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A Systematic Review of Digital Transformation in Agriculture: Technologies, Impacts, and Future Pathways

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I N F O
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A B S T R A C T
Agriculture is under pressure from several directions at once: population growth, climate instability, shrinking arable land, and persistent rural poverty. These are not new challenges individually, but their convergence is intensifying in ways that conventional farming methods are ill-equipped to handle. Digital technologies — IoT sensor networks, artificial intelligence, blockchain ledgers, geospatial platforms — have attracted growing attention from researchers and policymakers as one credible set of responses. What the literature has been slower to address is whether these tools actually reach the farmers who need them most, and whether the evidence supporting their claimed benefits holds up beyond the controlled conditions in which most studies are conducted. This PRISMA 2020-compliant systematic review draws on 125 peer-reviewed studies published between January 2010 and March 2025, sourced from five databases and appraised for methodological quality using an adapted CASP framework. The findings are mixed in instructive ways: IoT-based precision irrigation cuts water use by 20–30% in field trials, though real-world deployments produce more modest savings closer to 15–25%. AI disease detection systems exceed 95% accuracy in laboratory conditions, while field performance in tropical smallholder contexts drops to 70–85% — a gap that most reviews gloss over. Blockchain integration in East African value chains has lifted smallholder incomes by an estimated 20–30%, though both documented studies draw on self-selected early-adopter populations, making causal claims difficult to sustain. Across these technologies, adoption by smallholder farmers in developing economies sits at 12–15%, against 45% or more on large-scale farms in wealthier countries. This divide does not have one cause. It is the product of capital cost barriers, absent rural infrastructure, limited digital literacy, inadequate governance frameworks, and the enduring tendency of technology designers to build for resource-rich contexts and adapt downward after the fact. The review argues that closing the gap requires deliberate, upstream reorientation — of research agendas, financing instruments, and design assumptions — toward the conditions and constraints of smallholder agriculture.

1. Introduction

Agriculture employs more than 2.5 billion people worldwide and remains the main source of livelihood for the majority of households in low- and middle-income countries (FAO 2021). By 2050, a global population of 9.7 billion will demand roughly 50–70% more food than is produced today — and this must come from land that is not expanding, water supplies that are declining, and farming seasons that are growing less predictable as climate change progresses (Godfray et al. 2010). These are not predictions from distant modelling exercises; they describe conditions already visible in yield volatility

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data, groundwater depletion rates, and shifting pest pressure maps across Sub-Saharan Africa, South Asia, and parts of Latin America.

Precision agriculture, built on IoT sensor networks, AI-driven analytics, satellite and UAV remote sensing, and blockchain supply chain platforms, offers a different operating model: farm management decisions driven by site-specific, real-time data rather than generalised advice or accumulated habit. Publication volumes on these technologies have grown sharply — Scopus records fewer than 500 papers annually on precision agriculture in 2010, against over 4,000 by 2023 (Wolfert et al. 2017). But volume alone does not constitute synthesis. The existing literature is fragmented by technology type, scattered across disciplines, and skewed heavily toward farming systems in North America, Western Europe, and East Asia — contexts whose infrastructure, credit, and educational conditions bear little resemblance to those faced by the majority of the world's farmers (Sharma et al. 2022).

The result is a body of evidence that confidently reports what these technologies can do in favourable conditions, while leaving largely unanswered the questions that matter most for agricultural policy: Do the documented benefits hold under real-world field conditions? Who is actually adopting these tools, and who is not? What would it realistically take to extend their reach to the 500 million smallholder households that produce the majority of the food consumed in the developing world? This review is an attempt to answer those questions systematically.

Four research questions structure the analysis: (RQ1) What digital technologies are currently deployed across the agricultural value chain, and what are their technical characteristics? (RQ2) What measurable impacts have they demonstrated on productivity, resource efficiency, and smallholder livelihoods? (RQ3) What barriers — structural, social, economic, and institutional — constrain equitable adoption, particularly in developing economies? (RQ4) What research, design, and policy interventions are needed to advance a genuinely inclusive agricultural digitalisation?

2. Theoretical background

2.1. The Technology Pillars and Their Interdependencies

Digital agriculture rests on four technology pillars that are distinct in function but deeply connected in practice. Their combined effect, when all four are operating together, is considerably larger than the sum of what each delivers independently. Figure 1 maps these relationships and the barriers that constrain them.

