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Human-Centered Precision Agriculture: A Conceptual Framework for Sustainable, Resilient, and Explainable Smart Farming Systems

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Abstract

Precision agriculture is increasingly shaped by sensors, remote sensing, artificial intelligence, automated machinery, digital platforms, and data-driven decision support. However, technical capability alone does not establish whether a smart farming system is usable, locally appropriate, socially responsible, environmentally beneficial, resilient under disruption, or worthy of farmer reliance. This conceptual article proposes a human-centered precision agriculture framework that places farmers, farm workers, agricultural advisors, local knowledge, farm conditions, usability, accessibility, explainability, decision confidence, human oversight, and responsible governance at the center of system design. The framework integrates sustainability and resilience assessment with user-centered artificial intelligence, participatory design, transparent data practices, uncertainty communication, accountable decision support, and iterative learning. It distinguishes decision confidence from decision quality, explainability from guaranteed trust, participation from assured adoption, and technological potential from demonstrated sustainability or resilience. The proposed structure organizes human-centered smart farming into interconnected stages covering problem definition, stakeholder mapping, farmer-needs assessment, data and system context, sustainability and resilience requirements, explainability design, participation, oversight, governance, evaluation, and feedback. Its main contribution is a socio-technical framework for structuring research and design priorities while maintaining explicit boundaries around empirical validation, farmer autonomy, responsible implementation, and claims of system readiness.

Keywords Explainable AI, Sustainability, Smart farming, Human-centered precision agriculture, Farmer participation, Decision confidence

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Introduction

Precision agriculture combines spatially and temporally differentiated data with sensing, analytics, decision-support tools, and automated or semi-automated interventions. Smart farming extends this orientation through connected devices, cloud services, platforms, machine learning, and data-sharing relationships that link farms with technology providers, advisors, researchers, supply-chain actors, and service organizations [1]. Digital agriculture is therefore not only a technical modernization process. It is also a socio-technical transformation that can alter agricultural work, professional roles, skills, knowledge relationships, institutional responsibilities, access to resources, and the distribution of decision-making power [2].

A human-centered interpretation shifts attention from what a system can technically calculate toward how it is understood, used, questioned, governed, and adapted within agricultural practice. Under this interpretation, farmers are not passive recipients of automated recommendations, and farm workers, advisors, cooperatives, data stewards, and local institutions are not peripheral to system performance. Responsible smart farming requires anticipatory reflection, meaningful inclusion, responsiveness to affected users, and consideration of the social purposes toward which innovation is directed [3]. Human-centered precision agriculture consequently treats technological functionality as one component within a broader system of human agency, local knowledge, work practices, environmental responsibilities, economic constraints, and governance relationships.

This perspective is important because the outcomes of Agriculture 4.0 are neither uniform nor predetermined. Different combinations of robotics, artificial intelligence, digital platforms, sensing systems, and advisory services may produce different patterns of inclusion, dependence, sustainability, labor change, and institutional control. Technology pathways that are beneficial in one production system may be impractical, exclusionary, or environmentally ambiguous in another. Responsible transition therefore requires attention to diversity, power, institutional context, and the possibility that apparently advanced solutions may generate new vulnerabilities or reinforce existing inequalities [4].

This article develops an original conceptual framework for human-centered precision agriculture. Its objective is to connect human-centered design, farmer participation, user-centered artificial intelligence, explainability, sustainability, resilience, decision confidence, data governance, human oversight, and implementation boundaries within a coherent socio-technical structure. The framework does not prescribe agronomic actions, endorse particular technologies, or claim that participation, transparency, or technical sophistication will automatically produce adoption, trust, sustainability, resilience, or better decisions. Instead, it provides a structured basis for defining design requirements, evaluating conceptual relationships, identifying governance safeguards, and organizing future empirical research on responsible smart farming systems.

Human-Centered Precision Agriculture

Human-centered precision agriculture can be defined as a socio-technical approach in which digital agricultural systems are designed around the needs, capabilities, rights, knowledge, constraints, and decision responsibilities of the people who use or are affected by them. It links the physical conditions of farms with digital infrastructures, data flows, institutional arrangements, and human relationships. A socio-cyber-physical perspective is useful because it makes clear that sensing devices, models, interfaces, farm practices, service organizations, regulatory environments, and stakeholder responsibilities operate as an interconnected system rather than as independent technical components [5]. Human-centered design within this setting must therefore address both immediate user interaction and the wider organizational and institutional environment in which that interaction occurs.

This approach differs from technology-centered automation, which may begin with a technical capability and subsequently search for an agricultural application. It also differs from generic smart farming when digital connectivity, prediction, or automation is treated as sufficient evidence of practical value. Human-centered precision agriculture begins with the agricultural problem, the farm context, the affected users, and the consequences of potential system failure. Socio-ethical concerns should consequently be integrated throughout problem framing, design, development, evaluation, and revision rather than appended after a system has already been constructed [6]. Anticipation, inclusion, reflexivity, and responsiveness become design functions that help reveal whose objectives are prioritized, whose knowledge is represented, and who retains authority over consequential decisions.

Usability is central to this distinction. A technically sophisticated tool may still be unsuitable when it does not align with farm workflows, seasonal decision calendars, available skills, infrastructure limitations, or the interpretive practices of intended users. Agricultural decision-support tools create value through the relationship between their functions and the actions users can reasonably perform in a particular context [7]. Human-centered system design should therefore examine whether information is timely, understandable, actionable, and compatible with existing practices. It should also

consider whether users can inspect inputs, question outputs, record exceptions, communicate local observations, and reject recommendations without losing access to essential services.

