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Research paper

AI and Precision Agriculture for Food Security and Rural Livelihoods in Developing Countries: A Systematic Review

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ABSTRACT

Artificial intelligence (AI) and precision agriculture technologies are increasingly promoted as tools for addressing food insecurity and improving rural livelihoods in developing countries, but the evidence on their developmental outcomes and governance implications is fragmented across disciplines. This study conducted a PRISMA 2020-guided systematic review of peer-reviewed journal articles and scholarly book chapters published between 1 January 2012 and 15 January 2026 and retrieved from Scopus, Web of Science Core Collection, and the Directory of Open Access Journals (DOAJ). Of 412 records identified, 52 studies met the inclusion criteria. Empirical studies were appraised at the study level with the Mixed Methods Appraisal Tool (MMAT 2018), while reviews and conceptual papers were used for context. Studies were coded against an a priori framework of four governance mechanisms (targeting and allocation; delivery and service provision; monitoring and evaluation; accountability and participation) and synthesised thematically across six domains. The strongest evidence concerns the technical performance of AI models for crop and food-insecurity prediction and for pest and disease detection. Evidence that these tools improve farm incomes, food security or livelihood resilience in practice is limited: few studies measured livelihood or food-security outcomes, were longitudinal, or disaggregated results by gender or farm size. Recurrent constraints include infrastructure deficits, low digital literacy, unrepresentative training data, weak institutional capacity and regulatory gaps. The study contributes a framework that links AI applications to food-security and livelihood outcomes through governance mechanisms and identifies where evidence is strong, emerging or absent. Potential benefits should be regarded as plausible but not yet demonstrated at scale. Priorities include impact evaluations with livelihood endpoints, gender-disaggregated and distributional analysis, and comparative studies of the institutional conditions under which AI-enabled agriculture benefits smallholders.

Keywords: artificial intelligence, precision agriculture, food security, rural livelihoods, developing countries, systematic review, MMAT

The convergence of artificial intelligence (AI) and precision agriculture has become a prominent theme in development policy. In developing countries, where smallholder farming underpins rural livelihoods and national food systems, AI-driven tools are promoted as a means of raising productivity, improving food security and stabilising incomes (Mhlanga, 2021; Bahn et al., 2021). Yet despite rapid advances in remote sensing, machine learning and digital advisory systems, it is unclear how far these technologies translate into sustained developmental

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outcomes in low-resource settings, and the relevant evidence is scattered across agricultural science, computer science, development economics and governance studies.

Conventional agricultural extension and food-security monitoring in developing countries are constrained by sparse and infrequent data, limited institutional capacity and slow responses to changing agroclimatic conditions. AI methods can analyse large, heterogeneous and frequently updated data such as satellite imagery, sensor readings and mobile-phone records, and reviews of the poverty-prediction literature show that such methods can produce spatially detailed welfare estimates where survey data are scarce (Hall et al., 2023; Usmanova et al., 2022; McBride et al., 2022). At the same time, there is concern that AI may entrench existing inequalities if it is deployed without attention to inclusion, data justice and institutional readiness (Nemorin et al., 2023; Sinanan & McNamara, 2021).

Existing reviews have examined adjacent questions: machine learning and satellite imagery for poverty prediction (Hall et al., 2023; Usmanova et al., 2022), prediction for targeting and early warning (McBride et al., 2022), and digitalisation of agri-food systems in the Middle East and North Africa (Bahn et al., 2021). A related review, published after the search for the present study was completed, examines AI in poverty governance across finance, agriculture, health and education (Sheik & Kabanda, 2026). The present study narrows the focus to the intersection of AI, precision agriculture, food security and rural livelihoods in developing countries, and adds study-level quality appraisal and an explicit distinction between technical-performance evidence and evidence on outcomes for farmers.

The study pursues three objectives:

1. To map the domains in which AI and precision agriculture technologies are applied to food-security and rural-livelihood challenges in developing countries, and the governance mechanisms through which they operate.
2. To synthesise the evidence on benefits, constraints and risks, distinguishing technical performance from intermediate outcomes (adoption, use, cost) and final outcomes (food security, livelihoods), and grading the strength of evidence for each.
3. To identify evidence gaps and methodological weaknesses in the literature in order to inform research and policy.

The study is reported in accordance with the PRISMA 2020 statement (Page et al., 2021). Presents the theoretical and conceptual framework; details the methods, including the coding and appraisal procedures; reports study characteristics, quality appraisal and the thematic synthesis; discusses the findings through the four governance mechanisms; and concludes.

THEORETICAL FRAMING AND CONCEPTUAL FRAMEWORK

AI is best understood as a socio-technical system rather than a purely computational artefact: its performance and impact are co-produced by algorithms, data infrastructures, institutions, regulation and the social contexts in which systems are designed and used (Liang et al., 2022; Nemorin et al., 2023). This matters especially in low-income agrarian settings, where structural inequalities, limited connectivity and weak institutions shape who benefits from digital innovation and who is left behind.