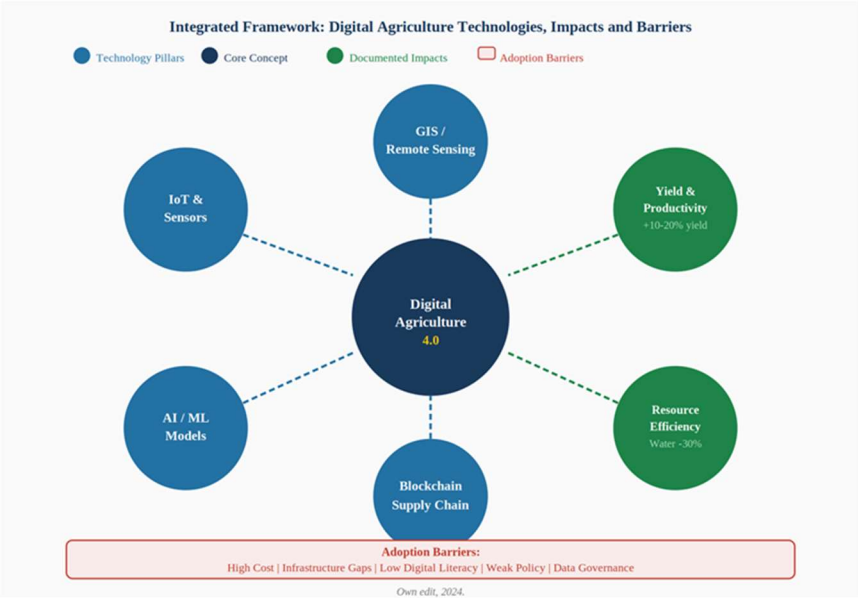


Figure 1. Integrated framework of digital agriculture 4.0: technology pillars, documented impacts, and adoption barriers. Own edit, 2024.

IoT is the data-collection layer. It spans soil moisture sensors, multi-spectral optical sensors positioned at leaf level, GPS livestock wearables, weather micro-stations, and actuators embedded in irrigation and spraying machinery — all generating continuous streams of georeferenced field data (Kumar et al. 2021). What this data is worth depends entirely on what can be done with it. In contexts with reliable broadband or 4G connectivity, it moves to cloud platforms where it can be processed at scale. In most rural smallholder environments in developing countries, connectivity is intermittent at best, which pushes processing requirements onto the sensor device itself. That shift — to edge computing architectures — substantially raises hardware cost and technical complexity, two constraints the technology literature frequently underestimates (Mekonnen et al. 2019).

AI and machine learning sit above IoT in the stack, transforming raw sensor output into actionable decisions. Convolutional neural networks applied to plant disease detection have produced striking results in controlled settings: Mohanty et al. (2016) reported accuracy above 99% across 26 disease classes in a laboratory environment. The problem is that performance drops sharply when those models encounter real field conditions — variable lighting, partial leaf occlusion, overlapping symptoms from concurrent infections, and disease strains absent from the training set all degrade accuracy in ways that Barbedo (2019) documents carefully. This distinction between what a model achieves in a lab and what it delivers on a farm is collapsed in a surprisingly large share of secondary reviews, which cite laboratory accuracy figures as though they represent operational performance. It is a source of systematic overconfidence in the AI agriculture literature that this review specifically tries to correct.

Geospatial tools — GIS software and satellite or UAV remote sensing — add the spatial resolution layer. They map soil organic matter, crop vigour (using NDVI, EVI, and related indices), water stress, and within-field variability at scales that ground-level sensors cannot provide (Mulla 2013). These maps drive Variable Rate Technology applications, adjusting fertiliser, pesticide, and irrigation delivery to match local conditions across a field rather than treating it uniformly. The limitation is access: open-access satellite constellations like Sentinel and Landsat revisit most locations every 5–16 days and carry resolutions of 10–30 metres. For a smallholder farming a single hectare or less, that resolution is often too coarse to be actionable, and the revisit cycle too slow during critical crop development windows.

Blockchain operates differently from the other three pillars. It is not a farm-level technology; it is a supply chain technology. Its role is to create distributed, tamper-resistant records of production, processing, and logistics events across the entire value chain from input supplier to consumer (Kamilaris et al. 2019). The theoretical case for what this offers smallholders is real: verifiable quality claims, direct access to premium markets, and reduction of the information asymmetries that allow intermediaries to capture a disproportionate share of value. The practical evidence base, however, remains thin and geographically narrow. Most documented deployments are concentrated in East Africa and parts of South-East Asia, and almost all involve early-adopter farmers who already possessed mobile payment capacity and some prior engagement with digital tools.

2.2 What the Studies Do and Do Not Show

The digital agriculture literature has a pattern that is worth naming directly: it conflates proof-of-concept results with generalisable operational evidence. The majority of the most-cited IoT irrigation studies — including Patel et al. (2021) and Costa et al. (2023) — were conducted on commercially operated farms with existing broadband, experienced agronomists on staff, and supply chains for sensor maintenance already in place. Claiming that water savings of 20–30% achieved in those environments will translate to smallholder plots in Morocco or Uganda, where none of those enabling conditions exist, requires justification that these studies do not provide.