Human-centered precision agriculture also extends beyond direct farmer–machine interaction. Agricultural knowledge is produced and interpreted through networks involving farmers, farm workers, advisors, extension services, researchers, cooperatives, technology providers, and other intermediaries. Digitalisation may reconfigure these relationships by changing how expertise is accessed, how advice is delivered, and how data are exchanged [8]. The proposed framework therefore includes agricultural advisors where they are available and appropriate, while avoiding the assumption that advisory support is universal, neutral, or equally accessible. Digital inclusion, language, literacy, connectivity, affordability, accessibility, and local institutional capacity must be treated as substantive design requirements rather than secondary implementation considerations.

Sustainability and Resilience in Smart Farming

Sustainability in human-centered precision agriculture includes environmental, social, and economic dimensions. Environmental considerations may involve resource-use efficiency, soil and water protection, energy demand, input targeting, emissions, and ecological effects. Social sustainability concerns inclusion, labor, access, autonomy, skills, and the distribution of benefits and burdens. Economic sustainability concerns affordability, maintenance requirements, uncertainty, long-term viability, and the relationship between technological investment and farm-specific objectives. Digital agriculture may help structure the design and comparison of more sustainable agricultural systems when sustainability goals, boundaries, assumptions, and trade-offs are explicitly defined [9]. It should not, however, be assumed that a data-driven system is sustainable merely because it is precise, automated, or information-rich.

Precision technologies may improve the targeting of inputs and support more differentiated management, but their environmental and economic effects vary across technologies, production systems, user capacities, and institutional settings. Potential reductions in resource use may be offset by energy consumption, infrastructure requirements, rebound effects, costs, unequal access, or inappropriate recommendations. Evidence at the production–environment interface therefore supports a conditional interpretation in which sustainability outcomes require empirical assessment rather than technological presumption [10]. The framework accordingly includes baseline definition, impact indicators, trade-off analysis, independent evaluation, and periodic reassessment as necessary elements of sustainability-oriented design.

Resilience concerns the ability of agricultural systems to anticipate, absorb, adapt to, and recover from disturbances. Climate resilience relates to changing weather patterns, extreme events, and uncertainty. Production resilience concerns the continuity or recovery of crops, livestock, and farm outputs. Operational resilience concerns the capacity to function during sensor failure, connectivity loss, platform interruption, power disruption, inaccurate data, or service withdrawal. Smart farming may support adaptation through timely information, site-specific management, and improved coordination, but these opportunities depend on infrastructure, competence, management capacity, and the continued availability of human judgment [11]. Resilience cannot be reduced to prediction accuracy or technical redundancy because social relationships, service access, fallback procedures, and institutional responsiveness also affect recovery.

Local context determines how sustainability and resilience requirements should be interpreted. Farm size, production system, climate, labor availability, connectivity, language, market conditions, and access to independent advice influence whether a digital system can be used meaningfully. Global inequalities in connectivity, data infrastructure, affordability, and digital services create unequal opportunities to benefit from data-driven farming [12]. A human-centered framework must therefore include accessibility, digital inclusion, low-bandwidth alternatives, local adaptation, and manual or non-digital fallback pathways. It must also retain explicit no-sustainability-guarantee and no-resilience-guarantee boundaries because responsible design can improve alignment and evaluation without independently proving environmental benefit, economic viability, social fairness, or performance under future disturbances.

Explainability and User-Centered AI Design

Explainability in agricultural artificial intelligence concerns the capacity of a system to provide information that helps users understand how outputs were produced, which inputs were influential, what assumptions were made, and where uncertainty or limitations remain. Interpretability refers more specifically to the extent to which model behavior or relationships can be comprehended by relevant users or reviewers. In agricultural analysis, prediction accuracy alone is insufficient when users cannot inspect the basis of a recommendation, identify implausible relationships, or determine whether a model is operating outside its intended context [13]. Explainability should therefore be linked to the decision task, the user's role, the consequences of error, and the type of understanding required.

User-centered explainability requires more than attaching a technical explanation method to an existing model. Feature-attribution displays, local explanations, visual summaries, rule-based accounts, and comparative rationales can differ substantially in fidelity, comprehensibility, and practical usefulness. Agricultural explanation systems should be designed for intended audiences such as farmers, advisors, agronomists, data specialists, or governance reviewers rather than for an undefined generic user. Comparative assessments of explainable artificial intelligence in smart-agriculture settings show that explanation methods have distinct strengths and limitations and require audience-sensitive presentation and evaluation [14]. The presence of an explanation should not be treated as evidence that a model is accurate, fair, safe, or suitable for operational use.

A user-centered AI system should make relevant inputs visible, document data provenance and data quality, disclose model purpose and limitations, communicate uncertainty, and provide a rationale for why a recommendation is presented rather than an alternative. These functions are also governance mechanisms because they help expose hidden assumptions, missing data, inappropriate generalization, and responsibility gaps. Agricultural AI can create systemic risks and externalities that extend beyond the immediate accuracy of a model, including environmental effects, economic concentration, exclusion, dependency, and consequences for food-system actors [15]. Human-in-the-loop review, escalation procedures, model documentation, incident reporting, and accountability mapping are therefore necessary complements to explainability.

