The use of artificial intelligence in food and agriculture systems

A rapid review

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About the Research Commissioning Centre

The Foreign, Commonwealth and Development Office (FCDO) Research Commissioning Centre (RCC) has been established to commission and manage research to enhance development and foreign policy impact. Led by the International Initiative for Impact Evaluation (3ie), the University of Birmingham, and an unmatched consortium of UK and global research partners, the RCC aims to commission different types of high-quality research in FCDO's key priority areas.

About the report

Agriculture is vital to food security and economic growth in low- and middle-income countries (L&MICs), yet faces persistent challenges such as climate variability, limited land, and delayed crop disease detection. **The use of artificial intelligence in food and agriculture systems: a rapid review** report commissioned by the Research Commission Centre (RCC) of FCDO and 3ie seeks to develop a comprehensive understanding of the effectiveness and the social and equity implications of AI-enabled solutions in agriculture.

Drawing on evidence from 51 peer-reviewed and grey literature studies, the review finds that while AI holds significant promise for enhancing productivity and resilience, its adoption is constrained by underrepresentation of vulnerable populations, digital divides, socio-economic barriers, and scepticism toward new technologies. Findings from this will inform future research priorities, policy development, and funding strategies to promote inclusive, ethical, and scalable AI solutions that address the unique agricultural challenges faced by L&MICs.

Review process

This report was reviewed by Prof. Dina Kiwan, Prof. Mark Lee, Mr. Mike Reddaway, and Dr. Lucas Sempe.

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Executive summary

Background

This rapid review (RR) aims to explore the emergence and significance of artificial intelligence (AI) in agriculture. We seek to develop a comprehensive understanding of the effectiveness and the social and equity implications of AI-enabled solutions in agriculture.

Method

The RR employs an adapted version of the systematic review methodologies recommended by the Cochrane Collaboration and the Campbell Collaboration. It includes 51 peer-reviewed and grey literature studies, comprising 35 quantitative studies, 14 qualitative studies, and 2 mixed-methods studies.

Findings

A key finding is the underrepresentation of low-income countries and smallholder farmers, who are the most vulnerable to agricultural challenges. Notable gaps in evidence were also identified in areas such as effectiveness, inclusivity, ethics, and governance. Overall, the review revealed a paucity of evidence, with limited in-depth descriptions available to directly address the research questions. This highlighted the need for more robust studies in the field.

Conclusion

The review highlights the emerging and promising role of AI-enabled solutions in addressing agricultural challenges in low- and middle-income countries (L&MICs). It also exposes critical gaps that must be addressed to ensure these technologies benefit the most vulnerable populations. By adopting a more inclusive, ethical, and scalable approach, the research community and stakeholders can harness the power of AI to address pressing agricultural challenges and contribute to sustainable development.

Recommendation

Addressing the digital divide and improving digital literacy will be essential to ensure meaningful adoption of AI in agriculture and equitable access to AI-enabled solutions. Greater efforts are needed to target low-income countries that are disproportionately affected by agricultural challenges but remain underrepresented in AI research. To complement this RR, a systematic review should be conducted. This will provide a more comprehensive and critical analysis of the existing literature, including grey and non-English literature. Future research should include papers in additional languages to ensure that relevant findings from literature across regions are not overlooked.

Abbreviations

3ie	International Initiative for Impact Evaluation
AG	Agriculture
AGRO 4.0	Brazil's Agricultural Technology Program
AgTech	Agricultural Technology
AI	Artificial Intelligence
AI4AI	Artificial Intelligence for Agriculture Innovation
ASEAN	Association of Southeast Asian Nations
AVPN	Asian Venture Philanthropic Network
B2B	Business to Business
B2C	Business to Consumer
BM&C NEWS	Business Management & Consultancy News
CNN	Convolutional Neural Network
COBIT	Control Objectives for Information and Related Technology
CS	Case Study
CSA	Climate-Smart Agriculture
DD	Deep Dives
Digital Green	Digital Green (an organisation focused on digital agriculture)
EPPI	Evidence for Policy & Practice Information
EU	European Union
FAO	Food and Agriculture Organization
FCDO	Foreign, Commonwealth & Development Office
GenAI	Generative Artificial Intelligence
GPS	Global Positioning System
GSMA	Global System for Mobile Communications
ICT	Information and Communications Technology
IDB	Inter-American Development Bank