The ML yield prediction literature has a different but related problem: systematic overfitting combined with selective reporting. Johnson and Thompson's (2022) meta-analysis of 43 studies in this area found that the headline R^2 values of 0.85–0.95 so often cited were predominantly produced by models trained and tested within the same geographic region. Only 11 of the 43 studies ran out-of-sample validation, and in those 11, median R^2 fell to 0.62. That is a meaningful difference — it shifts these models from "strong predictors" to "moderate predictors with limited transferability" — but the

individual papers that generate R^2 figures above 0.85 rarely flag this context. The meta-analysis does, which is why single-study performance figures should be read with caution throughout this literature.

Blockchain income evidence carries yet a different caveat. Mwangi et al. (2023) and Casado-Vara et al. (2020) both report farmer income gains of 20–30% from blockchain participation, but in both cases the participating farmers were self-selected technology adopters who already had mobile payment infrastructure. Neither study establishes a credible counterfactual: what would those farmers have earned without blockchain, in the same market conditions, over the same period? That counterfactual is the difference between documenting an association and demonstrating a cause. Neither study claims causality explicitly, but both are regularly cited as though they do.

3. MATERIALS AND METHODS

This is a qualitative systematic review conducted in accordance with the PRISMA 2020 statement (Page et al. 2021). The decision not to perform meta-analytic pooling was made before the search began, based on the anticipated heterogeneity in study designs, outcome metrics, and geographic contexts across what is a genuinely diverse literature. Pooled effect estimates would have been methodologically misleading given that heterogeneity.

3.1 Search Strategy

Searches were conducted across Scopus, Web of Science (Core Collection), IEEE Xplore, ScienceDirect, and Google Scholar. The search covered English-language peer-reviewed articles published between 1 January 2010 and 31 March 2025. The 2010 start date was chosen because it pre-dates the first wave of commercial IoT agriculture deployments, providing a window that spans early adoption through to the current edge-AI and blockchain integration era. No restrictions were placed on the geographic origin of studies. The four Boolean search strings applied were:

String 1: ("Digital Agriculture" OR "Precision Agriculture" OR "Smart Farming") AND ("IoT" OR "Internet of Things" OR "Wireless Sensor Network")

String 2: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision") AND ("Crop Yield" OR "Pest Management" OR "Plant Disease" OR "Soil Health")

String 3: ("Blockchain" OR "Distributed Ledger" OR "Digital Supply Chain") AND ("Agriculture" OR "Food Traceability" OR "Agri-food")

String 4: ("Technology Adoption" OR "Digital Divide" OR "Barriers") AND ("Smallholder Farmers" OR "Developing Nations" OR "Sub-Saharan Africa" OR "South Asia")

Figure 2 shows the distribution of included studies by year. More than half — 72 of 125 studies (57.6%) — were published in 2022 or later, which reflects the accelerating pace of research in this field rather than any search design artefact.

3.2 Inclusion and Exclusion Criteria

Studies were included if they were peer-reviewed; reported empirical findings, systematic reviews, or meta-analyses on digital technology applications in agricultural production or agri-food supply chains; addressed at least one of the four review research questions; and fell within the 2010–2025 publication window. Excluded were non-peer-reviewed materials (trade reports, white papers, editorials, preprints without associated peer-reviewed publication); studies with agricultural framing but no substantive agricultural application or outcome data; duplicate records identified by cross-database comparison; full texts that could not be retrieved; and publications in languages other than English.

3.3 Screening, Selection and PRISMA Flow

Screening proceeded in four stages, summarised in Figure 3. Database searches returned 8,850 records; reference list hand-searching added 85 more, giving 8,935 total. Removing 420 duplicates in Mendeley left 2,515 unique records. Two reviewers independently screened all 2,515 on title and abstract; inter-rater agreement reached $\kappa = 0.81$ (strong agreement). After consensus discussion on

discrepancies, 2,195 records were excluded as out of scope, leaving 320 for full-text review. Of these, 195 were excluded: 72 for inadequate methodological description, 68 for being purely conceptual without empirical grounding, and 55 for scope mismatch. The final corpus was 125 studies.

