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Artificial Intelligence in Agricultural Extension Services: Opportunities, Evidence, Challenges, and Future Directions

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The function of agricultural extension is critical in linking farmers to scientific information, technology, markets, institutions and risk-management methods. But there are often shortages of qualified staff, high operating expenses, poor last-mile connection, fragmented information flows, and the challenges of delivering location-specific guidance to vast and varied agricultural communities in traditional extension systems. Artificial intelligence provides new approaches to solve some of these constraints using machine learning, computer vision, predictive analytics, natural language processing, voice-based interfaces, recommender systems, and generative AI. These technologies may assist extension organisations diagnose crop issues, provide personalised advice, translate technical information, predict production hazards, automate routine communication, and improve the analytical capacity of extension professionals. But the success of AI-driven extension relies on much more than just algorithmic precision. Connectivity, institutional capability, reliable local datasets, farmer confidence, language accessibility, data governance, human monitoring, and procedures to amend wrong suggestions are all equally crucial. Evidence from previous digital advice projects indicates that farmers frequently prefer information that is easily available, although implications on technology adoption, productivity, income and welfare differ among situations. Evidence directly related to generative AI and extension with AI integration is still rather few and dominated by pilot studies, technical assessments and observational studies. This study integrates literature on digital agricultural guidance, smart farming, responsible AI, machine learning, and developing generative AI applications in extension. It recommends that AI is created as a decision assistance and knowledge augmentation technology, rather than a substitute for extension experts. A responsible implementation methodology is presented based on farmer-centred design, locally verified knowledge, human-in-the-loop decision-making, inclusive delivery channels, transparent governance, constant monitoring and independent effect evaluation.

Introduction

Agricultural extension is often considered as a collection of educational, advisory, facilitation and institutional services that enable farmers to increase their knowledge, skills, decision making, productivity, resilience and access to markets. Modern extension is not just transfer of production guidelines. Extension organisations are increasingly supporting farmers to manage climate unpredictability, plant and animal health, food safety, natural resources, collective action, financial services, value chains and compliance with quality requirements. They also link academics, government agencies, commercial firms, producer organisations and rural communities. Agricultural extension is important but is often hampered by significant limitations. In many countries a relatively limited number of extension staff have to service geographically scattered farmers growing diverse crops under extremely varying ecologic and socioeconomic situations. Extension staff may not have timely access to current research, diagnostic labs, weather information, market intelligence, transportation or professional assistance. Recommendations may thus come too late to farmers, be too generic, or fail to consider local variations in soil, climate, crop stage, production resources and market goals. The expansion of extension has long been advocated via information and communication technology. Mobile telephones, text messaging, radio, call centres, films and internet platforms may lower the cost of communication and increase access to information. However, evidence from digital agriculture guidance suggests that knowledge does not always lead to technology adoption or financial gains. The value of a digital service is determined by the relevance, timeliness, credibility, comprehensibility and actionability of its information, and farmers' capability to act on the information.

Artificial intelligence is another step in the digitalisation of extension. Unlike traditional information platforms which often transmit pre-made messages, the AI systems are capable of analysing data, seeing trends, classifying photos, forecasting results, generating answers and customising material for particular users. Generative AI and big language models can also have conversations with people, summarise technical material, translate content, and pull information out of enormous knowledge resources. These functionalities have generated interest in AI-enabled advice services that might potentially be accessible 24/7 and can benefit both farmers and extension professionals. The aim of this study is to critically explore the possible uses of AI in agricultural extension, to assess the evidence available, to identify the significant technical and institutional concerns, and to offer guidelines for responsible adoption. The main thesis is that AI may improve extension systems but the extent to which this is achieved will rely on the level of integration with human expertise, local institutions, farmer knowledge and responsible governance.

Review Approach

The methodology used in this research is a narrative and multidisciplinary review. Literature was obtained from peer-reviewed publications in the fields of agricultural extension, agricultural economics, agricultural systems, digital agriculture, computer applications in agriculture, machine learning, development economics, and responsible innovation. Priority was given to authoritative reviews, experimental research on digital advice services, empirical evaluations of agricultural AI and new works pertaining to big language models and generative AI in extension. The literature encompasses the evolution of mobile agricultural advice services, smart farming systems, big-data analytics, machine learning, computer vision, and generative AI. In the absence of clear causation evidence on the role of AI integrated extension, data from well-established digital advice programs is utilised to identify variables that influence farmer engagement, trust, behavioural change and service sustainability. The study does not assume that every digital platform is AI but utilises evidence of digital extension to make sense of the organisational context into which AI is being introduced.