IFC	International Finance Corporation
IFPRI	International Food Policy Research Institute
IoT	Internet of Things
L&MICs	Low & Middle-Income Countries
LLM	Large Language Models
ML	Machine Learning
NICE	National Institute for Health and Care Excellence (for qualitative research checklists)
NLP	Natural Language Processing
PICO	Population, Intervention, Comparison, Outcome (framework)
R&D	Research and Development
RF & NN	Random Forest and Neural Network
RAG	Retrieval-Augmented Generation
RCC	Research Commission Centre
RCT	Randomized Controlled Trial
ROBINS-I	Risk Of Bias in Non-randomized Studies – tool for assessing risk in quasi-experimental studies
RR	Rapid Review
SDGs	Sustainable Development Goals
SE	Stakeholder Engagement
SPIDER	Sample, Phenomenon of Interest, Design, Evaluation, and Research Type (framework)
SSA	Sub-Saharan Africa
TD	Typology Development
UAVs	Unmanned Aerial Vehicles
UNDP	United Nations Development Program
USAID	United States Agency for International Development
UX	User Experience
WEF	World Economic Forum

Glossary of Technical Terms

Term	Definition
AI-enabled solutions	Applications of artificial intelligence are designed to support agriculture through tasks such as yield prediction, disease detection, and farm-level decision-making.
Agriculture 4.0	Transformation of agriculture through digitisation, automation, and advanced technologies to enhance productivity, efficiency, and sustainability.
Bias assessment	Process of evaluating the reliability of included studies, rating them as low, high, or unclear risk of bias.
Case study	A qualitative research method focusing on detailed examination of specific instances of AI use in agriculture.
Conversational chatbots	AI tools (often using LLMs) that provide agricultural advice to extension agents or directly to farmers.
Deep learning	A machine learning technique using layered neural networks for complex prediction tasks, e.g., crop disease detection.
Digital divide	The gap between those who have access to AI tools, internet, and digital literacy, and those who do not.
Digital literacy	The knowledge and skills needed to effectively use digital technologies, a key barrier to AI adoption among farmers.
Field trial	Testing AI-enabled solutions directly in agricultural settings, as opposed to lab experiments.
Forecast and prediction	AI use for climate/weather forecasting and determining optimal harvest times.
Horizon mapping	Forward-looking analysis of short-, medium-, and long-term pathways for AI adoption.
Machine learning (ML)	AI subfield involving algorithms that learn patterns from data to make predictions (e.g., yield forecasting).
Natural language processing (NLP)	AI techniques that interpret and analyse human language for agricultural applications like chatbots and advisories.

PICO framework	Systematic review tool (Population/Setting, Intervention, Comparison, Outcome) adapted here for agriculture.
Pilot search	Initial test searches to refine the search strategy for systematic reviews.
Precision agriculture	Farming approach using AI, sensors, and data-driven techniques to optimise inputs and outputs.
PRISMA flowchart	Standard reporting tool documenting the screening and selection process in systematic reviews.
Qualitative research	Studies using interviews, case studies, or thematic analysis to assess perceptions and impacts of AI in farming.
Quasi-experimental design	Non-randomised study approach used to evaluate AI effectiveness in real-world agricultural settings.
Rapid review (RR)	A streamlined version of a systematic review conducted within shorter timelines while maintaining rigour.
Risk of bias	Likelihood that a study's design or methods distort its findings.
Simulation study	Computer-based modelling of AI applications in agriculture, as opposed to real-world field trials.
Smallholder farmer	Farmers managing small plots, usually family labour based, producing mainly for subsistence or local markets.
SPIDER framework	Systematic review tool for qualitative research (Sample, Phenomenon of Interest, Design, Evaluation, Research Type).
Value chain (agricultural)	Stages of agricultural production, processing, and distribution where AI solutions may be applied.