The multidimensional poverty framework provides the first pillar. Poverty is understood as deprivation across income, nutrition, education, health and access to productive resources, which interact to generate cumulative disadvantage. Machine learning applied to satellite and survey data has been used to estimate the spatial distribution of poverty and malnutrition in data-poor settings. Predictive performance is higher for asset-based welfare measures than for income or consumption (Hall et al., 2023), and different uses such as targeting, mapping and early warning require different data and methods (McBride et al., 2022). These estimates are relevant to food security because they can inform where agricultural and nutritional support is directed.

The capability approach offers a complementary normative lens, evaluating AI applications by whether they expand or constrain substantive freedoms. In principle, AI-supported advisory services could enhance farmers' capability to achieve food security by providing actionable information on soil, weather, pests and prices (Mhlanga, 2021), and alternative-data credit scoring could expand economic capabilities by widening access to finance (Jejeniwa & Mhlongo, 2024). Whether this capability gains materialise in practice is an empirical question examined in results section.

Digital development (ICT4D) scholarship stresses that technology adoption and impact are mediated by power structures, institutional capacity, regulation and cultural practice (Al-Emran & Griffy-Brown, 2023; Sinanan & McNamara, 2021). It cautions against technologically deterministic narratives and emphasises local adaptation, capacity building and participatory design.

Complexity theory frames food insecurity as the product of interacting climatic, economic, social and institutional subsystems. AI models can capture nonlinear relationships and update as new data arrive, which is why they are proposed for early warning of food crises (McBride et al., 2022).

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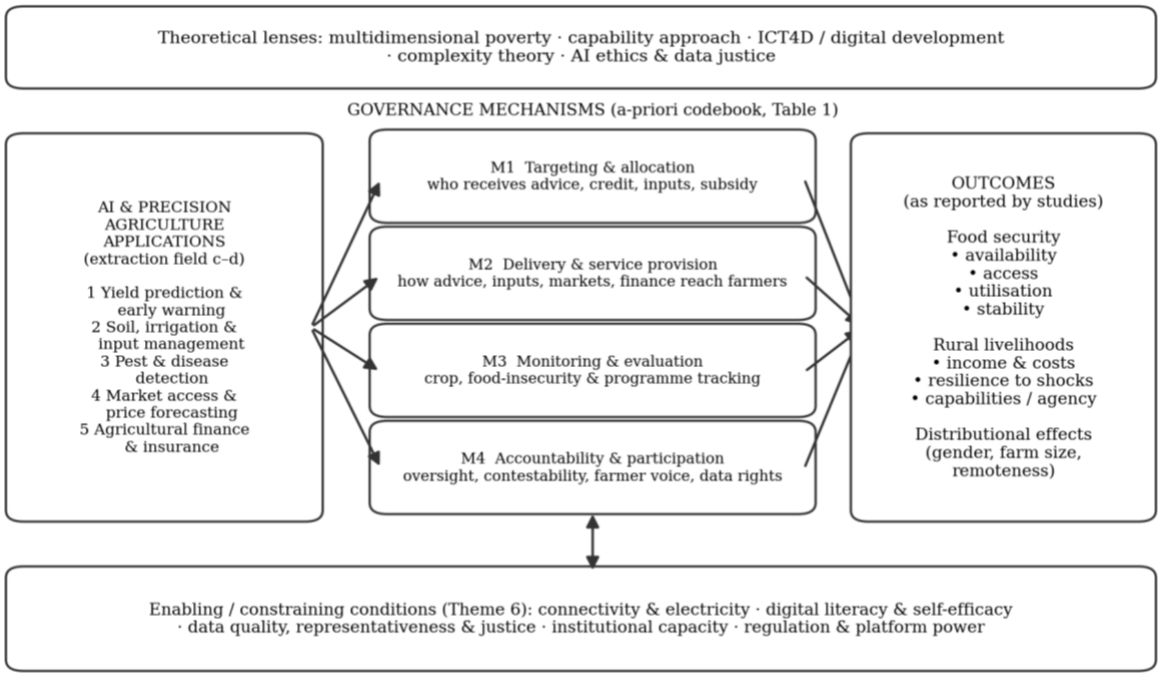
Finally, AI ethics and data justice raise questions of fairness, transparency, accountability and privacy (Liang et al., 2022; Al-Emran & Griffy-Brown, 2023). Algorithmic bias arising from skewed training data can exclude marginalised farming communities from advice, credit or subsidies. Data-justice perspectives ask who is visible in agricultural data, who controls data infrastructures and how benefits and harms are distributed (Nemorin et al., 2023; Sinanan & McNamara, 2021).