Explainability must also be separated from trust. A clear interface may increase understanding, but it cannot independently demonstrate that reliance is warranted. Trust depends on a wider combination of technical performance, data quality, institutional conduct, fairness, accountability, user experience, and the ability to challenge or override system outputs. Agricultural AI ethics research identifies transparency and explainability as important but incomplete components of responsible design alongside autonomy, justice, accountability, labor effects, environmental consequences, and power relations [16]. The proposed framework therefore includes a no-explainability-sufficiency boundary and a no-trust-guarantee boundary. Its objective is not to maximize trust, but to support informed, conditional, and revisable reliance while preserving farmer judgment, professional interpretation, and meaningful human oversight.

Farmer Participation and Decision Confidence

Farmer participation is a design and governance process through which farmers can influence problem definition, system requirements, data practices, interface choices, evaluation criteria, and the conditions under which decision-support outputs are used. Participation should not be limited to collecting preferences after core technical decisions have already been made. Evidence from smart-farming data relationships indicates that farmer trust is affected by whether organizations explain how data are collected and used, how benefits are distributed, and who exercises control over resulting information [17]. Transparency and benefit-sharing are therefore trust-building conditions, but they do not independently guarantee trust because reliance also depends on demonstrated competence, fairness, accountability, and experience over time.

Co-design and participatory design can provide more substantive forms of involvement by enabling farmers and other affected users to shape system goals, prototypes, explanations, workflow arrangements, and feedback mechanisms.

Such participation is especially important when digital agriculture may distribute opportunities unevenly or concentrate data, infrastructure, and bargaining power among a limited set of organizations. Competing visions of agricultural big data show that access, inclusion, institutional support, and co-creation influence whether digital development serves a broad farming community or primarily benefits well-resourced actors [18]. Participation should consequently influence the allocation of decision rights and benefits rather than operate merely as a method for encouraging acceptance of a predetermined technology.

Decision confidence refers to a user's ability to understand available information, compare alternatives, recognize uncertainty, and determine whether an output is sufficiently relevant for further consideration. It is distinct from trust because a farmer may understand an explanation while remaining appropriately cautious about the organization or model that produced it. It is also distinct from decision quality because confidence can be misplaced. Farmers' perceptions of smart-farming technologies vary according to production system, prior experience, farm conditions, accessibility, perceived usefulness, and available advisory support [19]. Decision-confidence support should therefore be calibrated to specific users and contexts rather than inferred from interface clarity or generalized assumptions about farmer needs.

Farmer autonomy requires meaningful authority to accept, modify, postpone, or reject system outputs. Decision rights, consent arrangements, data controls, override mechanisms, and opportunities to contribute local knowledge should be defined explicitly. Human oversight may include farmer review, advisor involvement where appropriate, or escalation to agronomic and technical expertise for consequential or uncertain recommendations. Smart-farming risks are interpreted differently by actors according to their values, responsibilities, and expectations, making transparent deliberation and accountability necessary when disagreements remain [20]. The framework therefore incorporates a no-adoption-guarantee boundary and a no-decision-quality-claim boundary: participation does not ensure adoption, and increased confidence does not prove that a decision is correct.

Human-Centered System Requirements

Human-centered system requirements begin with a user-needs assessment that identifies the agricultural problem, intended users, decision timing, work practices, local conditions, and consequences of system error. Farm workflow integration should determine when information becomes available, who interprets it, and how it interacts with existing records, equipment, labor responsibilities, and advisory relationships. Agricultural advisors may help farmers contextualize digital outputs, compare them with field observations, and interpret uncertainty, but smart-farming systems can also alter advisor roles, service models, and access to data [21]. Advisor involvement should therefore be treated as a context-dependent oversight and learning pathway rather than a universal requirement.

A farmer feedback loop should permit users to identify incorrect inputs, record unusual conditions, question explanations, report observed outcomes, and propose changes to system requirements. Feedback must be accompanied by a defined process for review, response, documentation, and revision; collecting comments without acting on them does not constitute meaningful participation. Digital agricultural extension research emphasizes the importance of two-way learning, locally relevant content, adaptive service design, and connections between digital communication and wider knowledge networks [22]. Feedback mechanisms should similarly support reciprocal learning rather than one-directional delivery of recommendations.

Usability, accessibility, and digital inclusion must be assessed across intended user groups. Relevant factors include language, literacy, disability, device availability, connectivity, cost, technical support, interface complexity, and the time required to interpret system outputs. Actual use of smart-farming technologies is affected by individual characteristics, farming-system conditions, experience, and perceived barriers, demonstrating that technical availability does not establish practical usability [23]. Systems should consequently provide comprehensible interfaces, accessible alternatives, low-bandwidth functions where relevant, and clear visibility of material inputs, data-quality concerns, uncertainty, and decision rationale.

Implementation readiness requires evidence across technical, human, organizational, economic, environmental, and governance dimensions. A system may operate as designed in a technical setting while remaining unsuitable for a particular farm because of cost, support limitations, uncertain returns, workflow disruption, weak oversight, inaccessible interfaces, or insufficient evidence of sustainability and resilience. Farmer intentions toward precision technologies vary with incentives, financial conditions, perceived risk, farm heterogeneity, and access to support [24]. Readiness review should therefore identify unresolved requirements rather than function as certification, and the framework must preserve a no-farmer-replacement boundary under which digital decision support supplements rather than displaces farmer judgment. **Table 1** summarises human-centered system requirements for sustainable, resilient, and explainable smart farming systems.

