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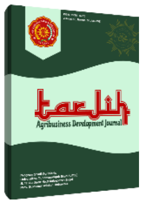

Transformation of Agricultural Extension Communication in the Artificial Intelligence Era: A Systematic Literature Review

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ABSTRACT

The digital transformation of agriculture has reshaped how extension information is produced, delivered, and used by farmers. This study synthesizes research on agricultural extension communication in the artificial intelligence (AI) era, identifies major communication changes, and examines the benefits, challenges, and social implications of AI-based advisory services. A systematic literature review was conducted using the PRISMA 2020 framework. Articles published from 2019 to 2025 were searched in Scopus, ScienceDirect, SpringerLink, Taylor & Francis, and Google Scholar. After identification, duplicate removal, screening, eligibility assessment, and quality appraisal, 15 studies that directly met the inclusion criteria were analyzed through content analysis and thematic synthesis. The findings show that AI shifts extension communication from a conventional, linear, and top-down model toward a data-driven, interactive, personalized, and participatory advisory system. Machine learning, decision support systems, predictive analytics, agricultural chatbots, virtual assistants, and smart farming platforms improve information delivery, advisory personalization, and farmer decision-making. However, implementation is constrained by rural digital divides, limited technological literacy, data quality and bias, algorithmic opacity, inadequate infrastructure, and the risk of weakening farmer-extension worker relationships. The study proposes a Human-Centered AI Extension Communication Model that positions AI as an augmenting tool for participatory extension rather than as a substitute for the social, cultural, and facilitative roles of agricultural extension workers.

Keywords: *Digital advisory services, Farmer decision-making, Human-centered technology, Smart farming, Thematic synthesis*

INTRODUCTION

Digital technologies have generated profound changes in contemporary agricultural systems. Digital agriculture, smart farming, big data analytics, the Internet of Things (IoT), machine learning, and artificial intelligence (AI) are increasingly used to improve production efficiency, risk management, and agricultural decision-making (Bacco et al., 2019; Birner et al., 2021; Klerkx et al., 2019). These changes do not only affect technical production practices; they also reshape how agricultural information is collected, processed, communicated, and applied by farmers.

In agricultural extension systems, communication is the central mechanism that links scientific knowledge, farmers' local experience, public policy, and technological innovation. Conventional extension models, which are often linear and top-down, have long faced limitations related to the number of extension workers, the spatial scale of service areas, delays in information delivery, and limited capacity to provide recommendations that match farmers' specific conditions (Aker, 2011; Anderson & Feder, 2004). These limitations become more critical when farmers must respond quickly to climate variability, price volatility, pest and disease outbreaks, and increasingly complex farm-management decisions.

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AI offers new opportunities to strengthen extension communication because it can process large volumes of data, detect patterns, predict risks, and generate context-specific recommendations. In agricultural practice, AI can be integrated into decision support systems, predictive analytics, agricultural chatbots, virtual assistants, pest and disease diagnostic systems, and input recommendation tools (Benos et al., 2021; Javaid et al., 2023). Through these technologies, extension information no longer depends exclusively on face-to-face encounters; it can be delivered in real time, interactively, and with a greater degree of personalization.

Nevertheless, the digital transformation of extension cannot be understood merely as a technical issue. Previous studies have emphasized that agricultural digitalization may reproduce or intensify inequalities when access to devices, digital literacy, data quality, and technology governance are not adequately addressed (Carolan, 2020; Hackfort, 2021). Other challenges include algorithmic bias, limited farmer trust in automated recommendations, and the possible weakening of interpersonal relationships between farmers and extension workers. Therefore, AI in extension should be positioned within a socio-communicative framework that emphasizes participation, trust, local context, and sustainability.

Although research on AI in agriculture is expanding rapidly, much of the existing literature remains focused on precision agriculture, production automation, and technical efficiency. Studies that explicitly integrate AI with extension communication, farmer-extension worker relationships, and human-centered AI remain comparatively limited. This study therefore aims to analyze the development of research on agricultural extension communication in the AI era, identify emerging forms of communication transformation, synthesize the benefits and risks of AI implementation, and formulate a Human-Centered AI Extension Communication Model as a conceptual framework for inclusive digital extension.

RESEARCH METHODS

Study Design and Review Protocol

This study used a systematic literature review (SLR) method guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework (Page et al., 2021). The SLR approach was selected because it enables the systematic identification, evaluation, and synthesis of scientific evidence on the transformation of agricultural extension communication in the AI era.

The review focused on articles addressing AI, digital extension, agricultural advisory services, smart farming, decision support systems, agricultural chatbots or virtual assistants, and data-driven extension communication. The unit of analysis was the scientific article, and the scope of analysis was the relationship between digital or AI-based technologies and agricultural extension communication practices.

