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Human-in-the-Loop Intelligence in Smart Farming: A Conceptual Framework for Farmer-Centered AI Decision Support

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Abstract

Artificial intelligence is increasingly embedded in smart farming through decision-support systems that integrate sensor data, remote sensing, machinery data, farm records, and predictive analytics. Yet agricultural decision-making cannot be reduced to automated recommendations because farm decisions are shaped by agronomic uncertainty, local field conditions, economic constraints, environmental goals, labor availability, machinery limitations, farmer experience, advisory relationships, and risk preferences. This conceptual framework article develops a farmer-centered account of human-in-the-loop intelligence for AI decision support in smart farming. The framework positions AI not as a substitute for farmer judgment but as one component of an iterative socio-technical decision process. It emphasizes farmer judgment, experiential knowledge, contextual validation, explainability, uncertainty communication, human oversight, trust calibration, advisor mediation, feedback, accountability, and adaptive decision-making. The article argues that human-in-the-loop intelligence is more than human approval of algorithmic outputs; it involves interpretation, questioning, correction, practical adaptation, and responsibility for situated decisions. By integrating agricultural AI, precision agriculture decision support, farmer knowledge, responsible innovation, and human-centered design perspectives, the manuscript contributes a structured conceptual basis for designing smart farming systems that preserve farmer agency while improving the practical relevance, transparency, and accountability of AI-supported decisions.

Keywords Precision agriculture, Explainable AI, Smart farming, Digital agriculture, Farmer-centered AI, Decision support systems

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Introduction

AI decision support has become a central feature of smart farming because agricultural data are now produced across sensors, machinery, remote sensing systems, farm-management platforms, supply-chain infrastructures, and digital advisory services. These data streams can support more timely agronomic interpretation, but they also create complex dependencies among data quality, platform interoperability, analytics, ownership, and decision responsibility. Smart farming should therefore be understood as a data-intensive decision ecosystem rather than as a simple transfer of algorithmic outputs to farmers [1].

The agricultural AI literature increasingly shows that digital agriculture is not only a technical transformation but also a socio-technical reorganization of farming knowledge, advisory work, platform power, labor arrangements, and institutional relationships. Farmers, advisors, researchers, technology providers, cooperatives, and policymakers participate in

shaping how digital tools are developed, trusted, interpreted, and used. Treating AI decision support as a purely technical intervention risks overlooking the social and organizational conditions that determine whether recommendations are understandable, usable, accountable, and compatible with farm realities [2].

Decision support in agriculture has long depended on the alignment between technical outputs and the practical conditions of decision-making. A successful agricultural decision-support system must connect with users' actual decisions, timing, information needs, confidence thresholds, advisory networks, and operational constraints. This means that AI-supported decisions should not be evaluated only by whether a model can generate a prediction, classification, alert, or recommendation; they should also be evaluated by whether the recommendation can be interpreted, questioned, adapted, and responsibly integrated into farm management [3].

This article develops a conceptual framework for human-in-the-loop intelligence in farmer-centered AI decision support for smart farming. The aim is to explain how farmers, advisors, AI models, sensor systems, machinery, digital platforms, contextual knowledge, and feedback loops can interact to support agronomic decision-making while preserving human agency and accountability. The article is grounded in the view that digital agriculture requires transdisciplinary attention to governance, practical implementation, unintended consequences, business models, skills, and socio-ethical responsibilities [4].

Human-in-the-Loop Intelligence in Agriculture

Human-in-the-loop intelligence in agriculture refers to an iterative decision process in which AI-generated analysis is interpreted, validated, questioned, adapted, and acted upon by farmers and supporting actors. It differs from fully automated AI decision-making because the farmer remains an active decision-maker rather than a passive endpoint of prediction. It also differs from simple human approval because the human role includes contextual reasoning, practical judgment, oversight, correction, feedback, and responsibility for consequences. Human-centered AI in smart farming therefore positions intelligence as a shared human–AI capability rather than as a property of the algorithm alone [5].