Table 1. Human-Centered System Requirements for Sustainable, Resilient, and Explainable Smart Farming Systems: User Needs, Local Context, Farm Workflow Integration, Explainability Interfaces, Uncertainty Communication, Decision-Support Rationale, Farmer Feedback, Co-Design, Accessibility, Digital Inclusion, Sustainability Assessment, Resilience Assessment, Governance Safeguards, and Human Oversight

System requirement	Core design question	Required input	Human-centered function	Potential output	Failure risk	Evaluation need
User needs assessment	What decisions and problems do intended users consider important?	Interviews, observation, workflow evidence, task analysis, and user priorities	Prevents technology-first problem selection	Prioritized and bounded user-needs statement	Developer assumptions replace expressed needs	Validation with diverse intended users
Local context mapping	Which regional, cultural, infrastructural, and institutional conditions affect usefulness?	Climate, language, markets, connectivity, service access, and local institutions	Grounds the system in its place of use	Local-context profile	Superficial localization of a generic system	Review by local users and relevant experts
Farm workflow integration	How will the system interact with actual farm tasks and decision timing?	Production calendar, labor roles, equipment, records, and existing tools	Aligns digital functions with practical work	Workflow-integrated use pathway	Added workload, duplication, or poorly timed outputs	Observation-based workflow evaluation
Data quality documentation	Are data sufficiently complete, timely, calibrated, and representative for the	Missingness records, calibration evidence, timestamps, transformations,	Allows users and reviewers to judge evidential reliability	Data-quality statement and warning indicators	Poor data produce false precision	Continuous technical and domain-specific review

	intended decision?	and quality checks				
Explainability interface	Can users access explanations relevant to their role and task?	User roles, explanation needs, model outputs, and interface prototypes	Supports inspection, comprehension, and questioning	Role-specific explanation interface	Technically detailed but practically irrelevant explanation	Comprehension, fidelity, and task-based usability testing
Uncertainty communication	Are material uncertainties, limitations, and data gaps visible?	Calibrated uncertainty, scenario ranges, and known failure modes	Supports cautious interpretation	Confidence range, uncertainty category, or limitation notice	False certainty or confusing probability displays	Calibration and user-comprehension evaluation
Decision-support rationale	Why is an option presented, and what alternatives or trade-offs exist?	Decision objectives, constraints, assumptions, and alternatives	Preserves deliberation and user choice	Comparative decision rationale	Hidden optimization priorities or value assumptions	Agronomic, technical, and user review
Human oversight design	Which outputs require human review, and who has authority?	Risk classification, user roles, expertise, and escalation criteria	Preserves judgment and accountability	Review, modification, rejection, and escalation protocol	Symbolic or overloaded oversight	Evaluation of authority, workload, and intervention quality
Farmer feedback loop	Can farmers correct data, add context, report outcomes, and challenge outputs?	Accessible feedback functions and response responsibilities	Enables learning and system correction	Feedback record and revision log	Feedback is collected but ignored	Assessment of response quality and feedback closure
Co-design process	How do users influence consequential design choices?	Representative participants, facilitation, prototypes, and decision records	Shares design influence and integrates experiential knowledge	Co-designed requirements and revised prototypes	Tokenism, consultation fatigue, or dominance by powerful participants	Participation-quality and influence audit
Accessibility	Can users with different language, literacy, ability, and device needs use	Accessibility requirements, language options, device constraints, and user testing	Reduces avoidable exclusion	Accessible interfaces and alternative formats	Important user groups are excluded by default assumptions	Testing with diverse users

	core functions?					
Digital inclusion	Are connectivity, cost, infrastructure, and support barriers addressed?	Affordability, broadband, device, training, and service-access assessment	Broadens practical opportunity to participate	Inclusion strategy and non-digital or low-bandwidth alternatives	Benefits concentrate among well-resourced farms	Distributional and access monitoring
Sustainability assessment	Which environmental, social, and economic effects require evaluation?	Baselines, indicators, system boundaries, and trade-off criteria	Links system design to explicit sustainability questions	Multidimensional sustainability-evaluation plan	Sustainability inferred from precision or automation	Empirical and, where relevant, longitudinal impact assessment
Resilience assessment	How will the system and farm function during shocks or component failures?	Climate scenarios, dependency maps, failure modes, and fallback processes	Supports preparedness, adaptation, and recovery planning	Resilience-testing and continuity plan	Technical redundancy is mistaken for whole-system resilience	Stress testing and incident-based evaluation
Governance safeguard	Which safeguards correspond to identified data, AI, power, and externality risks?	Risk register, data flows, affected groups, and responsibility analysis	Converts responsible-AI principles into actionable controls	Governance-safeguard portfolio	Principles remain symbolic and unenforced	Governance audit and ongoing monitoring
Accountability mapping	Who is responsible for data, model, interface, service, and decision failures?	Actor roles, contracts, escalation duties, and redress mechanisms	Prevents responsibility gaps	Accountability and escalation matrix	Responsibility is diffused among providers and users	Incident simulation and accountability review
Implementation readiness review	Is there sufficient evidence and support for a bounded evaluation?	Technical, human, economic, sustainability, resilience, and governance evidence	Prevents premature deployment claims	Readiness profile with unresolved gaps	Checklist is treated as proof of operational suitability	Independent staged review
No farmer-replacement boundary	Which judgments and authorities	Decision criticality, local knowledge,	Protects farmer agency and	Defined human-decision boundary	Gradual de facto replacement	Audit of actual control and

	must remain human-led?	expertise, and override rules	professional judgment		through automation dependence	override practices
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Proposed Conceptual Framework

The proposed human-centered precision agriculture framework begins with problem and farm-context definition, stakeholder and user mapping, farmer-needs assessment, and data and system-context mapping. These stages establish what agricultural decision is being addressed, whose interests and responsibilities are involved, which forms of knowledge are relevant, and what physical, digital, organizational, and institutional dependencies shape the system. Ethical analysis of smart farming demonstrates that questions of data ownership, privacy, power, responsibility, and effects on human life are integral to digital agricultural development [25]. The framework therefore treats governance conditions as foundational design inputs rather than external constraints considered only after a technology has been developed.