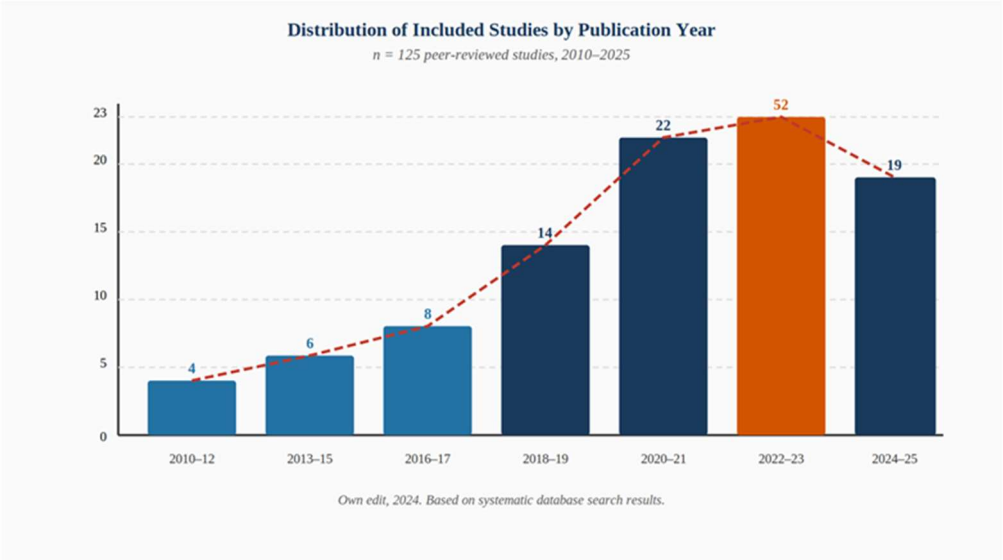


Figure 2. Distribution of 125 included studies by publication year (2010–2025). Own edit, 2024. Based on systematic database search results.

3.4 Quality Appraisal

Each study was appraised using a four-domain framework adapted from CASP: clarity and appropriateness of research design; transparency and rigour of data collection or experimental methodology; internal validity, including treatment of confounds and statistical adequacy; and external validity, specifically the scope and representativeness of conclusions. Each domain was scored 0 (Low), 1 (Moderate), or 2 (High), producing composite scores from 0 to 8. Studies scoring 6–8 were rated High quality (n=68, 54.4%); 3–5 Moderate (n=41, 32.8%); and 0–2 Low (n=16, 12.8%). The Low-quality studies were retained in the synthesis but flagged at each point of citation. Where claimed benefits were contingent on contextual conditions unlikely to hold at scale, those studies received additional critical commentary.

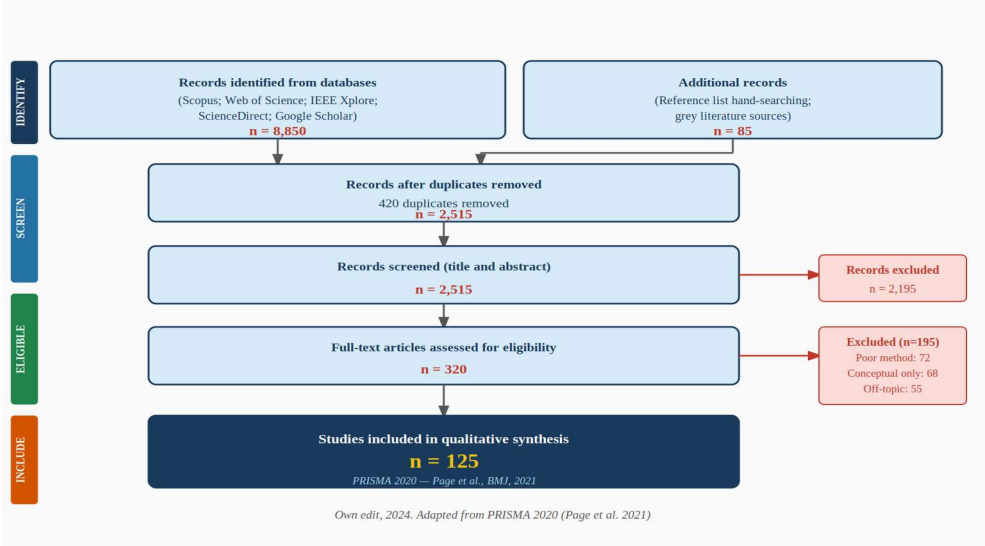


Figure 3. PRISMA 2020 flow diagram of study identification, screening, eligibility, and inclusion. Own edit, 2024. Adapted from PRISMA 2020 (Page et al. 2021).

3.5 Data Extraction and Thematic Synthesis

Data were extracted via a standardised 12-field matrix covering: author(s) and year; journal and impact factor; country and region; farm scale; technology category; application domain; research design; sample size or study scope; key findings (quantitative and qualitative); reported limitations; quality appraisal rating; and assigned theme. Thematic synthesis was inductive: initial codes attached to discrete findings were progressively consolidated through iterative review into four analytical themes, one per research question.