Conceptual framework and its operationalisation

Drawing on these traditions, this study positions AI applications as acting on food-security and livelihood outcomes through four governance mechanisms, conditioned by enabling and constraining factors (**Figure 1**). The mechanisms were defined a priori, before data extraction, and were operationalised as a codebook (**Table 1**) that specifies inclusion indicators, exclusion notes and a worked example for each code. The framework therefore functions not only as an interpretive lens but as the coding structure used in extraction (Coding into governance mechanisms) and the organising structure of the discussion. Outcomes are recorded at three levels—technical performance, intermediate outcomes and final outcomes—so that the synthesis can distinguish between evidence that a tool works as designed and evidence that it improves people's lives.

Figure 1

Conceptual framework linking AI and precision-agriculture applications to food-security and livelihood outcomes through four governance mechanisms.



Source: Author. Theoretical lenses from theoretical framing and conceptual framework; mechanism definitions in Table 1.

MATERIALS AND METHODS

Protocol and reporting

The study is reported in accordance with PRISMA 2020 (Page et al., 2021). The protocol was not registered.

Information sources and search strategy

Scopus, Web of Science Core Collection and DOAJ were searched because together they provide interdisciplinary coverage of agricultural science, development studies, information systems, economics and public policy. The final search of all three databases was run on 15 January 2026. The Scopus string is shown below; equivalent strings were adapted to the syntax of Web of Science (topic field) and DOAJ.

Eligibility criteria

Studies were included if they: (a) were peer-reviewed journal articles or peer-reviewed scholarly book chapters; (b) were published in English with a version of record or online-first version available between 1 January 2012 and 15 January 2026; (c) examined AI or precision agriculture as a central subject; (d) addressed at least one dimension

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of food security (availability, access, utilisation, stability) or rural livelihoods; (e) concerned one or more developing countries, defined as low-, lower-middle- or upper-middle-income economies in the World Bank classification at the time of publication; and (f) reported empirical data or offered a substantive review or conceptual analysis of AI in agriculture or food systems. Studies were excluded if they: (a) discussed digital technologies without a substantive AI or precision-agriculture component; (b) applied AI to sectors unrelated to agriculture or food systems without an agricultural or food-security outcome; (c) were set exclusively in high-income countries; or (d) were editorials, conference abstracts, preprints or non-peer-reviewed reports.

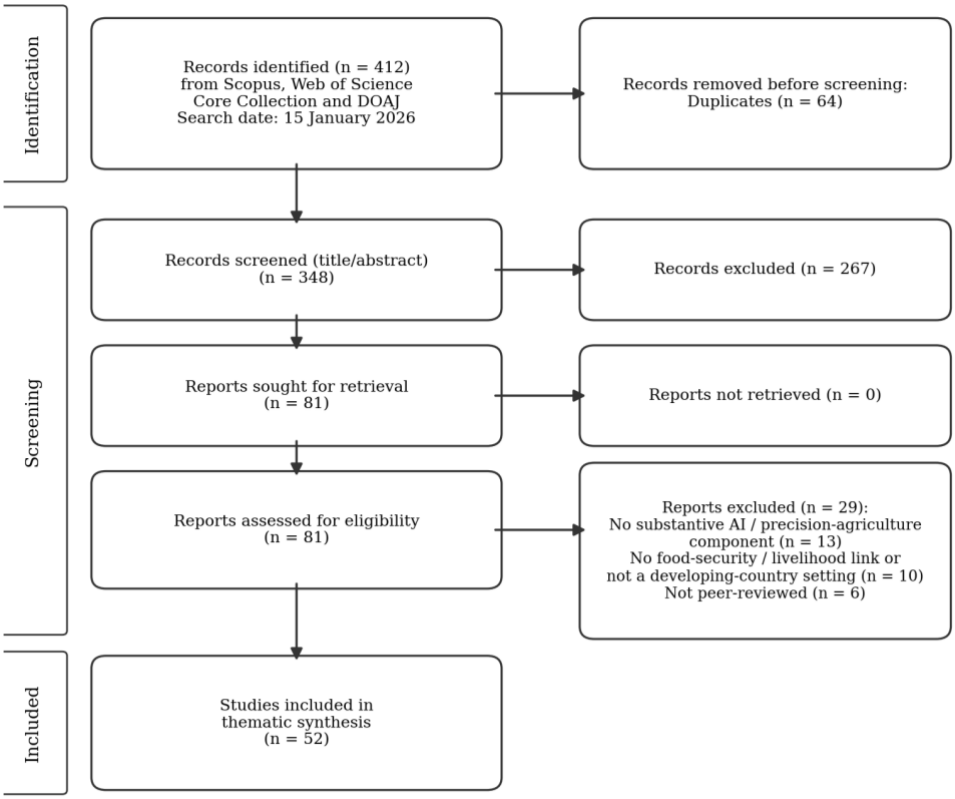
To ensure consistency with the search date, for every study with a 2025 or 2026 publication year, the date on which the version of record or online-first version became available was checked on the publisher's website against the search date. Studies first made available after 15 January 2026 were not eligible for inclusion. Literature published after the search is cited only in the Introduction and Discussion and does not form part of the evidence base.