Understanding AI-Enabled Agricultural Extension

Artificial intelligence (AI) is an umbrella word for computer systems that do things normally associated with human intellect, such learning from data, identifying patterns, understanding language, making predictions, and creating content. AI may function in agricultural extension at the three inter-related levels. First, AI can help make judgements at the farm level. A model may look at photographs, weather records, soil information, sensor data or management history and propose an action like as irrigation scheduling, disease control, fertiliser application or harvest timing. Second, AI may assist extension staff to get scientific knowledge, prepare communication material, prioritise field trips, summarise farmer data, and spot uncommon trends that need specialised attention. Third, AI may improve extension management by analysing service demand, mapping production risks, tracking program performance, and allocating resources to underserved regions. Machine learning algorithms find correlations in previous data and utilise them for prediction or categorisation. Deep learning is extremely effective to handle pictures, sound and complicated data-sets. Computer vision can recognise crop symptoms, weeds, insects, animal problems, or product quality from photos. Natural language processing allows computers to understand and produce words in either written or spoken form. Recommender systems rely on data about users, the production circumstances and the choices offered to provide personalised recommendations. Generative AI uses patterns learnt from massive data sets to create fresh text, graphics, summaries, or conversations. AI-enabled extension is not the same as completely autonomous decision-making. For example, a disease categorisation model may predict a probable disorder but an extension specialist must evaluate field history, symptom distribution, crop stage, local disease prevalence, pesticide restrictions, economic thresholds and other explanations. Agricultural suggestions are context sensitive actions and not just computer results. AI should therefore be considered an extra element in an agricultural knowledge and innovation system .

Applications of AI in Agricultural Extension

Personalized and Context-Specific Advisory Services

Traditional extension recommendations are often made for large areas or crop groups. AI may increase specificity by integrating data on farm location, crop type, planting date, soil qualities, weather, irrigation resources, prior practices, and farmer goals. This data is used in a recommendation system to rate management approaches and to provide the advise appropriate to a given farm and production stage. This kind of personalisation is especially significant for irrigation, nutrient management, pest control and climate-risk management. Machine-learning algorithms have been trained to estimate crop water needs, anticipate disease risk, detect constraints on yield and optimise the scheduling of agricultural activities. Applications of AI have also been investigated to reduce needless watering and improve the accuracy of pesticide and herbicide application. But a technically-optimised advice may be rendered impracticable if farmers do not have access to financing, manpower, materials, equipment or a secure water supply. Hence, personalisation should take into account socioeconomic and biophysical circumstances. Suggestions from AI might be provided via mobile apps, messaging platforms, telephone services, community information centers or extension-worker dashboards. For basic phone users, speech systems and interactive voice response are more inclusive than smartphone apps. The same analytical approach may be used by extension agents when they visit farms so they can explain suggestions and provide observations not accessible to the model.

Crop and Livestock Health Diagnosis

One of the most obvious uses of agricultural AI is crop disease identification. Farmers or extension professionals may submit a picture of a leaf, fruit, stem, bug or an impacted field. Then, computer vision algorithms compare the picture with annotated instances and predict the most probable situation. Such tools may also help with weed detection, pest monitoring, diagnosis of nutrient deficit and quality grading. Field-oriented systems are increasingly built to operate with restricted connection. A machine-learning recommender system, tested with cassava farmers, includes image-based illness detection and advice information, with both online and offline functionalities. The findings indicated the practical potential of real-time field diagnosis but also showed the dependency on the quality, variety and representativeness of the training data. Laboratory or benchmark accuracy does not guarantee field performance. Farmers' photographs may include poor illumination, complicated backdrops, various symptoms, damaged plant sections, or crops in phases not covered in the training dataset. Different pressures may create identical symptoms and more than one illness may be present at the same time. A model trained in one nation or manufacturing environment may not work well elsewhere. A accountable diagnostic system should generate confidence ratings, alternative diagnoses, requests for further information, and referrals of unclear or high-risk situations to experts. Strong protections are especially needed in respect of pesticides, antibiotics, hazardous chemicals or notifiable illnesses. Extension workers and diagnostic labs continue to play an important role in the confirmation and in separating a probable forecast from a confirmed diagnosis.