The next stages comprise sustainability assessment, resilience assessment, explainability-requirement definition, user-centered AI design, participation and co-design, and decision-confidence support. Sustainability and resilience are expressed as assessment domains whose criteria must be defined for the relevant farm and production context. Explainability requirements specify which users require which forms of understanding and for what decisions. User-centered AI design connects model functions, data, interfaces, workflow needs, accessibility, and uncertainty communication. Participation and co-design create opportunities to incorporate farmer knowledge and challenge design assumptions. However, human-centered methods can reproduce inequalities when participation is constrained by power, resources, digital capacity, or predetermined technical objectives [26]. The framework therefore includes participation-quality review rather than assuming that the use of co-design terminology establishes responsible development.

Human-oversight design, governance-safeguard selection, system-evaluation planning, practical-implication mapping, and future-research updating form the framework's accountability and learning stages. Oversight design specifies who can inspect, modify, reject, or escalate system outputs. Governance safeguards address data rights, documentation, externalities, provider responsibilities, complaints, correction, and redress. Evaluation planning connects technical performance with usability, accessibility, sustainability, resilience, decision-confidence calibration, and governance effectiveness. Digital agriculture is shaped by a diverse supply-side ecosystem that includes agribusiness firms, machinery manufacturers, software companies, start-ups, telecommunications providers, research organizations, and public institutions [27]. Implementation assessment must consequently account for provider dependency, market concentration, interoperability, service continuity, and the allocation of public and private responsibilities.

The framework operates through iterative feedback rather than a linear path ending in automated recommendation delivery. Farmer observations, advisor input where supported, system incidents, data-quality changes, usability findings, sustainability evidence, resilience testing, and governance concerns can return the process to earlier stages. A revised understanding of the farm problem may change data requirements; a usability finding may require interface redesign; a failure event may alter oversight rules; and new evidence may change the framework's evaluation priorities. Feedback updating should be documented so that changes to models, interfaces, assumptions, responsibilities, and intended uses remain traceable.

The proposed contribution is a conceptual architecture for organizing human-centered research and design, not a validated operational model. Its boundary conditions state that explainability does not guarantee trust, participation does not guarantee adoption, decision confidence does not establish decision quality, and responsible design does not prove sustainability or resilience. The framework also preserves a no-autonomy-replacement boundary under which farmers and appropriately qualified human actors retain defined decision authority. Empirical work is required to determine how the stages interact in particular agricultural settings, whether the specified requirements are feasible, and how outcomes

should be evaluated over time. **Table 2** presents the proposed human-centered precision agriculture framework. **Figure 1** presents the proposed human-centered precision agriculture framework, linking sustainability, resilience, explainability, user-centered AI design, farmer participation, decision confidence, human oversight, governance safeguards, and feedback.

Table 2. Proposed Human-Centered Precision Agriculture Framework: Farm Context Definition, Stakeholder Mapping, Farmer Needs Assessment, Data and System Context, Sustainability, Resilience, Explainability, User-Centered AI Design, Participation, Decision Confidence, Human Oversight, Governance Safeguards, Evaluation Planning, Feedback, and Claim Boundaries

Framework stage	Core purpose	Required input	Conceptual function	Potential output	Validation need	Failure risk
Problem and farm-context definition	Define the agricultural problem and its operational setting	Farm objectives, constraints, production system, environment, and workflow	Prevents generic or technology-led problem framing	Bounded problem statement	Farmer, worker where relevant, advisor where supported, and agronomic review	Solving a technically convenient but practically irrelevant problem
Stakeholder and user mapping	Identify affected users, responsible actors, and power relationships	Farmers, farm workers, advisors, providers, data stewards, researchers, institutions, and communities	Makes participation rights and responsibilities visible	Stakeholder and responsibility map	Review for missing or underrepresented groups	Indirectly affected or less powerful actors are omitted
Farmer needs assessment	Establish farmer priorities, capabilities, constraints, and decision practices	Direct user research, observation, task evidence, and local knowledge	Converts lived needs into design requirements	Prioritized farmer-needs specification	Validation across diverse intended users	Needs of early adopters or dominant participants are generalized
Data and system context mapping	Map data sources, infrastructure, platforms, and dependencies	Sensor, remote-sensing, weather, soil, crop, livestock where relevant, and provider information	Connects physical, informational, and organizational foundations	Data-flow, provenance, quality, and dependency map	Technical, agronomic, security, and governance audit	Hidden data transformations or provider dependencies
Sustainability assessment	Define environmental, social, and economic	Baselines, boundaries, stakeholder priorities, and	Makes sustainability an explicit,	Sustainability-assessment plan	Context-specific empirical assessment	Technical efficiency is treated as

