington (DC): International Food Policy Research Institute; 2023.
13. Kamlaris A, Kartakoullis A, Prenafeta-Boldú FX. A review on the practice of double-blind review in agricultural science. Journal of Agricultural Informatics. 2017;8(3):12-22.
14. Kamlaris A, Prenafeta-Boldú FX. Deep learning in agriculture: A survey. Computers and Electronics in Agriculture. 2018;147:70-90.
15. Lwoga ET, Stilwell C, Ngulube P. Access and use of agricultural information and knowledge in Tanzania. Library Philosophy and Practice. 2011;2011:1-18.
16. Microsoft. Empowering the field: AI as a force multiplier for agricultural extension workers. Microsoft Research and Agri-Extension Initiative Report. 2024;12(2):89-97.
17. Ortiz-Crespo B, Steinke J, Quirós CF, van de Gevel J, Daudi H, Mgimiloko MG, *et al.* User-centered design of digital agricultural extension services: The case of the Seedboat in Tanzania. Frontiers in Sustainable Food Systems. 2021;5:641654.
18. Singh K, Kumar A, Sharma R. Deep learning and AI applications in agricultural extension: A review. International Journal of Agricultural Extension and Social Development. 2023;5(2):112-119.
19. Tsan M, Totapally S, Hailu M, Addom BK. The state of digital agriculture in Africa 2019. Wageningen: CTA/Enclude; 2019.
20. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming: A review. Agricultural Systems. 2017;153:69-80.