In smart farming, human-in-the-loop intelligence must connect data acquisition, analytical processing, platform delivery, decision interpretation, and farm action. Agriculture 4.0 decision-support systems may include sensor networks, data platforms, predictive models, alert systems, dashboards, and farm-management interfaces, but these components only become decision support when they are connected to specific decisions such as irrigation timing, input application, crop monitoring, machinery scheduling, pest management, and risk response. The human-in-the-loop perspective makes this connection explicit by asking how a recommendation is produced, interpreted, reviewed, and translated into action [6].

Machine-learning applications in agriculture can support tasks such as classification, prediction, monitoring, detection, and optimization, yet model outputs remain partial representations of farm conditions. A prediction about crop stress, disease risk, yield potential, or input requirement may be useful, but it does not automatically resolve the decision because the farmer must consider field access, weather variability, local experience, labor availability, machinery readiness, economic exposure, and acceptable risk. Human-in-the-loop intelligence therefore treats AI outputs as decision resources that require contextual interpretation rather than as complete decisions [7].

A farmer-centered human-in-the-loop system should support interpretation before action, feedback after action, and learning across repeated decision cycles. This means that explainable recommendations, uncertainty information, farmer annotations, advisor input, outcome observations, and data-quality checks should be part of the system design. In this view, AI decision support is not a one-way pipeline from data to prescription; it is a socio-technical loop in which farmers and advisors help determine whether an output is relevant, credible, actionable, and aligned with farm goals [5].

Farmer Judgment and Experiential Knowledge

Farmer judgment is a critical knowledge source in smart farming because many agricultural decisions are situated in local histories, field-specific patterns, tacit observations, and practical constraints that may not be fully represented in digital data. Farmers interpret soil behavior, drainage patterns, crop appearance, pest pressure, machinery limitations, and seasonal anomalies through experience accumulated across repeated cycles of observation and action. Research on agricultural decision-support systems shows that farmers' situated knowledge shapes how digital tools are understood and used in practice [8].

Digital tools do not enter neutral decision spaces; they are interpreted within farm routines, spatial practices, advisory relationships, and existing knowledge systems. Farmers may accept, modify, delay, ignore, or reinterpret digital recommendations depending on how they fit field conditions, operational timing, confidence in the data, and previous experience with similar situations. This process of user interpretation and re-scripting shows why AI decision support should be designed for practical negotiation rather than simple compliance with a model-generated recommendation [9].

Experiential knowledge also matters because digitalization changes how agricultural knowledge is produced, circulated, and valued. AI systems may privilege data that are machine-readable, standardized, and platform-compatible, while farmer knowledge often includes local nuance, historical memory, embodied observation, and informal comparison across seasons. Farmer-centered AI must therefore avoid treating experiential knowledge as inferior to algorithmic knowledge and instead create mechanisms through which farmer observations, corrections, and contextual explanations can influence decision interpretation [10].

The complementarity between farmer knowledge and AI analysis is central to human-in-the-loop intelligence. AI can process large volumes of sensor, machinery, remote-sensing, and record-based data, while farmers can assess whether the resulting recommendation is realistic under current field, labor, weather, financial, and machinery conditions. The decision value of AI therefore depends on how well it supports farmer reasoning, not on whether it displaces farmer reasoning. A farmer-centered system should make space for judgment, disagreement, contextual adjustment, and decision responsibility [8].

AI Decision Support and Human Oversight

AI decision-support systems in smart farming may contribute predictive analytics, crop monitoring, irrigation scheduling support, pest and disease detection, yield forecasting, input-use recommendations, and risk alerts. However, adoption barriers show that the usefulness of machine-learning decision support depends on more than technical capability. Concerns about cost, black-box recommendations, data ownership, privacy, training, workforce capacity, and trust in existing advisors can limit whether farmers accept and use AI-based tools. Human oversight is therefore required to connect AI outputs to farmer confidence, advisory support, and practical decision contexts [11].

Human oversight is also necessary because smart farming raises ethical questions about autonomy, responsibility, data control, surveillance, power asymmetries, and the distribution of benefits and risks. If an AI recommendation contributes to an inappropriate input application, missed disease response, irrigation error, or financial loss, responsibility cannot be assigned only to the model. Farmer-centered AI decision support must clarify who controls data, who interprets recommendations, who can contest outputs, who is accountable for system design, and how decision responsibility is shared without erasing farmer agency [12].