Study selection

After removal of 64 duplicates, 348 records were screened on title and abstract by two researchers working independently, and disagreements were resolved through discussion; 267 records were excluded at this stage. The full texts of the remaining 81 reports were assessed independently by the same two researchers, and 29 were excluded: no substantive AI or precision-agriculture component (n = 13); no link to food security or rural livelihoods, or not set in a developing country (n = 10); and not peer-reviewed (n = 6). The final set comprised 52 studies (**Figure 2**).

Figure 2

PRISMA 2020 flow diagram of study identification, screening and inclusion.



Source: Author, adapted from Page et al. (2021).

Data extraction

Data were extracted using a standardised form with the following fields: (a) bibliographic details; (b) country and region; (c) application domain; (d) AI or precision-agriculture method; (e) study design and MMAT category; (f) sample and data sources; (g) governance mechanism(s), coded as described in Coding into governance mechanisms section; (h) outcome level (technical performance, intermediate or final); (i) reported benefits, constraints and risks; (j) whether results were disaggregated by gender, farm size or another equity dimension; (k) study duration (cross-sectional or longitudinal); and (l) theoretical frameworks used.

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Coding into governance mechanisms

Coding combined a deductive and an inductive stage. In the deductive stage, each study was coded against the four a priori mechanisms using the codebook in **Table 1**, which was fixed before extraction began. In the inductive stage, sub-codes were developed within each mechanism from the study content (for example, "subsidy targeting" and "credit eligibility" within M1), following the line-by-line coding and descriptive-theme stages of Thomas and Harden (2008). The six application domains used to organise results emerged from grouping these descriptive codes and were not defined in advance.

Because many studies bear on more than one mechanism (an early-warning model, for instance, both monitors conditions (M3) and informs who receives assistance (M1)), each study was assigned one primary mechanism—the mechanism most directly addressed by the study's research question or main outcome—and up to two secondary mechanisms. Where the primary code was ambiguous, the decision rule was to code the mechanism to which the study's main outcome measure relates. Coding decisions were discussed by the two researchers until agreement was reached.

Table 1

Codebook for the four governance mechanisms (defined a priori).

Code	Definition	Coded when the study…	Not coded when…	Example
M1 Targeting & allocation	Use of AI to decide who or where receives agricultural support, advice, inputs, credit, insurance or food assistance	identifies, ranks, scores or selects farmers, households or areas for an intervention	prediction is reported without any stated use for allocation (code M3)	Alternative-data credit scoring of smallholders
M2 Delivery & service provision	Use of AI to deliver or improve a service or input to farmers	provides advice, diagnosis, recommendations, market information or finance directly to users, or optimises input use	the tool is evaluated only offline on a test dataset with no delivery channel (code M3)	Smartphone disease-diagnosis app used by extension agents
M3 Monitoring & evaluation	Use of AI to track conditions or programme performance over time	measures or forecasts yields, crop condition, food insecurity or programme outcomes	the monitoring output feeds directly into a named allocation decision (code M1 primary, M3 secondary)	Satellite-based yield estimation; food-crisis early warning
M4 Accountability & participation	Arrangements through which AI-mediated decisions are overseen, contested or shaped by affected people	examines transparency, oversight, grievance, consent, data ownership, farmer participation in design, or regulation	risks are mentioned only in passing without analysis	Study of data-ownership terms in digital-agriculture platforms

Source: Author. Enabling and constraining conditions (Figure 1) were coded separately as a descriptive field and form Theme 6.

Quality appraisal and operationalisation of confidence categories

Empirical studies were appraised with the Mixed Methods Appraisal Tool, version 2018 (MMAT; Hong et al., 2018), by two researchers working independently, and disagreements were resolved through discussion. The MMAT has two screening questions and five design-specific criteria for each of five categories: qualitative, quantitative randomised, quantitative non-randomised, quantitative descriptive, and mixed methods. Model-development studies that train and test a predictive model on observational data were appraised as quantitative non-randomised or quantitative descriptive, depending on whether a comparison or counterfactual was involved; the category assigned to each study was recorded during extraction.

The MMAT developers advise against computing a single overall score and recommend reporting ratings for each criterion (Hong et al., 2018). Accordingly, each study was rated on every criterion, and these ratings were retained at criterion level. To inform the synthesis, studies were additionally grouped into three confidence categories using the following pre-specified rule:

- Higher confidence: both screening questions answered "yes" and all five design-specific criteria rated "yes".
- Moderate confidence: both screening questions "yes" and three or four criteria "yes", provided that the unmet criteria did not include the core validity criterion for the design. The core criteria were 3.4 (confounders accounted for) for quantitative non-randomised studies, 4.2 (sample representative of the target population) for quantitative descriptive studies, and 1.4 (interpretation substantiated by data) for qualitative studies. A study meeting three or four criteria but failing its core criterion was classed as lower confidence.