	questions and indicators	trade-off criteria	testable domain			overall sustainability
Resilience assessment	Identify shocks, vulnerabilities, dependencies, and recovery requirements	Climate, production, operational, infrastructure, and service-failure scenarios	Treats resilience as a socio-technical system property	Resilience and continuity evaluation plan	Scenario testing, field evidence, and incident review	Unknown, compound, or social disruptions are ignored
Explainability requirement definition	Specify what each user must understand and why	User roles, decisions, error consequences, model type, and explanation goals	Aligns explanation design with practical decisions	Explanation-requirements specification	Fidelity and comprehension testing	Generic explanations are produced without user relevance
User-centered AI design	Align models, interfaces, workflows, and access conditions with intended users	Needs, context, data, accessibility, uncertainty, and explanation requirements	Integrates technical design with human use	Prototype decision-support configuration	Model validation, usability evaluation, and accessibility testing	Accuracy optimization displaces human requirements
Participation and co-design process	Enable affected users to influence consequential design choices	Representative participation, accessible methods, prototypes, and decision records	Incorporates diverse knowledge, values, and concerns	Participation-informed requirements and design revisions	Assessment of representation and actual influence	Tokenism, fatigue, power imbalance, or extraction of local knowledge
Decision-confidence support	Help users interpret evidence, alternatives, uncertainty, and rationale	Explanations, data-quality information, alternatives, and uncertainty communication	Supports informed and revisable deliberation	Context-specific decision-support account	Evaluation of comprehension, calibration, and outcomes	Interface increases confidence without improving understanding
Human-oversight design	Define review points, authority, overrides, and escalation	Decision criticality, expertise, roles, workload, and risk thresholds	Preserves meaningful human judgment	Oversight and escalation protocol	Testing of authority, timeliness, competence, and workload	Human review becomes symbolic or automatic
Governance-safeguard	Match controls to data, AI,	Risk register, actor map,	Operationalizes responsible	Context-specific	Independent governance	Broad principles lack

selection	organizational, and distributional risks	data flows, externalities, and rights analysis	governance	safeguard portfolio	review	enforceable procedures
System-evaluation planning	Define multidimensional criteria before implementation claims are made	Technical, usability, accessibility, sustainability, resilience, and governance indicators	Prevents narrow performance assessment	Evaluation protocol and evidence plan	Representative and independent testing	Selective metrics conceal human or environmental failure
Practical-implication mapping	Identify bounded implications for users, designers, institutions, and researchers	Conceptual synthesis, stakeholder roles, evidence gaps, and constraints	Translates the framework without prescribing farm actions	Role-specific conceptual implications	Review by affected stakeholders	Implications become operational or procurement prescriptions
Future-research updating	Revise the framework as evidence, technologies, and risks change	New studies, evaluations, incidents, user feedback, and institutional developments	Keeps the framework provisional and adaptive	Versioned framework update	Transparent evidence and change review	The framework is treated as fixed or validated
No trust-guarantee boundary	Prevent explanation and participation from being equated with trust	Evidence of performance, fairness, accountability, and user experience	Defines trust as conditional and revisable	Warranted-reliance criteria	Design becomes persuasive rather than informative	Longitudinal and context-specific trust research
No sustainability-guarantee boundary	Separate sustainability intention from demonstrated outcome	Empirical impact evidence, system boundaries, and counterfactual analysis	Prevents unsupported environmental or social claims	Sustainability claim boundary	Precision or efficiency is presented as proof of sustainability	Independent impact and lifecycle evaluation
No autonomy-replacement boundary	Preserve farmer and qualified human decision authority	Decision-rights mapping, override functions, and accountability rules	Prevents gradual displacement of human control	Human-authority and refusal boundary	Automation dependence makes nominal choice meaningless	Audit of actual control, pressure, and override use