Responsible smart farming requires participation, anticipation, reflexivity, and responsiveness in the design and use of digital systems. Human oversight should therefore be understood as an active governance function rather than a final checkbox after automation has already shaped the decision pathway. Farmers and advisors need opportunities to understand the assumptions behind recommendations, express concerns, report errors, question uncertainty, and influence future tool development. This broader understanding of oversight supports responsible innovation by keeping agricultural AI aligned with affected users and contexts [13].

Table 1 summarises the main human oversight functions required for farmer-centered AI decision support in smart farming.

Human oversight function	Core meaning	AI system role	Farmer or advisor role	Decision-support relevance	Risk if absent	Risk if present
Contextual validation	Checking whether an AI output fits local farm conditions	Generates recommendation based on available data and model assumptions	Compares recommendation with field history, crop condition, machinery access, weather expectation, and operational feasibility	Prevents direct translation of model output into unsuitable action	Recommendation may be applied despite local mismatch	Over-reliance on AI may propagate local biases
Uncertainty interpretation	Understanding confidence limits and possible error sources	Communicates uncertainty, data gaps, and model limitations	Decides whether uncertainty is acceptable for the decision at hand	Supports cautious use of AI in high-risk decisions	Farmer may over-trust a recommendation that is uncertain or incomplete	Over-reliance on AI may lead to poor decisions in high-risk situations
Recommendation review	Examining the reasoning and practical implications of a recommendation	Provides explanation, supporting evidence, and alternative options	Reviews whether the recommendation is agronomically sensible and operationally possible	Enables informed acceptance, modification, or rejection	AI output may be followed without understanding its basis	Over-reliance on AI may lead to poor decisions in high-risk situations
Risk assessment	Identifying agronomic, economic, environmental, and operational risks	Flags predicted risks and possible consequences	Weights risks against farm goals, budget, timing, labor, and sustainability priorities	Connects prediction to decision consequences	Tool may optimize one target while creating unacceptable side effects	Over-reliance on AI may lead to poor decisions in high-risk situations

Farmer feedback	Returning farmer observations, corrections, and decisions to the system	Receives feedback, annotations, action logs, and outcome observations	Reports local observations, overrides, reasons for changes, and observed outcomes	Improves relevance of future recommendations and records decision rationale	System remains disconnected from user experience and observed field outcomes	Fe a vo e
Advisor mediation	Supporting interpretation through trusted human intermediaries	Shares outputs with advisors or extension services	Helps translate AI outputs into farm-specific options	Strengthens practical sensemaking and reduces isolation of the farmer	Farmers may face complex recommendations without adequate support	A d co
Accountability	Clarifying responsibility for data, recommendations, decisions, and system limits	Logs data sources, model version, recommendation history, and system warnings	Retains decision authority while identifying provider and advisory responsibilities	Makes decision pathways auditable and contestable	Responsibility may become unclear after harmful or costly outcomes	A
Decision adaptation	Modifying recommendations to fit changing conditions and learning over time	Updates recommendations when new data, feedback, or outcomes become available	Adjusts actions based on observation, experience, and changing constraints	Supports dynamic rather than one-off decision support	Recommendations may remain static despite changing farm conditions	A u co

Trust, Feedback, and Decision Adaptation

Trust in farmer-centered AI decision support should be understood as calibrated reliance rather than unconditional confidence in algorithmic output. Farmers may evaluate AI recommendations through perceived usefulness, uncertainty, fairness, transparency, privacy, provider responsibility, and compatibility with existing advisory relationships. In this sense, trust is not produced simply by presenting a recommendation; it emerges when farmers can understand why the system produced an output, what data informed it, what limitations remain, and whether the recommendation fits their agronomic and practical context [15].