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- Lower confidence: both screening questions "yes" but two or fewer criteria "yes", or failure of the core criterion. Studies failing either screening question were not appraised further and were excluded as not empirical.

Criteria rated "can't tell" were treated as not met. Lower-confidence studies were retained, but the synthesis did not rely on them alone for any claim: a finding supported only by lower-confidence studies is reported as "limited" evidence (synthesis and grading of evidence strength Section). Reviews, bibliometric analyses and conceptual papers are not appraisable with the MMAT. They were used to frame and interpret the findings and are not counted as independent evidence in the synthesis.

Synthesis and grading of evidence strength

Thematic synthesis followed the three stages of Thomas and Harden (2008): line-by-line coding, development of descriptive themes and generation of analytical themes. For each theme, the overall strength and consistency of the empirical evidence was then graded using the rules in **Table 2**, adapted from the logic of GRADE-CERQual.

Table 2.
Rules for grading the strength of evidence within each theme

Rating	Operational rule
Strong	≥ 3 higher-confidence empirical studies from ≥ 2 world regions, with findings pointing in the same direction
Moderate	≥ 2 empirical studies, at least one higher-confidence, with mostly consistent findings; or ≥ 3 moderate-confidence studies with consistent findings
Limited	A single empirical study, only lower-confidence studies, or studies with inconsistent findings
Insufficient	No empirical studies; the theme rests on reviews or conceptual papers

Source: Author. Ratings are applied separately to technical-performance, intermediate and final outcomes within each theme.

The wording used to report findings in results section reflects these grades, so that statements of consistency are confined to themes where the evidence is strong.

RESULTS

Characteristics of included studies

The 52 included studies comprise peer-reviewed journal articles and scholarly book chapters published between 2012 and 2026, spanning empirical studies, reviews and conceptual papers. Empirical evidence is concentrated in countries and regions with more developed digital infrastructure and research capacity, while evidence from fragile, conflict-affected and very low-income agricultural contexts is sparse. Most empirical contributions report technical performance metrics; longitudinal designs, gender-disaggregated analyses and measurement of final food-security or livelihood outcomes are uncommon.

Quality appraisal and evidence profile

The empirical studies were appraised against the MMAT criteria for their design category and assigned to the higher-, moderate- or lower-confidence categories defined in Quality appraisal and operationalisation of confidence categories section. Reviews, bibliometric analyses and conceptual papers were not appraised and were used only to frame and interpret the empirical findings. Across the six themes, the empirical evidence is strongest for technical performance, particularly in yield prediction, early warning, and pest and disease detection, and weakest for intermediate and final outcomes such as adoption, income and food security. The evidence grades defined in Table 2 informed the strength of the statements made in the thematic synthesis that follows.

Theme 1: Crop yield prediction and early warning

Studies in this theme use machine learning on satellite imagery, weather records, soil data and historical harvest or survey data to estimate crop production or food-security conditions at finer spatial and temporal resolution than conventional surveys allow. Included studies show that AI-enhanced monitoring can provide more frequently updated estimates than traditional survey-based approaches, which are slow, costly and often outdated.

Reviews of the adjacent poverty-prediction literature help interpret these results. Hall et al. (2023) find that models targeting asset-based welfare measures perform substantially better than those targeting income or consumption. Combining machine learning with deep learning also improves predictive power. Usmanova et al. (2022) document the dominance of ensemble methods such as random forests, and McBride et al. (2022)

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emphasise that targeting, mapping, monitoring and early warning are distinct tasks requiring different data and methods.

Nevertheless, most studies in this theme report predictive accuracy on held-out data. Few examine whether forecasts or warnings were used by decision-makers, and fewer still assess whether their use changed food-security outcomes. The evidence therefore supports conclusions about technical feasibility under study conditions, but not about impact on food security.

Theme 2: Soil health, irrigation and precision input management

This theme covers AI tools that analyse soil, weather and crop-growth data to recommend fertiliser rates, planting density and irrigation schedules. Included studies report reduced input wastage and improved resource-use efficiency among smallholders. A regional review of the Middle East and North Africa sets out the potential, current status and risks of digitalisation for agri-food systems in a water-scarce region (Bahn et al., 2021). As in the other themes, however, this evidence centres on technical and agronomic performance, and evidence on farm-level profitability and on sustained adoption after projects end is limited.

Theme 3: Pest and disease detection and management

Studies in this theme apply image recognition, typically convolutional neural networks, to leaf photographs or drone imagery in order to detect pest damage and crop disease. Mobile applications that return a diagnosis from a smartphone photograph are of particular interest for smallholders in sub-Saharan Africa and South Asia, where agronomists are few. Included studies report high classification accuracy for these tools. By contrast, evidence that these tools reduce crop losses, pesticide use or income losses when used by farmers and extension agents is limited.