Search Strategy and Eligibility Criteria

Articles were searched in five databases: Scopus, ScienceDirect, SpringerLink, Taylor & Francis, and Google Scholar. The publication period was limited to 2019-2025 to ensure that the synthesis reflected recent developments in digital agriculture and AI-based advisory services. The search string combined the terms "artificial intelligence" OR "machine learning" OR "digital agriculture" OR "smart farming" AND "agricultural extension" OR "extension communication" OR "agricultural advisory services" OR "digital extension".

Articles were included when they discussed AI, digital technologies, or intelligent systems in the context of agricultural extension, agricultural communication, or advisory services; presented empirical, conceptual, or review-based evidence relevant to the research objectives; were available in full text; and were directly related to communication transformation, extension-service improvement, farmer decision-making, or the social implications of agricultural digitalization. Articles were excluded when they addressed AI only as a technical production tool without a communication or extension dimension, focused only on hardware design or mechanization, lacked sufficient methodological information, or represented duplicate publications.

Screening, Selection, and Quality Appraisal

The selection process followed the four PRISMA stages: identification, screening, eligibility assessment, and inclusion. The initial search identified 1,236 records from databases and 34 additional records from other sources. After 336 duplicates were removed, 934 records were screened by title and abstract. At this stage, 612 records were excluded because they were not related to extension or advisory communication, did not have a clear AI or digital focus, or were outside the agricultural and extension context.

A total of 322 full-text articles were then assessed for eligibility. Of these, 307 articles were excluded because they did not address communication transformation (n = 132), did not focus on agricultural extension or advisory services (n = 78), did not contain an AI or digital advisory component (n = 61), or did not meet the minimum quality criteria (n = 36). Ultimately, 15 studies met all inclusion criteria and were retained for the final thematic synthesis. Additional sources cited in this manuscript were used only as contextual or methodological references and were not counted as included studies.

Quality appraisal considered the clarity of research objectives, appropriateness of methods, relevance to the extension context, transparency of analysis, and consistency of findings. Empirical articles were assessed in terms of research design, sampling, analytical validity, and the alignment between findings and objectives. Review articles were assessed in terms of search strategy, selection criteria, synthesis method, and completeness of reporting.

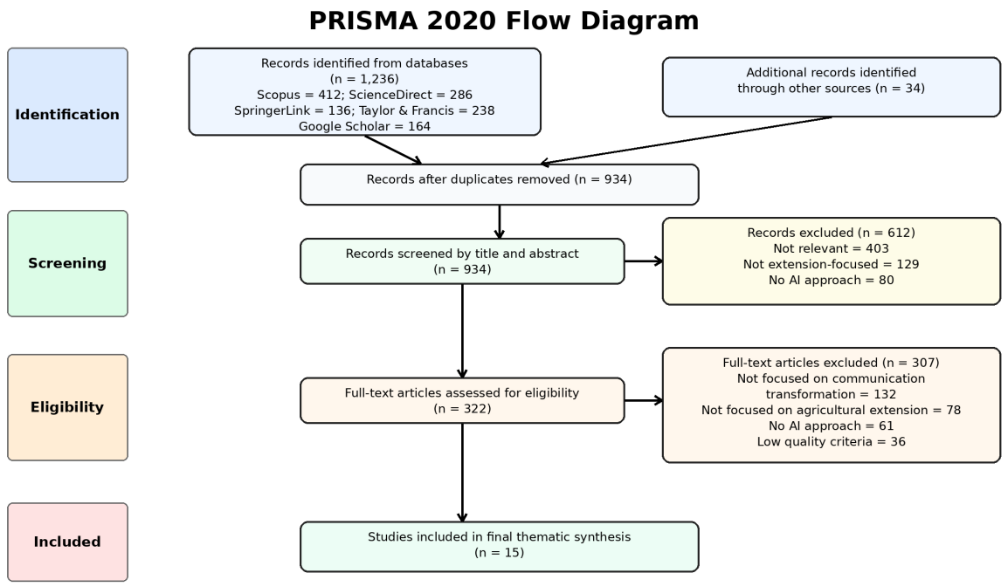

Figure 1. PRISMA flow diagram of study identification, screening, eligibility assessment, and inclusion.

Data Extraction and Thematic Synthesis

Data were extracted into a matrix for the 15 included studies. The matrix included author names, publication year, country or research context, study objectives, type of AI or digital technology, research design, extension context, principal findings, and implications for extension communication. This matrix facilitated cross-study comparison and the identification of conceptual patterns. Additional references cited elsewhere in the manuscript were used to frame the introduction and review method, but they were not included in the thematic evidence base.