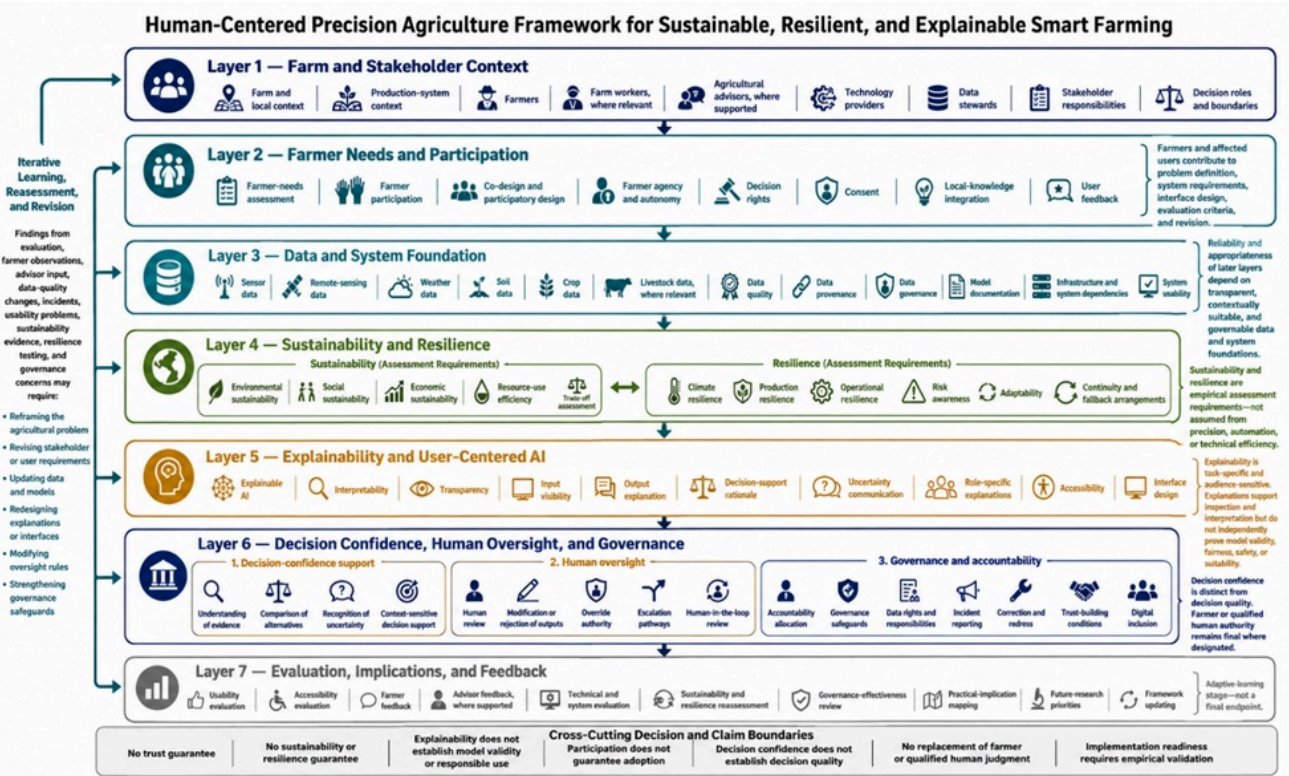


Figure 1. Human-Centered Precision Agriculture Framework for Sustainable, Resilient, and Explainable Smart Farming

Alt-text description:

A conceptual framework showing farm context and stakeholder mapping connected to farmer needs, sustainability, resilience, explainability, user-centered AI, participation, decision confidence, human oversight, governance safeguards, evaluation planning, and feedback loops.

Practical Implications and Future Research

For farmers, farm workers, advisors, cooperatives, and extension services, the framework highlights the need to define user roles, preserve decision rights, connect digital outputs with local knowledge, and provide meaningful channels for explanation, feedback, refusal, and escalation. Advisory organizations may need new competencies for interpreting data-intensive systems and helping users compare model outputs with contextual evidence [21]. Digital extension initiatives should similarly emphasize reciprocal learning and locally adaptable communication rather than treating technology as a substitute for agricultural knowledge networks [22]. These implications concern system design and research priorities; they do not prescribe specific farm-management actions.

For technology developers and researchers, future work should combine model evaluation with usability, accessibility, explainability, data-quality, sustainability, resilience, and governance assessment. Digital inclusion requires explicit attention because connectivity and data infrastructure remain unevenly distributed [12]. Agricultural XAI research should evaluate whether explanations are faithful, comprehensible, and relevant to actual decisions rather than assuming that technical explanation availability is sufficient [13]. Agricultural-AI risk research should also examine externalities, dependency, organizational responsibility, and failure across wider food and farming systems [15]. Human-centered methods themselves require reflexive evaluation because participation can remain constrained by unequal power and capacity [26].

For policymakers, data stewards, cooperatives, research institutions, and service organizations, the framework identifies accountability, interoperability, data rights, provider responsibility, independent evaluation, and redress as important areas for further study. Smart-farming ethics research shows that data ownership and power relations should be considered alongside privacy and technical performance [25]. Supply-side structures also warrant attention because market concentration, service dependency, and unequal access can shape which technologies are available and whose interests they serve [27]. These observations are conceptual implications and future research directions rather than legal, regulatory, financial, procurement, or implementation advice. Long-term socio-technical research is required to examine how trust, autonomy, sustainability, resilience, usability, and decision practices evolve after systems enter real agricultural settings.

Conclusion

This article proposes a human-centered precision agriculture framework that integrates farm and local context, stakeholder mapping, farmer needs, sustainability, resilience, explainability, user-centered artificial intelligence, farmer participation, decision confidence, human oversight, governance safeguards, evaluation, and iterative learning. Its central contribution is to reposition smart farming as a socio-technical design challenge in which technical performance is necessary but insufficient. Precision agricultural systems should also be examined according to whether they preserve human agency, communicate uncertainty, accommodate local knowledge, remain accessible, distribute responsibilities clearly, and support responsible and revisable decision-making. The framework does not guarantee trust, adoption, sustainability, resilience, decision quality, or implementation readiness, and it does not replace farmer or expert judgment. Instead, it provides a structured conceptual basis for future empirical investigation and for designing smart farming systems whose value is judged not by technical sophistication alone but by their capacity to remain locally relevant, accountable, understandable, and supportive of human decision authority.