Theme 4: Market access, price forecasting and post-harvest loss

This theme concerns AI tools that forecast prices, match buyers and sellers, or optimise storage and logistics in order to reduce information asymmetries and post-harvest losses. Conceptual work argues that AI can support poverty reduction in emerging economies by improving access to information and services (Mhlanga, 2021). A review of AI applications to food waste identifies uses in monitoring and optimising food production and supply chains and in redistributing surplus food (Onyeaka et al., 2023), which are relevant to post-harvest loss in developing countries. However, empirical evidence on whether AI-based market tools raise the prices smallholders receive, strengthen their bargaining power or increase their incomes is thin, and this theme rests more heavily than the others on conceptual and review literature.

Theme 5: Agricultural finance and livelihood resilience

Smallholders are commonly excluded from formal finance because they lack credit histories and collateral and are perceived as high-risk. AI-based credit scoring using mobile-money transactions, phone metadata or satellite-derived farm data is proposed as a way to widen access to loans, insurance and savings products (Mhlanga, 2021; Jejeniwa & Mhlongo, 2024). Included studies describe how machine learning applied to mobile-money transactions and digital marketplace behaviour generates creditworthiness profiles for rural borrowers without formal credit histories. However, few studies have assessed exclusion errors, over-indebtedness, or effects on the poorest farmers and on women, and long-run effects on investment and consumption smoothing remain largely untested.

Theme 6: Cross-cutting governance challenges and ethical risks

Across all domains, the included studies identify conditions that constrain or distort the benefits of AI. Four of these recur most frequently and are discussed below. Most contributions to this theme are conceptual papers or reviews; the risks it identifies are therefore well theorised but have rarely been measured empirically.

Infrastructure deficits and the digital divide

Many rural farming communities lack reliable electricity, mobile internet and computing resources, which limits the feasibility of AI deployment (Mhlanga, 2021; Bahn et al., 2021). Edge-computing and mobile-first designs are proposed in response, but evidence on their performance at scale is limited.

Algorithmic bias and data justice

AI systems depend on large, representative data for training and validation. Where agricultural data are incomplete, skewed towards commercial farms or absent for marginalised groups, models may perform worse for those groups and reproduce existing inequalities (Liang et al., 2022; Nemorin et al., 2023). Very few empirical

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studies tested model performance separately across subgroups, so the extent of such bias in agricultural AI remains largely unmeasured.

Weak regulatory frameworks

Gaps in data-protection law, consent and purpose limitation are a recurrent concern, particularly where AI is used to identify beneficiaries in food crises (Al-Emran & Griffy-Brown, 2023). Critical scholarship also questions how responsibility for the provision, use and consequences of automated decision-making is allocated in development settings (Sinanan & McNamara, 2021).

Data colonialism and platform power

Much of the infrastructure used in agricultural AI—cloud computing, proprietary models and data platforms—is controlled from outside the settings where it is applied. This raises concerns about extractive data practices, dependency and limited local control. Development narratives about AI may also reinforce rather than reduce systemic inequalities in the Global South (Sinanan & McNamara, 2021; Bahn et al., 2021).

DISCUSSION

This section interprets the findings through the four governance mechanisms of Figure 1. Throughout, it distinguishes between what the evidence shows about technical performance and what it shows about outcomes for farmers and food security. The overall pattern is that the evidence is strongest for technical performance, particularly in monitoring and prediction (M3), and weakest for final outcomes and for accountability (M4).

Targeting and allocation (M1)

AI-based prediction and scoring can in principle direct scarce agricultural support—advice, subsidies, credit—to where it is most needed, faster and more cheaply than survey-based registers (McBride et al., 2022; Hall et al., 2023). The key unresolved question is the balance of inclusion and exclusion errors. An allocation model that is accurate on average can still systematically miss the most food-insecure households if those households are under-represented in training data (Liang et al., 2022). Few included studies measured such errors directly, so claims that AI improves targeting in practice remain provisional.

Delivery and service provision (M2)

AI tools delivered through mobile phones and extension agents—diagnostic apps, advisory services, market information—are the channel through which technical performance could translate into farm-level change. However, the gap between a model's performance on a test dataset and its usefulness to a farmer in the field depends on connectivity, language, literacy, trust, and follow-up support (Mhlanga, 2021; Bahn et al., 2021). Evidence on adoption and sustained use is limited, and evidence on yield, cost or income effects is weaker still.

Monitoring and evaluation (M3)

Monitoring is the mechanism with the most developed evidence base, reflecting the maturity of satellite-based crop and welfare mapping (Hall et al., 2023; Usmanova et al., 2022). The shift from static registers to frequently updated estimates could support anticipatory rather than reactive responses to climatic and market shocks (McBride et al., 2022). However, better monitoring matters only if it changes decisions, and few studies traced monitoring outputs through to a policy or programme response. This is where evidence is most needed.

