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ARTIFICIAL INTELLIGENCE FOR ORGANIC FARMING EXTENSION: OPPORTUNITIES, CHALLENGES, AND ETHICAL CONCERNS

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ABSTRACT

Artificial intelligence (AI) is increasingly positioned as a technology capable of relieving the structural pressures facing agricultural extension systems, including shortages of trained advisors, rising agronomic complexity, and climate variability (Aker, 2011; Neeraja *et al*., 2026). Organic farming, which depends on ecological knowledge, site-specific soil and pest management, and certification integrity rather than synthetic inputs, presents both distinct opportunities and distinct constraints for AI-enabled extension (Brumă *et al*., 2023). This review synthesises peer-reviewed literature published between 2011 and 2026 on AI applications for agricultural and organic-farming extension, organising the evidence around three themes: opportunities, challenges, and ethical concerns. The review finds that machine learning and deep learning models support soil health monitoring, pest and disease diagnostics, and predictive decision support relevant to organic systems (Morellos *et al*., 2016; Upadhyay *et al*., 2025), while conversational and multilingual advisory platforms are extending reach to smallholder and low-literacy populations (Li *et al*., 2022; Javaid *et al*., 2023). At the same time, the literature consistently documents a digital divide, weak data governance, high technology costs, and limited farmer trust as persistent barriers to equitable adoption (Gardezi *et al*., 2023; Klerkx *et al*., 2019). Ethical concerns center on data privacy and ownership, algorithmic bias, accountability, and the risk that AI-driven extension could deepen inequities between large agribusinesses and smallholder or organic producers (Dara *et al*., 2022; Saha *et al*., 2026). The review concludes that realising the benefits of AI for organic farming extension requires farmer-centred design, transparent governance, and hybrid human–AI advisory models.

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INTRODUCTION

Agricultural extension services worldwide face a structural crisis marked by shortages of trained advisors, declining public investment, and growing agronomic complexity linked to climate change (Neeraja *et al*., 2026). Traditional extension models, which rely on face-to-face visits, radio broadcasts, and printed materials, struggle to scale to the number and diversity of farmers who require timely, location-specific advice (Aker, 2011). Artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), natural language processing (NLP), and the Internet of Things (IoT), has emerged as a prominent technological response to these constraints, offering scalable, personalised, and continuously improving advisory capabilities (Neeraja *et al*., 2026; Javaid *et al*., 2023). Organic farming occupies a distinctive position within this transformation. Organic systems prioritise ecological balance, natural pest and nutrient management, and the avoidance of synthetic agrochemicals, which places a premium on precise, real-time information about soil biology, pest pressure, and weather rather than blanket chemical prescriptions (Morellos *et al*., 2016; Brumă *et al*., 2023). Global organic farmland has expanded substantially over the past decade, yet productivity gaps relative to conventional agriculture persist, creating demand for decision-support tools that can help organic producers optimise yields without compromising certification standards (Brumă *et al*., 2023). AI-enabled sensors, predictive models, and advisory chatbots have been proposed as tools to help close this gap by enabling site-specific, low-input management appropriate to organic protocols (Javaid *et al*., 2023; Akkem *et al*., 2023). At the same time, the introduction of AI into extension services raises questions that extend beyond technical performance. Scholars have highlighted a widening digital divide between well-resourced agribusinesses and smallholder or organic farmers who often lack reliable connectivity, capital, and digital literacy (Gardezi *et al*., 2023; Klerkx *et al*., 2019).

Ethical concerns regarding data ownership, algorithmic transparency, and accountability have also been raised as AI systems collect and analyse increasingly detailed farm-level data (Dara *et al*., 2022). This review therefore synthesises the literature on AI in agricultural and organic farming extension around three organising themes: the opportunities AI creates for organic extension, the practical challenges limiting its adoption, and the ethical concerns that accompany its diffusion. The remainder of this review is organised as follows. Section 2 outlines the review methodology and scope. Section 3 examines opportunities across five domains of AI application relevant to organic extension. Section 4 discusses adoption challenges. Section 5 addresses ethical concerns in six categories. Section 6 discusses pathways toward responsible AI-enabled organic extension, and Section 7 concludes.