Feedback is also shaped by the quality and governance of agricultural data-sharing relationships. AI decision-support systems often depend on data generated across farms, platforms, machinery, sensors, advisory services, and external datasets, but farmers may hesitate to provide feedback or share data when data ownership, privacy, access rights, reuse conditions, and provider accountability are unclear. Human-in-the-loop intelligence therefore requires transparent data-sharing arrangements that make feedback meaningful, safe, and practically valuable for farmers and advisors [16].

Decision adaptation occurs when AI recommendations are revised through farmer interpretation, advisor mediation, observed outcomes, new data, and changing farm constraints. A recommendation may be appropriate at the time it is generated but become less suitable after rainfall, pest movement, machinery failure, labor shortage, market change, or

field observation. Digital agriculture adoption is shaped by trust, perceived relevance, usability, and institutional conditions, which means that adaptive decision support should respond to farmers’ changing decision contexts rather than assuming stable acceptance of a tool [17].

Figure 1 illustrates the iterative human-in-the-loop decision cycle through which AI recommendations, farmer judgment, contextual feedback, trust calibration, and decision adaptation interact in smart farming.

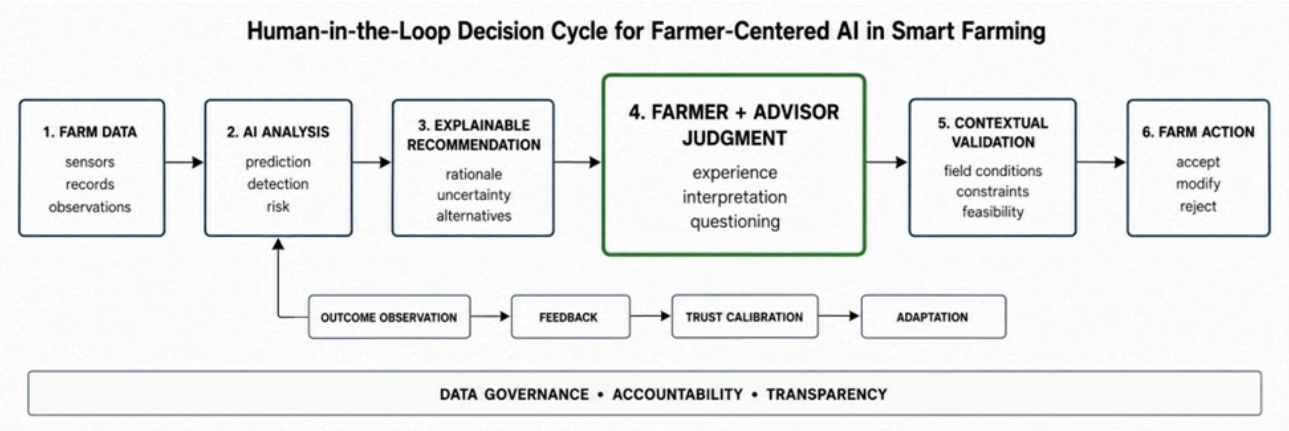


Figure 1. Human-in-the-Loop Decision Cycle for Farmer-Centered AI in Smart Farming. The figure shows an iterative cycle in which agricultural data are processed by AI decision-support systems, interpreted through explainable recommendations, evaluated by farmers and advisors using contextual knowledge, translated into farm decisions, and returned as feedback for monitoring, adaptation, trust calibration, and continuous learning.

Alt-text description: A circular decision-cycle diagram showing agricultural data flowing into an AI decision-support system, producing explainable recommendations that are reviewed by farmers and advisors. Farmer judgment, contextual knowledge, uncertainty interpretation, decision action, outcome observation, feedback, trust calibration, and model adaptation form a continuous loop.

When recommendations are explainable, contestable, and responsive to feedback, farmers can use AI as a decision-support partner while retaining responsibility for situated action [15].

Farmer-Centered Design Requirements

Farmer-centered AI decision support should begin with decision-context analysis rather than with model capability alone. Designers need to understand who will use the system, what decision is being supported, when the recommendation is needed, what information the farmer already has, how the decision is normally made, and what constraints affect implementation. Stakeholder involvement is therefore a design requirement because agricultural decision-support systems are more likely to be useful when farmers, advisors, and other users shape the problem definition, interface, terminology, timing, and decision workflow [18].