Predictive Analytics and Early Warning

Agricultural extension is generally reactive, with help being mobilised when a problem is identified by farmers. Predictive analytics may lead to more anticipatory services. AI models use past weather, remote-sensing measurements, pest monitoring, market arrivals, crop calendars and field reports to forecast emergent threats. Such projections may be used by extension organisations to identify regions experiencing drought, flood, heat stress, disease outbreaks or feed shortages. This way, advisories may be directed to the crop stage and vulnerabilities. Predictive systems may also assist with production forecasts, harvest planning, allocation of inputs, storage management and market coordination. A prediction is only valuable if it arrives in time to the right user to enable a possible reaction. The extension value of an accurate rainfall or pest prediction is minimal if the information is provided beyond the window of choice, if farmers are unable to grasp the advised action, or if the necessary inputs are not accessible. Extension professionals need to convert probabilistic projections into actionable risk-management alternatives. Forecasts also include uncertainty. It might harm farmer confidence if presented as promised results. AI-supported extension should: • Explain uncertainty in plain terms. • Offer alternate options for diverse circumstances. • Update recommendations when new information becomes available.

Natural-Language, Voice, and Conversational Advisory Systems

Natural-language processing may make it easier to find and retrieve agricultural information. Farmers may ask enquiries in natural language rather than having to go through sophisticated databases. Voice-based interfaces may be useful for persons with low literacy or difficulties typing. Extension institutes may give information in several languages using translation and text-to-speech technologies. The interest in conversational agricultural consulting systems has grown dramatically in the wake of large language models. These models may summarise papers, write replies, provide training material, generate frequently asked questions, and tailor explanations to various levels of technical expertise. Their potential contribution to extension is particularly important when extension workers have to deal with multiple disciplines yet have limited access to experts. But general-purpose language models are not authoritative agricultural knowledge repositories. They respond by guessing probable sequences of language and may provide wrong references, create facts, quote out-of-date legislation, suggest inappropriate pesticide advice or propose things that don't work in the local area. If you're a fluent speaker, you may find it difficult to spot these faults. A safer approach is to hook a language model to a curated knowledge base that is updated periodically. This knowledge base includes certified crop-production packages, weather information, local research, input labels, market standards and government laws. The system should retrieve necessary documents prior to producing a response, and it should indicate the source of the supporting information. Any question that involves doubt, contradicting evidence, animal or human health, restricted substances, or large financial ramifications should be escalated to expert professionals.

Knowledge Support for Extension Professionals

The greatest near-term usefulness of AI may be to enhance extension staff, rather than to communicate independently with farmers. Extension staff manage a wide variety of crops, animal species, illnesses, programs, markets and rural organisations. There is a lot for any one person to keep up to date with in all these areas. An AI-assisted workstation may help an extension worker pull up ideas, evaluate management choices, summarise studies, translate technical terms into farmer-friendly explanations, devise training programs, and log field observations. It could also be useful to develop localised calendars, demonstration materials, diagnostic checklists and follow-up communications. Recent studies of generative AI among extension professionals show increased interest but also great difference in understanding, perceived utility, trust and desire to utilise these technologies. A 2026 survey of agricultural extension workers in northern Benin showed a favourable relationship between the application of generative AI and self-reported advice performance. However, the observational approach does not demonstrate that AI is responsible for superior farmer results. The research also revealed difficulties about professional judgement, responsibility and trust showing that adoption can't be regarded as a technological issue. Extension workers should thus be educated to not just use AI technologies but also assess their outcomes. Key skills are: checking sources; identifying unsubstantiated claims; safeguarding data about farmers; understanding uncertainty; maintaining a record of revisions; knowing when to consult a professional.

Programme Planning, Monitoring, and Institutional Learning

AI has the potential to help extension administrators analyse vast amounts of service data. Farmer questions may uncover increasing pest concerns, often misinterpreted suggestions, unmet training requirements, or regional gaps in the delivery of services. Automated categorisation enables managers to sort requests by crop, location, urgency and topic, helping them to deploy staff more wisely. Extension initiatives may also utilise analytical models to determine patterns of involvement, technology uptake and dropout. But the algorithms employed to choose recipients may replicate previous injustices. Farmers with fewer digital records, less connection, less land, less literacy or less interaction with formal institutions might be labelled as low priority consumers even when their demand is larger. AI-supported programme targeting has to be assessed for distributive consequences. Decisions around access to public services, subsidies, credit, insurance or disaster aid should not be based only on opaque computerised scoring. Farmers need a clear way to challenge data and appeal decisions.

What Does the Evidence Show?

Important but varied lessons may be learned from existing digital agricultural advising programs. A randomised examination of SMS-based information in Maharashtra, India, demonstrated modifications in selected choices but limited average impacts across multiple outcomes. In comparison, a two-year voice-based advice intervention with Indian cotton farmers resulted in a significant demand, modified the information seeking behaviour and affected several agricultural practices. The different findings indicate that efficacy is affected by the channel, content, trust, crop situation, user participation and availability of supplementary resources.