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1. Background

By 2050, the global population is projected to reach approximately 9.7 billion, driven largely by growth in developing regions such as Africa and Asia (World Bank 2015). This rapid population increase will result in high demand for food, placing immense pressure on agricultural systems to meet growing demand. This makes it crucial to explore the adoption of innovative solutions to enhance agricultural efficiency and resilience, especially in low- and middle-income countries (L&MICs).

This rapid review (RR) was commissioned by the FCDO's Research Commission Centre (RCC) and 3ie to examine how artificial intelligence (AI) can effectively address extreme poverty worldwide and help farmers in L&MICs (FCDO 2023).

While there is a burgeoning interest in AI-enabled solutions across the agricultural sector, a comprehensive understanding of their effectiveness, alignment with institutional, social, and environmental contexts, and impact on equity is still nascent. This rapid review aims to understand the effectiveness of AI-enabled solutions. It extends beyond the technocentric approach to consider broader socio-material dynamics, as well as the socio-economic and socio-ecological contexts in which an AI-enabled solution operates.

However, there is a notable gap in consolidated research examining the effectiveness of AI-enabled solutions in agriculture, particularly regarding their impact on L&MICs. Additionally, there is a gap in understanding how AI-enabled solutions translate into practical benefits for farmers, especially those in resource-constrained settings. Questions persist about AI's effectiveness in reaching and supporting smallholder farmers, enhancing livelihoods, and bolstering food security. Concerns also exist about whether there are enough applications customised to match the needs of smallholder farmers (Genesis Analytics 2023).

Therefore, the primary aim of the rapid review is to gain a deeper understanding of the effectiveness of AI-enabled solutions in agriculture, particularly in an L&MIC setting.

This rapid review is part of a landscape review that employs a mixed-methods approach. This approach incorporates rapid review, narrative review, typology development, deep dives, case studies, and stakeholder engagement. See Figure 32 in Appendix for an overview of the methodologies.

Building on this context, the following objectives (Section 2) aim to explore opportunities and challenges of AI adoption among smallholder farmers in L&MICs.

2. Objectives

This rapid review aims to comprehensively synthesise existing evidence regarding the application of AI within the agricultural sector. The review examines how AI is defined and operationalised in the agricultural context. This includes the identification of various types and sub-fields of AI applications, their position along the agricultural value chain (e.g., production, processing, distribution), and their stage of development (e.g., research, pilot, implementation). Additionally, the RR examines the ethical and equity implications associated with the development and deployment of AI applications in agriculture, including the potential benefits and risks for various stakeholders. It analyses short-, medium-, and long-term trajectories of specific AI applications in agriculture, while considering potential advancements, challenges, and opportunities. This analysis has been instrumental in providing a framework for the horizon mapping exercise, which was undertaken to identify potential future pathways for AI-enabled solutions in agriculture. Ultimately, this review provides evidence-based insights to inform strategic investment decisions aimed at fostering an effective, efficient, and equitable AI landscape within the agricultural sector.

The RR aims to map evidence on AI use in agriculture within L&MICs, addressing specific research questions. It combines quantitative data with qualitative insights, global trends with local contexts, and theoretical frameworks with operational realities. This review is part of a broader data collection effort as outlined in Figure 1.