The synthesis was conducted using a thematic synthesis approach. Initial themes were derived from the research objectives and refined inductively from the literature. Six themes were generated: the development of AI research in agricultural extension; the shift from linear communication to digital-participatory communication; the main forms of AI application in extension services; the benefits of AI for information dissemination and farmer decision-making; implementation challenges and social risks; and the Human-Centered AI Extension Communication Model.

RESULT AND DISCUSSION

Development of AI Studies in Agricultural Extension

The thematic synthesis of the 15 included studies shows that research on AI and digital extension has increased since 2020, in parallel with the accelerated digital transformation of agriculture. The most prominent topics include smart farming, precision agriculture, decision support systems, machine learning, predictive analytics, digital advisory platforms, and the use of mobile applications to support agricultural information services. These findings are consistent with literature showing that digital agriculture develops through the integration of data, sensors, algorithms, and interconnected communication platforms (Bacco et al., 2019; Klerkx et al., 2019; Rijswijk et al., 2021).

Geographically, research has been concentrated in countries with relatively strong digital-agriculture infrastructure, including India, China, the United States, the Netherlands, Australia, and several European countries. In developing-country contexts, the literature emphasizes the role of digital tools in expanding access to information, reducing search costs, and supporting smallholder decision-making (Fabregas et al., 2019; Van Campenhout et al., 2021). In Indonesia and similar contexts, future research needs to focus more strongly on digital literacy, institutional capacity, and the adaptation of AI-based extension to local socio-cultural conditions.

Synthesis of Included Studies

Table 1 presents all 15 studies included in the thematic synthesis. The evidence indicates that AI in agricultural extension is associated not only with technological efficiency but also with data governance, participatory communication, digital inclusion, farmer learning, and the changing social role of extension workers.

Table 1. Included studies on AI and digital transformation in agricultural extension communication

Reference	Focus	Technology/Concept	Main implication for extension communication
Bacco et al. (2019)	Smart farming research activities	IoT; data platforms; smart systems	Extension services need to translate sensor-based data into usable farmer advice.
Benos et al. (2021)	Machine learning in agriculture	Machine learning models	AI improves prediction and decision support when data quality is adequate.
Birner et al. (2021)	Digital revolution in agriculture	Supply-side digital innovation	Advisory systems are influenced by private platforms, institutional capacity, and governance.
Carolan (2020)	Automated agrifood futures	Robotics and AI	Automation may create distributive inequalities when social impacts are ignored.
Eastwood et al. (2019)	Socio-ethical challenges in smart farming	Responsible innovation	Technology adoption must address ethics, responsibility, and farmer participation.
Fabregas et al. (2019)	Digital agricultural advice	ICT-based advisory services	Digital tools can expand advice but require trust, relevance, and local adaptation.
Hackfort (2021)	Inequality in digital agriculture	Digital agriculture review	Digital extension can reproduce exclusion when access and power relations are unequal.
Holzinger et al. (2024)	Human-centered AI in smart farming	Human-centered AI; Agriculture 5.0	AI should augment human agency rather than replace human judgment in farming.
Ingram & Maye (2020)	Digitalisation of agricultural knowledge	Digital knowledge systems	Digitalisation changes how knowledge is produced, shared, and legitimized.
Javaid et al. (2023)	AI applications in agriculture	AI applications; smart farming	AI applications require contextual translation before they become useful extension messages.
Klerkx et al. (2019)	Digital agriculture and Agriculture 4.0	Smart farming; datafication	Digital agriculture changes knowledge flows and requires new advisory capacities.
Li et al. (2022)	Smartphone-based digital extension	Mobile digital advisory service	Smartphone-based extension can support sustainable technology adoption when services are accessible.
Rijswijk et al. (2021)	Digital transformation of rural areas	Socio-cyber-physical systems	Digital agriculture should integrate technical systems with social responsibility.
Van Campenhout et al. (2021)	ICT-based agricultural advice	Digital advisory experiment	ICT advisory services can improve access to information when advice is timely and trusted.
Xu et al. (2023)	Technology applications in extension	Extension technologies	Extension technologies reshape advisory interactions and farmer learning processes.

Source: Authors' synthesis based on the systematic literature review, 2026.

Transformation from Linear Communication to Digital-Participatory Communication

One of the main findings of this review is the shift from linear extension communication toward digital-participatory communication. In conventional models, extension workers are often positioned as the primary source of information, while farmers are treated as message recipients. In AI-based systems, information flows become more dynamic because data can originate from sensors, mobile applications, satellite imagery, weather services, production records, and farmer feedback.

This transformation positions farmers not only as information recipients but also as data producers and active users of digital recommendations. Extension communication becomes more real-time, interactive, and contextual. However, participation does not occur automatically. Farmer engagement still requires facilitation by extension workers so that AI recommendations can be understood, negotiated, and adapted to local experience. Thus, the role of extension workers shifts from message delivery to socio-digital mediation and learning facilitation (Ingram & Maye, 2020; Xu et al., 2023).