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References

- Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming—A review. *Agric Syst*. 2017;153:69-80.
<https://doi.org/10.1016/j.agry.2017.01.023>.
- Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS Wageningen J Life Sci*. 2019;90-91:100315.
<https://doi.org/10.1016/j.njas.2019.100315>.
- Rose DC, Chilvers J. Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Front Sustain Food Syst*. 2018;2:87.
<https://doi.org/10.3389/fsufs.2018.00087>.
- Klerkx L, Rose DC. Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Glob Food Sec*. 2020;24:100347.
<https://doi.org/10.1016/j.gfs.2019.100347>.
- Rijswijk K, Klerkx L, Bacco M, Bartolini F, Bulten E, Debruyne L, et al. Digital transformation of agriculture and rural areas: A socio-cyber-physical system framework to support responsabilisation. *J Rural Stud*. 2021;85:79-90.
<https://doi.org/10.1016/j.jrurstud.2021.05.003>.
- Eastwood C, Klerkx L, Ayre M, Dela Rue B. Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. *J Agric Environ Ethics*. 2019;32(5-6):741-68.
<https://doi.org/10.1007/s10806-017-9704-5>.
- Ditzler L, Klerkx L, Chan-Dentoni J, Posthumus H, Krupnik TJ, López-Ridaura S, et al. Affordances of agricultural systems analysis tools: A review and framework to enhance tool design and implementation. *Agric Syst*. 2018;164:20-30.
<https://doi.org/10.1016/j.agry.2018.03.006>.
- Fielke S, Taylor B, Jakku E. Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agric Syst*. 2020;180:102763.
<https://doi.org/10.1016/j.agry.2019.102763>.
- Basso B, Antle J. Digital agriculture to design sustainable agricultural systems. *Nat Sustain*. 2020;3(4):254-6.
<https://doi.org/10.1038/s41893-020-0510-0>.
- Finger R, Swinton SM, El Benni N, Walter A. Precision farming at the nexus of agricultural production and the environment. *Annu Rev Resour Econ*. 2019;11:313-35.
<https://doi.org/10.1146/annurev-resource-100518-093929>.
- Walter A, Finger R, Huber R, Buchmann N. Smart farming is key to developing sustainable agriculture. *Proc Natl Acad Sci U S A*. 2017;114(24):6148-50.
<https://doi.org/10.1073/pnas.1707462114>.
- Mehrabi Z, McDowell MJ, Ricciardi V, Levers C, Martinez JD, Mehrabi N, et al. The global divide in data-driven farming. *Nat Sustain*. 2021;4(2):154-60.
<https://doi.org/10.1038/s41893-020-00631-0>.

Ryo M. Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. *Artif Intell Agric.* 2022;6:257-65.

<https://doi.org/10.1016/j.aiia.2022.11.003>.

Cartolano A, Cuzzocrea A, Pilato G. Analyzing and assessing explainable AI models for smart agriculture environments. *Multimed Tools Appl.* 2024;83(12):37225-46.

<https://doi.org/10.1007/s11042-023-17978-z>.

Tzachor A, Devare M, King B, Avin S, Ó hÉigeartaigh S. Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nat Mach Intell.* 2022;4(2):104-9.

<https://doi.org/10.1038/s42256-022-00440-4>.

Ryan M. The social and ethical impacts of artificial intelligence in agriculture: Mapping the agricultural AI literature. *AI Soc.* 2023;38(6):2473-85.

<https://doi.org/10.1007/s00146-021-01377-9>.

Jakku E, Taylor B, Fleming A, Mason C, Fielke S, Sounness C, et al. If they don't tell us what they do with it, why would we trust them? Trust, transparency and benefit-sharing in smart farming. *NJAS Wageningen J Life Sci.* 2019;90-91:100285.

<https://doi.org/10.1016/j.njas.2018.11.002>.

Fleming A, Jakku E, Lim-Camacho L, Taylor B, Thorburn P. Is big data for big farming or for everyone? Perceptions in the Australian grains industry. *Agron Sustain Dev.* 2018;38(3):24.

<https://doi.org/10.1007/s13593-018-0501-y>.

Kernecker M, Knierim A, Wurbs A, Kraus T, Borges F. Experience versus expectation: Farmers' perceptions of smart farming technologies for cropping systems across Europe. *Precis Agric.* 2020;21(1):34-50.

<https://doi.org/10.1007/s11119-019-09651-z>.

Regan Á. Smart farming in Ireland: A risk perception study with key governance actors. *NJAS Wageningen J Life Sci.* 2019;90-91:100292.

<https://doi.org/10.1016/j.njas.2019.02.003>.

Eastwood C, Ayre M, Nettle R, Dela Rue B. Making sense in the cloud: Farm advisory services in a smart farming future. *NJAS Wageningen J Life Sci.* 2019;90-91:100298.

<https://doi.org/10.1016/j.njas.2019.04.004>.

Steinke J, van Etten J, Müller A, Ortiz-Crespo B, van de Gevel J, Silvestri S, et al. Tapping the full potential of the digital revolution for agricultural extension: An emerging innovation agenda. *Int J Agric Sustain.* 2021;19(5-6):549-65.

<https://doi.org/10.1080/14735903.2020.1738754>.

Caffaro F, Cavallo E. The effects of individual variables, farming system characteristics and perceived barriers on actual use of smart farming technologies: Evidence from the Piedmont region, northwestern Italy. *Agriculture (Basel).* 2019;9(5):111.

<https://doi.org/10.3390/agriculture9050111>.

Barnes AP, Soto I, Eory V, Beck B, Balafoutis AT, Sanchez B, et al. Influencing incentives for precision agricultural technologies within European arable farming systems. *Environ Sci Policy.* 2019;93:66-74.

<https://doi.org/10.1016/j.envsci.2018.12.014>.

van der Burg S, Bogaardt MJ, Wolfert S. Ethics of smart farming: Current questions and directions for responsible innovation towards the future. *NJAS Wageningen J Life Sci.* 2019;90-91:100289.

<https://doi.org/10.1016/j.njas.2019.01.001>.

McC Campbell M, Schumann C, Klerkx L. Good intentions in complex realities: Challenges for designing responsibly in digital agriculture in low-income countries. *Sociol Ruralis*. 2022;62(2):279-304.
<https://doi.org/10.1111/soru.12359>.

Birner R, Daum T, Pray C. Who drives the digital revolution in agriculture? A review of supply-side trends, players and challenges. *Appl Econ Perspect Policy*. 2021;43(4):1260-85.
<https://doi.org/10.1002/aepp.13145>.