Evidence from big digital extension initiatives also displays great variety. Six text-message advising programme studies in East Africa indicated that effects were heterogeneous across treatments and results. Reviews of mobile agriculture services also warn that many studies are limited to consumption or satisfaction and not to independently evaluated gains in productivity, profitability, resilience or wellbeing.

AI might increase the relevance and interactivity of digital advice, but it does not remove behavioural, economic and institutional limits. Farmers may know a tip but cannot execute it because of input pricing, finance constraints, manpower shortages, unstable tenure, risk aversion or poor markets. On the other hand, if weather, pests or pricing change suddenly, then implementation of a tip doesn’t always lead to a great result.

The evidence on AI-specific agricultural extension is less developed than the evidence on traditional digital communication. The literature mostly shows technical performance in categorisation, prediction or language production. Field tests are proving the idea and recent polls suggest extension workers are starting to employ generative AI. Few studies follow the whole process from AI-generated recommendations to farmer comprehension, adoption, agronomic results, net income, environmental impacts and distribution implications.

Future evaluations will have to separate model correctness, service efficiency, farmer satisfaction, behaviour change and ultimate development effects. These are similar, but not interchangeable indicators.

Major Challenges and Risks

Digital and Social Exclusion

Services that use artificial intelligence generally need a mix of equipment, power, internet, digital skills and linguistic competence. Inequitable access to such resources. Women, elderly farmers, isolated areas, tenant farmers, landless livestock keepers and families with little money may be under-represented among users. A service provided only on smartphones might boost the efficiency of connected farmers but decrease relative access for others. Inclusive extension consequently needs numerous channels, such as extension visits, farmer groups, radio, call centres, basic-phone services, voice interfaces, community facilitators and written information. Technology should broaden the menu of services, not become a digital access requirement for obtaining public extended assistance.

Data Quality and Local Validity

AI systems are limited by the data, assumptions and aims on which they are developed. Agricultural datasets may be tiny, fragmented, subject to commercial restrictions, tagged inconsistently or concentrated in research stations and big farms. Important local crops, indigenous varieties, diversified farming systems, women's agricultural activities and low-input approaches may be under-represented. Data might also be out of date when cultivars, insect populations, climatic trends, laws and input items change. Models trained on previous associations may not perform well in new environmental situations. Therefore, local validation is needed before a model can be encouraged for operational expansion.

Hallucination, Bias, and Explainability

Generative AI may generate information that sounds true but isn't verified. Predictive models may produce mistakes that are difficult to comprehend as well. When a farmer asks why you made that advice, it is not enough to say "the algorithm calculated it" or to provide a complicated technical reason. Extension systems should include comprehensible explanations, supporting evidence, confidence indications and constraints. The explanations should include the data used and the situations under which the suggestion may not apply. If the uncertainty is large the system should say it cannot provide a reliable response.

Privacy, Ownership, and Control of Agricultural Data

Information about a farm may include its location, land tenure, costs of production, financial state, yields, inputs, photographs, disease incidences and commercial links. "Putting these records together might offer massive economic benefit. Without proper control, farmers might be sharing data without knowing how it would be kept, shared, monetised or utilised for automated decisions. Studies on big data in agriculture have shown shifts in power dynamics between farmers, technology providers, agribusinesses and governmental institutions . Responsible AI research also points to problems around data availability, quality, disparate adoption, limited optimisation, and externalities across systems. Farmers need clear understanding on how data will be collected and used. Only gather the data you need, safeguard critical documents and manage access. Contracts should specify ownership, retention, secondary usage, model training, commercial sharing, and deletion methods. Public institutions should not be reliant on suppliers in the long run that limit data mobility or do not allow independent audits.

Accountability and Professional Responsibility

When a farmer, an extension worker, a software provider, a data provider and an AI model interact and the advise is bad, who is responsible? A disclaimer is not a good form of government. Who approves the knowledge base? Who oversees the performance? Who investigates errors? Who may suspend a system? Institutions need to specify these. Extension staff should be able to veto AI outputs. Farmers should be able to easily report any inaccuracies and request a human evaluation. Verification should be increased for recommendations that concern regulated inputs, food safety, animal health or considerable financial risk.

Institutional Capacity and Sustainability

Many digital ventures work well during externally funded trials but fall apart when the money, technical support, content updates, or user involvement wane. AI systems incur ongoing expenditures related to data management, software maintenance, cyber security, model review and expert staff. Extension institutions need a realistic overall cost evaluation rather than a focus on early development alone. Sustainability relies on integration with current processes, personnel incentives, public infrastructure for data collection, long-term finances, and interface with other agricultural information systems. Reviews of digital agricultural knowledge networks emphasise that digital transformation transforms professional responsibilities, organisational connections and ownership over knowledge; it cannot be reduced to the mere purchase of software.