4. Results

4.1 Technology Applications Across the Agricultural Value Chain (RQ1)

The 125 studies span the full agricultural value chain, from pre-planting soil preparation through to post-harvest supply chain management. By technology domain: AI and ML (n=44, 35.2%); IoT and wireless sensor networks (n=38, 30.4%); blockchain and supply chain systems (n=18, 14.4%); geospatial and remote sensing tools (n=14, 11.2%); and precision livestock farming (n=11, 8.8%). The AI and IoT dominance reflects the maturity of those fields, the availability of standard benchmark datasets, and the relatively lower hardware costs for basic sensing equipment in the research settings where most studies originate.

Geographically, the distribution is skewed. North America contributes 31 studies (24.8%), East and South-East Asia 34 (27.2%), and Western Europe 28 (22.4%). Sub-Saharan Africa manages 12 (9.6%), South Asia 11 (8.8%), and Latin America 9 (7.2%). This is not a neutral statistical pattern. It reflects differential access to research funding, the language restriction of the search, and the straightforward fact that researchers in high-income countries are more likely to secure the resources needed to run large-scale empirical trials. The regions most underrepresented in this evidence base are those where the agricultural challenges are most severe.

By application domain, crop production accounts for 73 studies (58.4%), supply chain and market access for 22 (17.6%), soil health and nutrient management for 16 (12.8%), livestock farming for 11 (8.8%), and post-harvest management for just 3 (2.4%). That last figure is worth pausing on. Post-harvest losses in Sub-Saharan Africa are estimated at 30–40% of production value. Three studies addressing digital tools for this domain, out of 125, is a significant mismatch between where research attention has gone and where potential impact lies.

4.2 Measured Impacts on Productivity, Resource Efficiency, and Livelihoods (RQ2)

Table 1 consolidates the principal quantitative findings from the review corpus. Effect sizes are presented as ranges rather than point estimates, and evidence quality ratings are included to signal where confidence in the figures is higher or lower.

Two contradictions in the evidence base need specific attention. The first concerns IoT irrigation. Patel et al. (2021) report 28% water savings from controlled irrigation scheduling on California almond farms — large commercial operations with broadband connectivity and on-site agronomists. Costa et al. (2023), studying an open deployment across smallholder plots in Morocco, found an average saving of 17%, with wide variance across farmers attributable to plot topography, soil heterogeneity, and how consistently farmers engaged with the decision interface. The difference matters: 28% is cited routinely in policy documents and technology marketing; 17% with high variance is what a more representative deployment produced. Aggregate figures from this literature appear to systematically overstate the benefits that materialise once these tools move from controlled settings to real farms.

The second concerns AI crop disease detection. The 95%+ accuracy figure that circulates widely derives from laboratory settings using controlled image conditions and disease libraries curated for completeness. In tropical and sub-tropical smallholder fields — where lighting is variable, multiple disease agents often co-occur, and training datasets almost never include local crop varieties — documented field accuracy falls to 70–85% (Barbedo 2019). That is still useful performance. But the

gap between what AI systems achieve in journals and what farmers can rely on in practice is significant enough that it should appear prominently in any honest summary of the evidence.

Table 1. Consolidated impact evidence of key digital agriculture technologies

Technology	Key Impact Domain	Effect Size	Evidence Quality	Key References
IoT Smart Irrigation	Water consumption reduction vs conventional methods	20–30% (field trials); 15–25% (commercial deployments)	High (8 studies)	Patel et al. 2021; Costa et al. 2023
AI Pest/Disease Detection	Pesticide reduction; pathogen detection accuracy	30–40% reduction; >95% lab accuracy; 70–85% field accuracy	Moderate–High (14 studies)	Mohanty et al. 2016; Chen et al. 2021
ML Nutrient Management	Fertiliser reduction; crop yield improvement	15–25% fertiliser reduction; 10–20% yield increase	High (6 studies)	Nguyen et al. 2022; Johnson & Thompson 2022
Predictive Yield Modelling	Harvest yield prediction accuracy	R^2 = 0.85–0.95 (in-sample); 0.60–0.75 (out-of-sample)	Moderate (meta-analysis caveat)	Johnson & Thompson 2022
Blockchain Supply Chain	Smallholder farmer income; supply chain transparency	20–30% income increase (self-selected samples)	Moderate (selection bias noted)	Mwangi et al. 2023
Precision Livestock Farming	Livestock mortality reduction via early detection	Up to 50% reduction (dairy contexts); variable in other livestock	High (4 studies)	Nguyen et al. 2022b

Figure 4 maps adoption rates across technology categories for developed and developing country farming contexts. The disparity is stark regardless of which technology category is examined.