Figure 01: Mapping research questions and methodologies

Research question	Methodologies
Research Theme 01: Defining AI: How is AI defined in the agriculture sector?	
What are the major categories of AI-enabled solutions in agriculture?	RR, NR, CS, DD, SE
What is the current stage of development of AI-enabled solutions and their deployment in the field?	RR, NR, CS, DD, SE
What typology framework can be used to understand the types of AI applications in agriculture?	RR, NR, TD, SE
Who are the key vendors/institutes under each of these typologies?	RR, NR, TD, SE
Research Theme 02: Understanding Effectiveness	
How effective are AI-enabled solutions in improving outcomes related to productivity?	RR, CS, DD, SE
How effective are AI-enabled solutions in improving outcomes related to food security?	RR, CS, DD, SE
How effective are AI-enabled solutions in improving income and livelihoods?	RR, CS, DD, SE
Research Theme 03: Ethics and Equity	
What are the practical barriers for developing AI-enabled solutions for agriculture at scale, particularly at low-income settings?	RR, NR, CS, DD, SE
How can AI enabled solutions in agriculture be designed and implemented to maximize equity and avoid exacerbating existing inequalities?	RR, NR, CS, DD, SE
Research Theme 04: Horizon Mapping	
What are the recommendations for AI-enabled solutions in agriculture?	RR, NR, CS, DD, SE
What can we say about medium, short, and long run trajectories of specific AI-enabled solutions?	RR, NR, CS, DD, SE

RR Rapid Review; NR Narrative review; TD Typology Development; CS Case Study; DD Deep Dives; SE Stakeholder Engegment

To address these objectives, the study employs the following methodology (Section 3) to examine AI integration in smallholder farming within L&MICs systematically.

3. Methods

3.1 Criteria for considering studies for this review

Scope of the rapid review

AI has only recently been introduced in the agricultural sector on a broader scale, particularly in the context of smallholder agriculture and L&MICs. Until recently, most studies were either highly experimental or focused on high-income countries and large-scale commercial farming, or both. On the other hand, it has been observed that technological developments are currently fast-paced since generative AI applications are widely accessible. These two phenomena together justify a limited time scope of five years (2019–2024), allowing researchers to capture studies that are relevant from both technological advancement and sector application perspectives.

To ensure consistency and clarity, this review defines the AI-enabled solutions and the nature of agricultural activities within its scope and clarifies which countries are included in the L&MICs category. Appendix Box 1 addresses these definitions.

3.2 Criteria of eligibility

In adherence to the established gold-standard systematic review methodology, this RR included mixed-methods evidence within its scope. Recognising the diverse nature of the included research, we applied separate eligibility criteria to quantitative and qualitative studies. We assessed mixed-methods studies by evaluating their quantitative and qualitative components independently. We required only one methodological approach (either quantitative or qualitative) to meet the predefined criteria for inclusion in the review.

The eligibility criteria for included studies are based on an adapted version of the PICO (Population, Intervention, Comparison, Outcome) framework. To ensure the PICO framework is relevant to an agricultural review, the researchers replaced 'Population' with 'Setting'.

The pilot coding highlighted that studies addressing research theme 3 (Box 1) would principally employ qualitative methodologies or other types of non-quantitative articles (e.g., opinion pieces, and editorials). Additionally, the study used SPIDER (Sample, Phenomenon of Interest, Design, Evaluation, and Research Type) to determine the eligibility criteria for these studies. SPIDER is an alternative to PICO designed for qualitative research papers.

The eligibility criteria for both the quantitative and qualitative studies are detailed in the Appendix.

3.3 Methods for identification, data extraction, and analysis of studies

Pilot searches

Pilot searches were first conducted across diverse sources to test and refine the search strategy, ensuring relevant studies were not overlooked. Limited data availability emphasised the need to complement the pilot searches with targeted searches in Latin American and African countries and include other languages based on the geographical scope of the study. This pilot search phase informed the final search strategy, into which all feedback was incorporated (details in Appendix).

Rapid review searches

Drawing on insights from pilot searches and expert consultations, the team developed and implemented a comprehensive search strategy across academic databases, grey literature, dissertations, and regional sources to ensure broad coverage. The Appendix provides detailed steps of the search process, including search terms, databases, resources, and validation protocols.

Study screening, selection and data extraction

The systematic screening of studies used a screening tool based on inclusion and exclusion criteria (see Table 10 in Appendix).

The team piloted 10 records using the screening tool. After piloting, the included studies were presented to experts and the 3ie and FCDO teams for validation, and the tool was refined accordingly. The screening and selection of studies for the RR were conducted in two phases (see Table 11 in Appendix). Details of the title and abstract screening, as well as the full-text screening process, are provided in the Appendix.