Review Methodology and Scope

This review draws on peer-reviewed journal articles, systematic literature reviews, and bibliometric analyses concerning AI applications in agricultural extension, precision agriculture, and organic farming, published predominantly between 2011 and 2026. Sources were identified through searches of academic databases and publisher platforms, following an approach consistent with recent systematic reviews of AI in agricultural extension communication that used PRISMA-style screening of studies indexed in Scopus, ScienceDirect, SpringerLink, and Google Scholar (see the systematic review methodology reported for AI-era extension communication research). Bibliometric analyses of Scopus-indexed literature on AI in agricultural extension between 2010 and 2025 were also consulted to characterise overall research trends, authorship patterns, and thematic clusters (Saha *et al*., 2026). The review privileges empirical and peer-reviewed sources over general commentary, and organises findings thematically rather than chronologically, in keeping with conventions for narrative reviews in the agricultural sciences.

Opportunities: AI Applications in Organic Farming Extension

Precision Monitoring of Soil Health and Organic Inputs: Soil health monitoring is central to organic farming because organic systems depend on biological soil fertility rather than synthetic fertilisers. Machine learning models trained on visible and near-infrared (VIS-NIR) spectroscopy data have been shown to predict soil total nitrogen, organic carbon, and moisture content with good accuracy, offering organic farmers a rapid, non-destructive means of assessing soil condition (Morellos *et al*., 2016). Smart soil sensors combined with AI algorithms can continuously track fertility, nutrient levels, and microbial activity, allowing precision soil management consistent with organic protocols. IoT-enabled AI systems that integrate soil and weather data have similarly been used to generate real-time crop recommendations in precision agriculture contexts (Sharafat *et al*., 2025), while groundwater-quality forecasting models built on machine learning support more efficient, organic-compatible irrigation decisions (El-Bilali *et al*., 2021).

AI-Based Pest and Disease Diagnostics: Because organic systems restrict synthetic pesticide use, early and accurate pest and disease detection is especially valuable for reducing crop losses through non-chemical intervention. Convolutional neural networks (CNNs) and related deep learning architectures have achieved classification accuracies frequently exceeding 95% in identifying crop diseases from leaf images, with segmentation networks such as Mask R-CNN and U-Net enabling precise quantification of infection severity (Upadhyay *et al*., 2025). Lightweight, edge-deployable fusion models combining architectures such as MobileNetV2 and EfficientNetB0 have demonstrated real-time pest and disease detection on low-power devices, including smartphones and farm drones, without requiring cloud connectivity (Bilal *et al*., 2025). Unmanned aerial vehicles integrated with deep learning have likewise been applied to detect crop diseases and pests from remote-sensing imagery at scale (Zhu *et al*., 2024), while drone-based systems using edge computing and lightweight CNNs support real-time field-level detection in resource-constrained settings (Ahmed *et al*., 2022). Such tools can substitute for indiscriminate spraying, directly supporting organic and low-input pest management goals (Upadhyay *et al*., 2025).

Digital Advisory Systems, Chatbots, and NLP-Based Extension: Conversational AI and natural language processing tools are being deployed to extend advisory reach into multilingual, low-literacy, and remote farming communities, functioning as scalable alternatives to human extension officers where such officers are scarce (Javaid *et al*., 2023). Studies of AI-powered decision support chatbots report that they can integrate weather forecasts, pest and disease alerts, and market information from trusted institutional sources to support farmer decision-making (referenced in AI-chatbot decision-support literature for sustainable agriculture). Evidence from multilingual advisory deployments indicates that voice-enabled, native-language chatbots meaningfully improve usability among farmers who would otherwise be excluded by English-only or text-only interfaces, with reported gains in self-reported quality of life and decision confidence among both women and men users in India, Kenya, and Nigeria. Smartphone-based digital extension services have also been shown to positively influence farmers' adoption of sustainable agricultural technologies in China (Li *et al*., 2022), suggesting that mobile and conversational channels can complement organic-specific advisory content.

Predictive Analytics for Yield, Weather, and Resource Optimisation: Predictive modelling using machine learning and deep learning supports yield forecasting, crop-rotation planning, and climate-adaptive scheduling, all of which are relevant to organic systems that must compensate for the absence of synthetic yield boosters through better timing and input efficiency (Javaid *et al*., 2023; Akkem *et al*., 2023). Time-series analytical techniques applied to historical yield, weather, irrigation, and fertilisation data have been used to forecast production and support water-management decisions in smart farming contexts (systematic review of machine learning and deep learning in smart farming). Data-driven AI applications for precision agriculture more broadly have been documented to improve resource-use efficiency, with reported improvements in irrigation efficiency attributed to sensor-based interventions in digital agriculture reports (Linaza *et al*., 2021).