Framework for Responsible Implementation

A responsible AI-enabled extension strategy should be based on the following principles.

Farmer-centred issue definition: The development should start with a well defined extended problem and not with the availability of a trendy technology. Farmers and frontline extension professionals should be involved in the definition of the issue, testing of the prototype and evaluation of usefulness.

Locally verified knowledge: Recommendations should be based on the current scientific and regulatory sources from the area. Content should be validated before distribution by agronomists, veterinarians, extension professionals and local practitioners.

Human-in-the-loop operation: AI should be used for retrieval, categorisation, prioritisation, and routine communication but skilled individuals should maintain responsibility for difficult, unclear, or high-risk choices.

Inclusive delivery: Systems should be available in local languages, voice, low-bandwidth, basic phones if feasible, and aided usage via extension workers or community organisations.

Risk-based safeguards: Low-risk enquiries, such as defining a generic notion, might be automatically answered. Further verification should be done for recommendations on pesticides, veterinary medications, food safety, credit, insurance or serious indications of illness.

Transparency and traceability: All advisory outputs should have documentation of the data utilised, source documents, model version, date, confidence level, and any human alteration. Traceability enables organisations to analyse faults and update knowledge.

Privacy and rights of farmers: Data gathering should be proportionate to the service offered. Consent processes need to be transparent, and farmers should be able to modify records and to know how their data are utilised.

Continuous assessment : Models should be validated across real field circumstances and across locations, seasons, crops, languages, gender, farm size and device type. Monitoring should include misleading suggestions, missing diagnoses, user complaints, patterns of exclusion and unexpected behavioural impacts.

Outcome-based assessment: Assessment should not just focus on the number of users or messages delivered but also on understanding, implementation, productivity, profitability, risk reduction, environmental effects and equality.

These concepts are in line with widespread calls for human-centred experimentation in digital extension and more holistic approaches to the socio-ethical difficulties of smart farming.

Future Research Priorities

- The first priority is a careful examination in the field. Randomised, quasi-experimental and longitudinal studies are needed to compare AI-supported extension with traditional extension, non-AI digital services and hybrid models. Evaluations need to examine both costs and results and if AI increases the productivity of extension workers or just adds to administrative responsibilities.
- Second, research needs to build multilingual and culturally relevant agricultural language resources. We should assess performance on genuine farmer queries, local language, code-switching, partial descriptions, and voice recordings rather than solely on standardised written prompts.
- Third, investigations should investigate distributional implications. Average impacts of programmes might mask exclusion or damage to certain populations. Evaluation designs need to include gender, age, landholding, literacy, disability, connection and production system.

- Fourth, researchers require ways to check the agronomic as well as the factual veracity of generative AI. Standard standards should include citation correctness, local relevance, uncertainty communication, harmful suggestions, temporal validity and ability to correctly refer queries.
- Fifth, greater evidence on organisational transformation is necessary. AI might change extension people from information suppliers to translators, facilitators, data custodians, and coordinators. More research is needed on workload, professional autonomy, motivation, responsibility and trust between farmers and advisors.
- Finally, public policy studies should include agricultural data rights, procurement norms, interoperability, audit requirements, liability and independent certification. These governance problems will decide whether AI will reinforce public-interest expansion or generate new kinds of reliance and exclusion.

Conclusion

Artificial intelligence has the potential to improve the analytical ability, responsiveness and reach of agricultural extension services. Machine learning, computer vision, predictive analytics, natural-language processing and generative AI may help diagnostics, personalised suggestions, early warning, information retrieval, farmer communication and programme administration. AI is not a replacement for legitimate institutions, qualified extension specialists, farmer involvement, field observation, or locally verified knowledge. Evidence from digital advice services shows that information technology may modify farmer conduct, but their impacts are varied and largely dependent on service design and the surrounding economic circumstances. Direct evidence of the role of AI-enabled guidance in contributing to persistent increases in agricultural income, resilience and equality is still emerging. Therefore, the most acceptable approach is a hybrid extension model where AI is responsible for data-intensive and routine activities while human specialists offer contextual interpretation, ethical judgement, facilitation and accountability. AI can only improve extension if systems are accurate, inclusive, transparent, contestable and sensitive to farmers' circumstances. The future of agricultural extension should be less about choosing between human advisers and intelligent algorithms and more about designing institutions responsibly where technology becomes an amplifier of human knowledge and farmers maintain real autonomy.

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