Advisory integration is especially important because many farmers interpret complex digital information through relationships with consultants, extension agents, cooperatives, agronomists, machinery specialists, and platform support staff. Smart farming tools should therefore support shared interpretation rather than isolating the farmer in front of a dashboard. Farm advisory services can help translate digital outputs into practical sensemaking by connecting model outputs with local agronomy, farm goals, operational feasibility, and risk tolerance [19].

Farmer-centered AI should also be embedded in agricultural knowledge and advice networks rather than designed as a standalone technical product. Digitalization changes how advice is produced, circulated, commercialized, and trusted,

which means that system design must account for advisor roles, peer learning, platform governance, knowledge intermediaries, and institutional relationships. A human-in-the-loop framework should therefore include advisor mediation, collaborative interpretation, and feedback channels that connect individual decisions to wider knowledge systems [20].

Explainability is another core requirement, but it should not be reduced to a visual feature or a generic model explanation. For farmers, explanation must support practical understanding, uncertainty interpretation, questioning, comparison with local knowledge, and accountability for recommendations. Explainable AI design can contribute to trustworthy AI when explanations are meaningful to users, connected to the decision context, and able to support appropriate reliance rather than blind acceptance [21].

Proposed Conceptual Framework

The proposed framework begins with data lifecycle governance because AI decision support depends on the acquisition, processing, storage, sharing, interpretation, and reuse of agricultural data. Sensor and machinery data, remote sensing and geospatial data, farm-management records, weather information, soil data, and farmer observations all require quality assessment before they can responsibly inform recommendations. A farmer-centered framework must therefore include data provenance, data-quality warnings, privacy controls, ownership clarity, interoperability, and transparent data-use conditions as foundational elements [22].

The second component is the AI recommendation layer, where machine-learning methods and other analytical tools transform agricultural data into alerts, predictions, classifications, rankings, or decision options. These outputs may support crop monitoring, pest and disease detection, irrigation planning, yield forecasting, input management, and risk identification, but they should be framed as recommendations rather than automatic decisions. Agricultural machine-learning applications can support decision analysis across several agronomic domains, but their relevance depends on contextual validation and careful interpretation [23].

The third component is uncertainty-aware interpretation. Sensor coverage, data gaps, weather variability, changing crop conditions, model assumptions, and domain transfer limits can all affect the reliability of AI outputs. Machine-learning systems in agriculture rely on diverse data sources and modelling approaches, but these systems should communicate uncertainty in ways that help farmers and advisors judge whether a recommendation is sufficiently credible for the decision at hand. The framework therefore requires uncertainty labels, confidence ranges, explanation panels, alternative scenarios, and warnings when data quality is insufficient [24].

The fourth component is practical decision integration. Human-in-the-loop intelligence should connect data acquisition, model analysis, recommendation explanation, farmer review, advisor input, and machinery-supported or management-based action. Crop data management in smart farming shows that decision support must move across the chain from data collection to field application, but the final decision still requires practical alignment with machinery access, labor timing, input availability, regulatory constraints, field conditions, and farm goals [25].

The fifth component is accountable adaptive learning. Explainability, data integrity, security, and accountability mechanisms are needed so farmers and advisors can understand recommendations, contest outputs, and trace decision pathways when outcomes are uncertain or problematic [26]. The framework also closes the loop through farmer engagement, feedback, usability assessment, and learning from observed outcomes, because intelligent decision support becomes farmer-centered only when users can influence how recommendations are interpreted, corrected, and improved over time [27].

Table 2 presents the proposed human-in-the-loop intelligence framework for farmer-centered AI decision support in smart farming.