Accountability and participation (M4)

Accountability was the least studied mechanism. The concerns documented in Theme 6—opaque algorithms, weak data protection, concentrated platform power—are well theorised (Sinanan & McNamara, 2021; Nemorin et al., 2023; Al-Emran & Griffy-Brown, 2023). However, few empirical studies examined how farmers can see, question or shape the AI-mediated decisions that affect them. This matters because AI for food security redistributes power over data and resource allocation. If it is framed as a neutral technical fix, it may obscure structural drivers of food insecurity such as land tenure, market concentration and climate vulnerability (Sinanan & McNamara, 2021; Sampene et al., 2022).

Enabling conditions: infrastructure, capacity and context

Across mechanisms, AI cannot simply be transplanted into low-resource agricultural settings. Included studies point to connectivity, electricity, local technical expertise and institutional readiness as preconditions (Mhlanga,

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2021; Bahn et al., 2021). Human capacity is also likely to matter. Evidence from the Nigerian education sector, outside the corpus of the present study, points in the same direction. Technological self-efficacy was associated with the usability of AI tools among lecturers (Oyewole & Jatau, 2025), and technological proficiency and virtual collaboration predicted global adaptability among pre-service teachers (Ogundipe & Oyewole, 2025). Integrating AI into teaching was feasible but depended on institutional context and stakeholder buy-in (Jekayinfa et al., 2025). Whether the same factors shape the uptake of AI tools among farmers and extension agents has not yet been tested and is a promising line of enquiry.

Directions for future research

The findings point to clear priorities for future research. Most empirical studies report technical performance, such as accuracy and error rates, rather than effects on yields, incomes or food security; impact evaluations with livelihood endpoints are therefore needed. Evidence from fragile, conflict-affected and very low-income settings remains sparse and should be expanded. Longitudinal designs and analyses disaggregated by gender, farm size and other equity dimensions are required to establish whether AI narrows or widens gaps between better-connected and poorer farmers. Comparative and participatory studies are also needed to explain why interventions succeed in some institutional settings and fail in others, and to examine power relations and unintended consequences.

CONCLUSIONS

This study examined how AI and precision agriculture are applied to food-security and rural-livelihood challenges in developing countries, the governance mechanisms through which they operate, and the strength of the evidence on their effects. Six application domains were identified: yield prediction and early warning; soil, irrigation and input management; pest and disease detection; market access; agricultural finance; and cross-cutting governance and ethics.

The evidence supports a qualified conclusion: AI models can predict crop and food-security conditions and detect crop diseases with useful accuracy under study conditions. There is much less evidence that these tools, as deployed, improve yields, incomes, food security or resilience for smallholder farmers, and almost none on who gains and who loses. The potential benefits are plausible and worth pursuing, but they have not yet been demonstrated at scale and should not be presented as established.

The principal contribution of this study lies in organising the evidence by governance mechanism. This approach shows that the evidence base is concentrated in monitoring and prediction, and that the step from better information to better decisions and services is weakly evidenced. Accountability and participation, the mechanisms most relevant to preventing harm, are the least studied. The risks identified in the literature, including algorithmic exclusion, opaque decision-making, extractive data practices and dependence on external platforms, are well theorised but rarely measured.

For policy, investment in AI for agriculture should be accompanied by complementary measures: investment in rural connectivity and digital capacity; data-protection and transparency standards; and mechanisms through which farmers can shape and contest AI-mediated decisions. Most importantly, livelihood and distributional outcomes should be rigorously evaluated before tools are scaled. For research, the priority is to move beyond accuracy metrics towards longitudinal, gender-sensitive and comparative studies that test whether, and for whom, AI-enabled agriculture improves food security and rural livelihoods.

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Ethical statement

Ethical approval was not required for this study because it involved a systematic review of previously published literature and did not involve the recruitment of human participants or the collection of new personal data. The review was conducted in accordance with the PRISMA 2020 reporting guidelines.

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Competing interests

The author declares that there are no competing interests regarding the publication of this paper.

Author contributions

The author was responsible for the conceptualisation and design of the study, development of the review framework, literature search strategy, study selection, data extraction, quality appraisal, thematic synthesis, interpretation of the findings and preparation and revision of the manuscript. The author read and approved the final version of the manuscript.

Data availability

The evidence synthesised in this study was obtained from published literature retrieved from Scopus, Web of Science Core Collection and the Directory of Open Access Journals (DOAJ). The data extraction framework and the materials used for the synthesis may be requested from the corresponding author, subject to availability.

AI disclosure

AI tools were used solely to assist with language editing, grammar checking and improving the clarity of the manuscript. They were not used to collect research data or independently conduct the study selection, quality appraisal, data extraction or statistical analysis. The author takes full responsibility for the accuracy of the review, the interpretation of the evidence and the conclusions presented in the manuscript.