IoT–AI Integration for Organic Certification and Traceability: Because organic certification requires verifiable adherence to input restrictions and cultivation standards, AI-IoT integration offers a mechanism for continuous, auditable monitoring of organic parameters such as soil pH, moisture, and temperature, transmitted via low-power wide-area networks to farmers and, potentially, to certifying bodies (documented in reviews of AI and IoT integration in precision agriculture). Bibliometric analysis of the organic farming and certification literature indicates a growing research interest in linking digital monitoring tools with voluntary certification schemes, reflecting the sector's need for credible, low-cost verification mechanisms (Brumă *et al*., 2023). AI-assisted crop-planning models that integrate soil health records, historical yield data, and climate forecasts have also been piloted with organic producers, including organic cotton farmers, to inform sowing decisions and reduce crop-failure risk.

Challenges in AI-Enabled Organic Farming Extension

Digital Divide and Infrastructure Constraints: A consistent finding across the literature is that AI adoption in agriculture remains highly uneven, with smallholder and organic farmers in developing regions at greatest risk of exclusion. Reliable internet connectivity, satellite systems, cloud platforms, and stable electricity, all of which underpin continuous data collection and AI-driven decision-making, are far more available in high-income countries than in the developing-country contexts where much organic smallholder production occurs. Structural barriers including cultural norms and limited female participation further reinforce this digital divide, and data on digital literacy remain scarce, compounding the risk that AI adoption could

deepen rather than reduce agricultural inequality (see the reviewed report on AI use in food and agriculture systems).

Data Quality, Availability, and Interoperability: AI models are only as reliable as the data used to train them, and agricultural data in organic and smallholder contexts are frequently sparse, inconsistently labelled, or unrepresentative of local agroecological conditions. Reviews of deep learning for plant disease and pest detection note that many models depend on large, well-labelled image datasets that are costly to assemble and may not generalise well across crop varieties, growing environments, or organic-specific pest and disease profiles (Upadhyay *et al*., 2025). Edge-deployment studies similarly find that model complexity and the need for real-time inference in low-resource field settings remain unresolved for many pest and disease detection systems (Bilal *et al*., 2025).

Cost, Technical Complexity, and Farmer Trust: Even where infrastructure exists, AI-driven technologies such as robotic harvesters, autonomous equipment, and advanced analytics require substantial financial investment that smallholder and organic farms often cannot afford, contributing to a divide between large agribusinesses and family-run operations (Gardezi *et al*., 2023). Some farmers remain reluctant to shift toward AI-based decision-making, particularly where they have farmed successfully without such tools, and trust in AI-generated recommendations is not automatic; it is shaped by how transparently AI providers communicate the basis for recommendations and how fairly the resulting benefits and risks are distributed (Gardezi *et al*., 2023). Building farmer trust has therefore been identified as a prerequisite for meaningful adoption, requiring model transparency, explainability, and clear allocation of responsibility for AI-informed decisions (Gardezi *et al*., 2023).

Institutional and Policy Gaps: Bibliometric evidence indicates that while research on AI in agricultural extension has grown rapidly since 2016, with a peak around 2022, thematic emphasis has shifted toward advanced applications such as machine learning, deep learning, IoT, and robotics, often at the expense of continued attention to digital infrastructure and governance foundations (Saha *et al*., 2026). Structural constraints including inadequate public extension infrastructure, data governance deficits, and algorithmic opacity continue to constrain equitable deployment of AI-based extension at scale (Neeraja *et al*., 2026). Although some countries are developing national AI frameworks, these frameworks mainly address AI in general terms and rarely address agriculture-specific needs, leaving a policy gap for organic and smallholder-specific extension contexts.

Ethical Concerns

Data Privacy, Ownership, and Governance: Data privacy, ownership, and security represent a primary ethical concern associated with AI adoption in agriculture. AI systems rely heavily on large datasets collected from farmers, satellites, sensors, and other digital tools, yet clear policies on who owns and controls this data are often absent (see the reviewed ScienceDirect analysis of AI ethics in agriculture). In developed-country contexts, large agribusiness firms may analyse datasets derived from farmers' fields while the farmers themselves have limited access to the resulting insights, a pattern that risks being replicated or intensified in developing-country organic farming contexts where data governance is weaker still. Weak data governance is described as most pronounced in developing regions, where farmers often have little control over how their data is collected, used, or monetised.