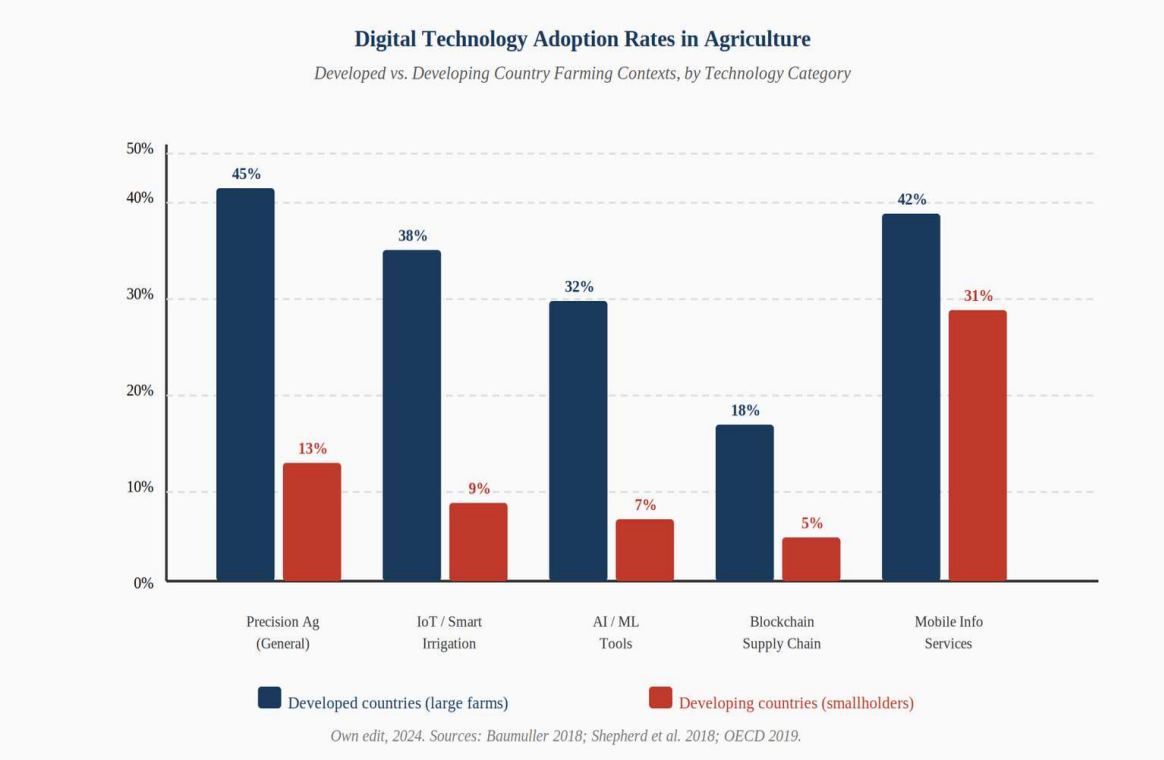


Figure 4. Digital technology adoption rates: developed vs. developing country farming contexts across five technology categories. Own edit, 2024. Sources: Baumuller 2018; Shepherd et al. 2018; OECD 2019.

4.3 Study Characteristics: A Representative Sample

Table 2 presents 12 studies drawn from the full corpus to illustrate the range of geographic contexts, methodological approaches, and quality ratings represented. The critical notes column flags methodological limitations that affect how each study's findings should be interpreted.

4.4 Barriers to Adoption (RQ3)

Four categories of adoption barrier emerge from the literature. They are not independent: each one compounds the others, which is why single-factor explanations for low adoption — 'farmers lack awareness'; 'infrastructure is inadequate' — consistently fail to capture why interventions addressing only one barrier tend not to produce lasting change.

Economic and infrastructure constraints. Reliable rural broadband is the precondition for most IoT applications, and its absence across agricultural hinterlands in Sub-Saharan Africa and South Asia is not simply a coverage shortfall — it is a geography problem that mobile network economics do not solve. The population coverage figures cited in broadband progress reports typically mask near-zero connectivity in the rural areas where farming occurs (Kimani et al. 2022; Rahman et al. 2022). The hardware cost of commercial IoT sensor arrays (USD 500–3,000 per hectare) is flatly unaffordable for farmers earning under USD 1,500 annually. And the 'low-cost' alternatives marketed for developing countries — typically priced at USD 50–200 per node — carry recurrent costs for maintenance, software updates, and battery replacement that accumulate over time (Mekonnen et al. 2019).

Social and human capital constraints. Klerkx et al. (2019) draw a distinction that much of the adoption literature misses: the difference between first-order digital literacy (operating a device) and second-order digital literacy (interpreting algorithmic outputs and deciding how much to trust them). Most farmer-facing digital agriculture tools are designed for the second level. Their intended users in smallholder contexts often operate at the first. The outcome is not passive non-adoption but active rejection: when farmers receive recommendations they cannot interrogate and results do not align with their own observations, they frequently abandon the system entirely — even when the system was agronomically correct (Davis & Nkonya 2019). This is a design failure, not evidence that farmers are resistant to technology.