Biographical sketch

Lasisi Modinat Iyadunni is affiliated with the Department of Agricultural Economics and Extension, Tai Solarin Federal University of Education, Nigeria. Her research interests, as reflected in the present study, include artificial intelligence in agriculture, precision agriculture, food security, rural livelihoods and the application of emerging technologies to agricultural development in developing countries. Her scholarly interests also encompass the governance, ethical implications and developmental outcomes of AI-enabled agricultural technologies, particularly their potential benefits and challenges for smallholder farmers and rural communities.

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REFERENCES

Al-Emran, M., & Griffy-Brown, C. (2023). The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society, 75*, 102420. https://doi.org/10.1016/j.techsoc.2023.102420

Bahn, R. A., Yehya, A. A. K., & Zurayk, R. (2021). Digitalization for sustainable agri-food systems: Potential, status, and risks for the MENA region. *Sustainability, 13*(6), 3223. https://doi.org/10.3390/su13063223

Hall, O., Dompae, F., Wahab, I., & Dzanku, F. M. (2023). A review of machine learning and satellite imagery for poverty prediction: Implications for development research and applications. *Journal of International Development, 35*(7), 1753–1768. https://doi.org/10.1002/jid.3751

Hong, Q. N., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., Vedel, I., & Pluye, P. (2018). The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *Education for Information, 34*(4), 285–291. https://doi.org/10.3233/EFI-180221

Jejeniwa, T. O., & Mhlongo, N. Z. (2024). AI solutions for developmental economics: Opportunities and challenges in financial inclusion and poverty alleviation. *International Journal of Advanced Economics, 6*(4), 108–123. https://doi.org/10.51483/IJAE.6.4.2024.108-123

Jekayinfa, J. R., Egbetola, O. T., & Oyewole, O. (2025). Integrating AI in teaching family concepts in schools in Nigeria. *International Journal of Interdisciplinary and Current Studies in Education, 2*, 315–328.

Liang, W., Tadesse, G. A., Ho, D., Fei-Fei, L., Zaharia, M., Zhang, C., & Zou, J. (2022). Advances, challenges and opportunities in creating data for trustworthy AI. *Nature Machine Intelligence, 4*(8), 669–677. https://doi.org/10.1038/s42256-022-00516-1

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McBride, L., Barrett, C. B., Browne, C., Hu, L., Liu, Y., Matteson, D. S., Sun, Y., & Wen, J. (2022). Predicting poverty and malnutrition for targeting, mapping, monitoring, and early warning. *Applied Economic Perspectives and Policy, 44*(2), 879–892. https://doi.org/10.1002/aepp.13175

Mhlanga, D. (2021). Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies? *Sustainability, 13*(11), 5788. https://doi.org/10.3390/su13115788

Nemorin, S., Vlachidis, A., Ayerakwa, H. M., & Andriotis, P. (2023). AI hyped? A horizon scan of discourse on artificial intelligence in education (AIED) and development. *Learning, Media and Technology, 48*(1), 38–51. https://doi.org/10.1080/17439884.2022.2095568

Ogundipe, O. G., & Oyewole, O. (2025). Technological proficiency and virtual collaboration as predictors of global adaptability among social studies pre-service teachers in Oyo State, Nigeria. *African Journal of Social and Behavioural Sciences, 15*(1), 166–178.

Onyeaka, H., Tamasiga, P., Nwauzoma, U. M., Miri, T., Juliet, U. C., Nwaiwu, O., & Akinsemolu, A. A. (2023). Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and minimising environmental impact: A review. *Sustainability, 15*(13), 10482. https://doi.org/10.3390/su151310482

Oyewole, O., & Jatau, S. N. (2025). Technological self-efficacy and online database access as predictor of AI usability for research among social sciences lecturers in Oyo State. *Wukari International Studies Journal, 9*(1), 210–221.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., & Chou, R. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Systematic Reviews, 10*, 89. https://doi.org/10.1186/s13643-021-01626-4

Sampene, A. K., Agyeman, F. O., Brenya, R., & Wiredu, J. (2022). Artificial intelligence as a pathway to Africa's transformations. *Journal of Multidisciplinary Engineering Science and Technology, 9*(1), 14939–14951.

Sheik, I., & Kabanda, G. (2026). The role of artificial intelligence in poverty governance: A systematic literature review of innovations and implementation challenges. *Administrative Sciences, 16*(6), 269. https://doi.org/10.3390/admsci16060269

Sinanan, J., & McNamara, T. (2021). Great AI divides? Automated decision-making technologies and dreams of development. *Continuum, 35*(5), 747–760.

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology, 8*, 45. https://doi.org/10.1186/1471-2288-8-45

Usmanova, A., Aziz, A., Rakhmonov, D., & Osamy, W. (2022). Utilities of artificial intelligence in poverty prediction: A review. *Sustainability, 14*(21), 14238. https://doi.org/10.3390/su142114238

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