Algorithmic Bias, Fairness, and Transparency: Ethical frameworks for AI in agriculture identify fairness, transparency, accountability, sustainability, privacy, and robustness as six core categories of concern requiring proactive management by agricultural technology providers and policymakers (Dara *et al*., 2022). Algorithmic bias may disproportionately disadvantage certain groups of farmers, including women, smallholders, and organic producers whose practices and data may be underrepresented in training datasets originally developed for large-scale conventional agriculture. Recommendations to address this include adopting established ethical AI frameworks and explainability tools so that AI-driven agricultural recommendations remain interpretable and less prone to embedding structural bias (Dara *et al*., 2022).

Accountability and Explainability: A lack of clarity regarding who is accountable when an AI-informed recommendation leads to crop loss, animal harm, or environmental damage is repeatedly cited as an unresolved ethical issue in digital agriculture (Dara *et al*., 2022). Model transparency and explainability are proposed as mechanisms to help farmers understand the reasoning behind AI recommendations, which in turn supports meaningful accountability and informed consent when farmers choose to follow or reject AI-generated advice (Gardezi *et al*., 2023).

Equity, Gender, and Inclusion: Structural inequalities in digital access, including gendered disparities, are identified as a persistent equity concern in AI-enabled extension (Neeraja *et al*., 2026). Evidence from chatbot-based advisory deployments suggests that when interface design accounts for gender-differentiated needs and constraints, including differential access to independent income for data costs, engagement among women farmers can match or exceed that of men, indicating that inclusive design choices can partially offset structural barriers rather than eliminate them entirely. Nonetheless, reviewers caution that data on digital literacy disaggregated by gender remain scarce, limiting the ability to monitor whether AI-enabled extension is narrowing or widening gender gaps in agricultural knowledge access.

Environmental and Animal Welfare Ethics: Beyond human-centred concerns, ethical frameworks for digital agriculture also address environmental sustainability and animal welfare, noting that robotic technologies such as automated milking systems can raise welfare concerns if not carefully designed and tested (Dara *et al*., 2022). For organic farming specifically, where ecological integrity and animal welfare are often embedded in certification standards, ensuring that AI and robotic tools are tested and incentivised to protect these outcomes, rather than solely optimising for yield or cost efficiency, has been highlighted as a governance priority (Dara *et al*., 2022).

DISCUSSION

Toward Responsible AI-Enabled Organic Extension: Across the literature reviewed, a recurring conclusion is that hybrid systems, in which AI supplements rather than replaces human extension expertise, are likely to be the most successful and inclusive model for future advisory services (Saha *et al*., 2026). Such hybrid models can combine the scalability of AI-driven diagnostics and predictive analytics with the contextual judgement, trust, and accountability that human extension officers provide, which is particularly important in organic systems where management decisions are highly context-dependent (Neeraja *et al*., 2026). Several concrete pathways emerge from the reviewed studies. First, AI developers are encouraged to design farmer-centred solutions that are affordable, low-bandwidth, and adaptable to diverse organic farming contexts, rather than assuming infrastructure and capital levels typical of large commercial farms (Gardezi *et al*., 2023). Second, policymakers and agricultural technology providers are encouraged to establish clear data governance frameworks that specify data ownership, consent, and benefit-sharing arrangements before large-scale data collection from organic and smallholder farms proceeds (Dara *et al*., 2022). Third, model transparency and explainability should be prioritised so that organic farmers can understand and evaluate AI-generated recommendations against their own ecological knowledge, supporting rather than undermining farmer agency (Gardezi *et al*., 2023). Finally, continued investment in multilingual, voice-enabled, and culturally adapted advisory interfaces is needed to extend the reach of AI-enabled extension to the smallholder and organic farming communities that stand to benefit most, yet are currently least well served (Li *et al*., 2022).

CONCLUSION

This review has examined the opportunities, challenges, and ethical concerns associated with AI-enabled extension for organic farming. The evidence indicates that AI technologies, including machine learning-based soil and pest diagnostics, predictive analytics, and conversational advisory platforms, offer genuine potential to support the precision, low-input management practices that organic farming requires (Morellos *et al*., 2016; Upadhyay *et al*., 2025; Javaid *et al*., 2023). However, this potential is tempered by persistent challenges related to the digital divide, data quality, cost, and institutional readiness (Gardezi *et al*., 2023; Klerkx *et al*., 2019), as well as by ethical concerns spanning data privacy, algorithmic bias, accountability, and equity (Dara *et al*., 2022). Realising the benefits of AI for organic farming extension will depend less on the sophistication of the underlying algorithms and more on whether AI systems are designed, governed, and deployed in ways that are transparent, affordable, and responsive to the specific ecological and socio-economic realities of organic producers.

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