AI Applications in Extension Services

AI applications in agricultural extension can be grouped into four categories. First, machine learning is used to predict productivity, pest and disease risks, water requirements, and crop responses to production inputs (Benos et al., 2021). Second, decision support systems combine agronomic, climatic, economic, and market data to produce more specific technical recommendations for farmers.

Third, chatbots and virtual assistants provide digital consultation services that can be accessed at any time. Their functions include answering cultivation questions, providing preliminary diagnosis of pest and disease symptoms, delivering price information, presenting weather forecasts, and recommending fertilization practices. Fourth, smart farming platforms integrate IoT, sensors, weather data, and analytical dashboards to strengthen real-time communication among farmers, extension workers, researchers, and other stakeholders. These applications show that AI can expand extension capacity, but their quality depends on data validity, system design, local language, user literacy, and field validation mechanisms (Javaid et al., 2023; Li et al., 2022).

Benefits, Challenges, and Social Implications

The first benefit of AI is improved service efficiency. Digital systems enable extension services to reach more farmers in a shorter time, especially in regions with limited numbers of extension workers. The second benefit is information personalization. AI can process data on crop type, land conditions, weather, production history, and pest risk to generate recommendations that are more relevant to local needs. The third benefit is stronger data-driven decision-making, because extension workers and farmers can use predictive information to anticipate risk before losses occur. The fourth benefit is the acceleration of innovation adoption, particularly when information is accessible, relevant, and accompanied by facilitation (Fabregas et al., 2019; Van Campenhout et al., 2021).

Despite its potential, AI implementation faces several challenges. The digital divide remains a major barrier, particularly for smallholder farmers with limited access to devices, internet connectivity, data costs, and digital skills. If poorly governed, digital extension may widen inequality by benefiting farmers who already possess stronger technological resources (Hackfort, 2021). A second challenge concerns data quality and algorithmic bias. AI recommendations built on unrepresentative data may generate advice that does not fit local conditions. A third challenge is transparency and trust. Farmers and extension workers need to understand the limitations of AI, the rationale behind recommendations, and the possibility of system error.

These challenges imply that AI-based extension transformation must be guided by fair and responsible governance. AI should be designed as a system that is explainable, supervisable, correctable, and sensitive to the socio-cultural diversity of farming communities. Principles of responsible innovation and human-centered AI are essential so that digitalization improves not only efficiency but also farmer autonomy, trust, and community sustainability (Eastwood et al., 2019; Holzinger et al., 2024).

Human-Centered AI Extension Communication Model

Based on the thematic synthesis, this study formulates a Human-Centered AI Extension Communication Model as a conceptual framework for balancing technological innovation with participatory and humanistic extension communication. The model positions AI as an augmenting tool that expands communication capacity, not as a replacement for extension workers. Its primary orientation is to improve the quality of farmer decision-making through the integration of data analytics, human facilitation, local knowledge, and ethical governance.

The model consists of six components. First, an AI-based information system transforms agricultural data into usable recommendations. Second, human facilitation by extension workers enables AI recommendations to be explained, validated, and contextualized. Third, participatory communication supports two-way dialogue, allowing farmers to provide feedback and participate in decision-making. Fourth, local knowledge integration recognizes farmers experience, values, and practices. Fifth, ethical data governance ensures data protection, algorithmic transparency, and accountability of recommendations. Sixth, a sustainable digital ecosystem provides infrastructure, digital literacy, institutional support, and policies that maintain service continuity.

Through this model, the success of AI in extension is measured not only by the speed of information delivery but also by the capacity of the system to strengthen social relationships, build trust, enhance farmer capabilities, and support sustainable agricultural decisions. AI-based extension should therefore be understood as a process of knowledge co-production among intelligent systems, extension workers, and farmers.

CONCLUSION

This study concludes that AI has transformed agricultural extension communication from a conventional, linear model into a data-driven and digital-participatory communication system. Technologies such as machine learning, decision support systems, predictive analytics, chatbots, virtual assistants, and smart farming platforms can improve the speed of information dissemination, service personalization, and the quality of farmer decision-making. However, AI implementation also creates challenges related to the digital divide, limited technological literacy, inadequate infrastructure, uneven data quality, algorithmic bias, weak system transparency, and the potential reduction of social relationships in extension. Therefore, AI should be developed through a human-centered approach that positions extension workers as socio-digital facilitators. The Human-Centered AI Extension Communication Model proposed in this study emphasizes the integration of AI-based information systems, human facilitation, participatory communication, local knowledge, ethical data governance, and a sustainable digital ecosystem. Future policy should strengthen rural digital infrastructure, farmer digital literacy, transparent data governance, and the institutional capacity of extension workers to use AI without losing the participatory and humanistic foundations of agricultural extension.

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