Table 2. Proposed Human-in-the-Loop Intelligence Framework for Farmer-Centered AI Decision Support in Smart Farming: Farmer Judgment, AI Recommendations, Contextual Knowledge, Explainability, Trust Calibration, Feedback, Human Oversight, Decision Adaptation, Data Governance, and Accountability

Framework component	Core purpose	Human contribution	AI contribution	Required interface or design feature	Trust or accountability function	Design adaptation
Farmer judgment	Preserve human agency in farm decisions	Interprets recommendations through agronomic experience, goals, constraints, and risk preferences	Provides decision-relevant outputs for review	Farmer-controlled decision dashboard with editable assumptions	Clarifies that final decision responsibility remains human and contextual	Adaptation of recommendations to be more locally relevant
Experiential knowledge	Integrate local and historical farm knowledge	Adds field history, seasonal memory, soil understanding, pest observations, and machinery constraints	Uses structured data and prior patterns where available	Annotation tools, field notes, and local-context input fields	Makes farmer knowledge visible in the decision pathway	Supports correction of local knowledge
Contextual knowledge	Connect AI outputs to current farm realities	Assesses weather, labor, access, market conditions, field state, and operational timing	Updates recommendations using available contextual data	Context panels and scenario comparison tools	Reduces risk of context-blind recommendation use	Enables revision of context
AI recommendations	Provide analytical decision options	Reviews relevance, practicality, and alignment with farm objectives	Generates alerts, predictions, rankings, classifications, or options	Explainable recommendation cards with supporting data	Makes algorithmic reasoning reviewable	Provides potential for decision
Data quality	Ensure decision outputs are based on credible inputs	Reports missing observations, sensor issues, and field-level anomalies	Detects gaps, inconsistencies, and potential data errors	Data-quality indicators and provenance labels	Supports confidence in the recommendation pathway	Triggers review of correct data
Explainability	Support understanding and questioning	Interprets reasons and checks whether explanations fit local knowledge	Presents drivers, assumptions, evidence, and alternatives	Plain-language explanation panels and “why this?” functions	Supports appropriate reliance and contestability	Helps identify adaptation needs

Decision adaptation	Convert AI support into situated action	Adjusts, delays, rejects, or implements recommendations	Updates outputs as new data and feedback become available	Revision history, adaptive alerts, and scenario updates	Shows how recommendations changed and why	Enables correction, adjustment, field correction
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Practical Implications and Future Research

For AI developers and digital agriculture platform designers, the framework implies that technical performance should be paired with usability, explainability, uncertainty communication, feedback capture, and accountability mechanisms. Design teams should build systems that allow farmers and advisors to inspect recommendations, understand data inputs, report contextual corrections, and adapt outputs to real farm constraints. This direction is consistent with the broader need for decision-support systems that connect technical functions with user needs, social conditions, and responsible digital agriculture governance [2, 3].

For farm advisors, extension services, cooperatives, and precision agriculture consultants, the framework highlights the importance of mediation between AI outputs and situated farm decisions. Advisors can support farmers by interpreting uncertainty, comparing recommendations with field observations, explaining trade-offs, identifying risk, and helping adapt AI-supported options to local agronomic and economic conditions. Advisory integration is therefore not an optional supplement to AI decision support but a core mechanism through which digital tools can become understandable, trustworthy, and practically useful [19, 20].

Future research should empirically examine how farmers engage with human-in-the-loop AI systems across different farm types, crops, advisory settings, and digital maturity levels. Needed studies include participatory design research, farmer trust measurement, explainability evaluation, longitudinal human–AI interaction analysis, cross-farm comparison, advisory integration studies, responsible AI governance assessment, and decision-outcome evaluation. Such work should avoid assuming that AI benefits are automatic and should instead investigate how data quality, farmer understanding, institutional trust, feedback responsiveness, and practical decision integration shape the value of AI-supported smart farming [15, 27].

Conclusion

This article proposed a conceptual framework for human-in-the-loop intelligence in farmer-centered AI decision support for smart farming. The framework argues that agricultural AI should complement rather than replace farmer judgment, because farm decisions require experiential knowledge, contextual validation, uncertainty interpretation, risk assessment, advisor mediation, trust calibration, feedback, accountability, and practical adaptation. Effective smart farming AI depends not only on analytical capability but also on explainable recommendations, usable interfaces, transparent data governance, human oversight, and learning feedback loops that preserve farmer agency. By positioning intelligence as a shared socio-technical process, the framework offers a foundation for designing AI decision-support systems that are accountable, context-sensitive, and aligned with the realities of agricultural decision-making.

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