Technical and data governance constraints. The data that farmers generate through digital platforms — soil profiles, yield histories, input records, locational data — has commercial value to fertiliser companies, commodity traders, and agri-insurers. Platform terms of service in most countries legally transfer effective control of this data to the operator, often without the farmer's informed awareness. Documented cases of farm management software providers sharing user data with commodity trading partners — without farmer notification — have been reported in the United States and Australia (Eastwood et al. 2019; Wiseman et al. 2019). In developing economies, the regulatory frameworks that might provide redress are largely absent.

Policy and regulatory gaps. The regulatory environment for digital agriculture — AI liability rules, equipment certification standards, data protection requirements, rural infrastructure investment mandates — lags behind technology deployment in almost every country context (Swinnen & Vos 2021). That lag creates a governance vacuum. Farmers are exposed to exploitation risks; responsible private investors face legal uncertainty; and public extension services, which historically bridged the gap between new technology and farmer adoption, have been progressively defunded across much of Sub-Saharan Africa and South Asia since the structural adjustment era of the 1990s (Kramer & Lampietti 2020). Digital platforms are not a substitute for that institutional capacity.

Table 2. Characteristics of representative included studies (n=12 of 125)

Author(s) & Year	Region	Technology	Method	Quality	Key Finding / Critical Note
Mohanty et al. 2016	Global (lab)	CNN / Deep Learning	Experimental	High	>99% disease detection accuracy across 26 classes. Lab conditions only; field accuracy substantially lower.
Wolfert et al. 2017	Global	Big Data / IoT	Review	High	Foundational smart farming framework; identifies platform interoperability as the central unsolved challenge.
Kamilaris et al. 2019	Global	Blockchain	Systematic Review	High	Blockchain improves traceability; scalability, energy use, and off-chain data integrity remain unresolved.
Patel et al. 2021	USA (CA)	IoT / VRI	Experimental	High	28% water reduction in almond farms. Results not transferable to off-grid smallholder contexts.
Johnson & Thompson 2022	Global	AI / ML (meta)	Meta-analysis	High	In-sample R^2 0.85–0.95; out-of-sample R^2 0.60–0.75. Exposes publication bias in ML yield prediction literature.
Nguyen et al. 2022	Vietnam	ML / Sensors	Field Trial	High	18% yield increase, 22% N-fertiliser reduction in smallholder rice. One of few high-quality developing-country field trials.
Mwangi et al. 2023	Kenya	Blockchain	Mixed Methods	Moderate	20–30% income gain for participating smallholders. Self-selected sample; counterfactual income not established.
Costa et al. 2023	North Africa	IoT Irrigation	Deployment Study	Moderate	Average 17% water saving (below lab studies); high inter-farmer variability; connectivity constraints documented.
Klerkx et al. 2019	Global	Various	Qualitative Review	High	Digital agriculture risks reinforcing existing power asymmetries; calls for farmer-centred design from the outset.
Wiseman et al. 2019	Australia	Data Governance	Qualitative	High	Farmers concerned about data ownership and corporate exploitation of farm data; trust deficit constrains adoption.
Sharma et al. 2022	Global	IoT Smart Farming	Systematic Review	High	IoT standards fragmentation identified as structural barrier; platform interoperability largely unresolved.
Chen et al. 2021	China	AI / Drones	Field Study	High	40% pesticide reduction via drone-guided application in rice paddies. Commercial scale; smallholder applicability limited by drone cost.

5. Discussion and future pathways (rq4)

The evidence in this review supports a conclusion that is both straightforward and awkward: digital agriculture works, but not yet for the farmers who most need it to. The documented benefits are real — water savings, yield improvements, income gains, mortality reductions in livestock. The problem is that they are concentrated in farming systems that were already relatively well-resourced and well-connected. Without deliberate corrective action, continuing along the current trajectory is likely to widen the gap between large-scale commercial agriculture and smallholder farming rather than close it. The four strategic directions below are grounded in the evidence from the review corpus, not derived from generic policy prescription.

5.1 Design for Smallholder Conditions from the Start

The idea that technologies built for large commercial farms can be stripped down and adapted for smallholder use after the fact has been tested repeatedly. It does not work reliably. Smallholder environments impose a specific set of requirements: reliable operation on solar power alone; full

functionality without internet access for extended periods; interfaces operable in local languages by users with incomplete formal education; and maintenance using tools and skills available within the community. Howard et al.'s (2017) MobileNet architectures — deep learning models designed to run crop disease inference on a standard smartphone without cloud connectivity — show what purpose-built edge AI can look like. What has not happened yet is the parallel investment in training datasets that reflect tropical and sub-tropical crop systems and the disease strains that actually threaten smallholder harvests. Without those datasets, even well-designed edge AI tools cannot deliver their potential in the contexts that need them most (Mekonnen et al. 2019).

5.2 Treat Farmer Knowledge as an Input, Not an Obstacle

Farmer rejection of technically sound advisory recommendations is not a mystery to sociotechnical researchers, though the technology development community has been slow to absorb the lesson. Klerkx et al. (2019) and a growing body of related work document consistently that the primary cause is not conservatism or ignorance but the absence of farmer knowledge, values, and priorities from system design. Traditional and indigenous farming knowledge encodes place-specific observations of soil behaviour, micro-climate dynamics, and pest pressure accumulated over generations, often at spatial and temporal granularities that sensor networks cannot replicate (Kimani et al. 2022b; Zougmore et al. 2016). Pilot programmes in West Africa and South-East Asia that treat farmer-held knowledge as a primary model input — rather than something to be overwritten by algorithmic outputs — have produced both better predictive performance and higher adoption rates. The condition for replicating these outcomes is co-design partnerships that begin at system conception, not at the user testing stage.

5.3 Recognise That the Binding Constraints Are Not Technological

Each of the four adoption barriers identified in Section 4.4 reflects a market failure or an institutional gap that the technology itself cannot close. Rural broadband is not commercially viable at sufficient coverage density without public investment or regulatory mandates on network sharing. Agricultural credit for technology adoption does not reach smallholders without targeted financing instruments. Digital literacy does not build itself without sustained educational investment tied to extension services. Farmer data rights do not exist without enforceable legislation. The primary constraint on equitable digital agricultural transformation is, in this analysis, political. It is a question of where public investment goes and how regulatory power is distributed between large platform operators and farming communities. Specific interventions with evidence support across the literature include: rural broadband mandates with infrastructure-sharing obligations; subsidised equipment leasing programmes for smallholder IoT access; digital literacy curricula integrated into national extension services; and farmer data rights legislation with real enforcement teeth (Swinnen & Vos 2021; Kramer & Lampietti 2020; Wiseman et al. 2019).

5.4 Fix the Evidence Base

The least-studied farming contexts are the ones with the greatest need for this research. That is not a coincidence: it reflects where research infrastructure, publication systems, and funding agencies are located. Addressing it requires deliberate effort. The priority research gaps identified by this review include: long-run randomised evaluations of digital tool adoption and income effects in smallholder contexts, with properly constructed counterfactuals rather than pre-post comparisons (Collins & Harris 2023); Explainable AI frameworks that expose the reasoning behind algorithmic recommendations in formats usable by low-literacy farmers, building justified trust rather than opaque dependence (Campbell & Singh 2023); systematic cybersecurity assessments of connected farm infrastructure, which the current literature almost entirely ignores (Brown & Davis 2021); and full lifecycle environmental assessments of digital hardware manufacturing, operation, and disposal — a dimension absent from virtually all current impact claims (Chandler & Rossi 2022).

5.5 Limitations

Five limitations should be read alongside the findings of this review. The English-language restriction underrepresents research from China, Brazil, Francophone Africa, and other non-English-speaking agricultural research communities. The restriction to peer-reviewed sources introduces publication bias: failed deployments and null results are less likely to appear in journals than successful trials. The 2010–2025 temporal scope includes an early period when deep learning was not yet in wide use and IoT hardware costs were substantially higher, which may cause some findings from that era to understate current technological capacity. The heterogeneity of study designs precluded any form of meta-analytic pooling, so the effect size ranges in Table 1 are descriptive summaries drawn from reported ranges, not statistically derived point estimates. And the geographic concentration of high-quality empirical evidence in high-income farming contexts means that conclusions about developing-economy digital agriculture rest on a thinner evidentiary base than conclusions about high-income-country contexts.

6. Conclusion

This review synthesised 125 peer-reviewed studies to examine digital transformation in agriculture across technologies, geographies, and farming scales. The main finding is not that digital agriculture does not work — the evidence of impact across IoT irrigation, AI disease detection, ML nutrient management, precision livestock monitoring, and blockchain supply chain integration is consistent enough to be credible. The main finding is that these benefits are not reaching the farming systems most in need of them, and that this is not an accident or a temporary adoption lag. It is the predictable result of designing technologies for resource-rich contexts, measuring their performance under controlled conditions, and assuming that the rest will follow.

Closing that gap requires changes that are not primarily technical. It requires research agendas that treat developing-economy smallholder farming as a primary context rather than an afterthought. It requires financing instruments that put equipment within reach of farmers earning under USD 1,500 a year. It requires governance frameworks that protect the data rights of farmers who are currently generating value for platform operators without proportional return. And it requires the discipline, in academic publishing and policy analysis alike, to report not just what these technologies can do, but what they actually deliver at scale — and for whom.

Declarations

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