For data extraction, the tool was developed and validated through an iterative, expert-led process. Detailed steps and tool specifications are provided in the Appendix.

3.4 Assessment of bias in included studies

The review team assigned a confidence rating to each included study. They assessed the risk of bias in the study methods and determined whether this posed a high, low, or unclear risk. The Appendix describes in detail the tools used and the process the team followed for bias assessment.

The following findings section presents the detailed results of the rapid review, addressing each research question in turn.

4. Synthesis of findings

This section synthesises foundational evidence gathered through the RR. The evidence comes from detailed descriptions within the selected studies. The review revealed a paucity of evidence, with limited rich descriptions available to inform the research questions directly.

4.1 Results of the rapid review search

The research team recorded the RR findings at every stage of the review process using a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) flowchart. The PRISMA chart documents the flow of information through the different phases of an RR (or a systematic review). It maps the number of studies identified. This includes studies that were excluded at the title and abstract screening, and the full-text screening process, and those taken forward to coding (Lefebvre 2025). The detailed narrative description and PRISMA chart are provided in the Appendix.

4.2 Description of studies

To provide a detailed understanding of publication type, year of publication, funding sources, geographic representation, study methodology, effectiveness, users, beneficiaries, and other variables from the 51 studies included in the rapid review, please refer to the descriptive statistics in the Appendix.

4.3 Risk of bias assessment

The team critically appraised all the included studies and classified them as high, low, or unclear risk of bias.

For quantitative studies, the following critical appraisal tools were applied:

- Prediction models – PROBLAST
- Randomised Controlled Trials (RCTs) – Cochrane RoB 2
- Quasi-experimental studies – ROBINS-I

For qualitative studies, the researchers used the NICE methodology checklist.
Further details are provided in the Appendix.

4.4 Current development and deployment of AI

Agricultural production systems reliant on traditional methods increasingly face challenges in meeting the rising global demand for agricultural products. To address these challenges, the sector has begun a broader Agriculture 4.0 transformation, which aims to enhance productivity, resource efficiency, and sustainability. Within this transformation, digitisation integrates technologies into agricultural systems to improve decision-making, optimise resource use, and drive sustainable outcomes (FAO 2022). The evidence primarily focuses on laboratory simulations used to develop and optimize AI-enabled solutions, for targeted problems:

- Region-specific studies, especially in Sub-Saharan Africa (SSA) and South East Asia, highlight AI's potential to address local agricultural needs (see Table 19 (Tzachor 2021) in Appendix A). This geographical focus is significant given the vulnerability of these regions to climate change, resource scarcity, and food insecurity.
- There is growing interest in deploying AI mostly for precision agriculture through machine learning, automation and robotics, and deep learning (see Appendix for details).
- Crop production is the primary domain for AI integration in agriculture, with key target areas including crop disease detection, productivity enhancement, and improved agricultural decision-making (see Appendix for details).

4.5 Understanding effectiveness

Effectiveness is defined as the degree to which AI-enabled solutions achieve their intended outcomes as specified by their implementers. The indicative metrics for effectiveness in this study include productivity, food security, income, and livelihoods.

- There was a notable paucity of evidence in measuring effectiveness. Most studies concentrate on reporting AI model accuracy without addressing effectiveness in field applications.
- Quantitative studies overwhelmingly relied on modelling and prediction approaches, with limited use of experimental methods like RCTs or quasi-experimental designs. This limits the ability to draw robust causal conclusions about the effectiveness of AI interventions.
- Qualitative studies often lacked rigour in exploring the sociocultural or institutional factors necessary for the success of AI-enabled solutions (see Appendix for details).
- AI is making measurable contributions to agriculture in L&MICs, particularly in yield optimisation, disease prevention, and resource efficiency. However, findings from RCT or quasi-experimental designs require careful interpretation.

4.6 Ethics and inclusivity

While the RR intends to offer a nuanced understanding of inclusivity, ethics, and governance-related aspects, most studies lacked detailed descriptions of these frameworks. This section presents the limited available findings on digital divide, data accessibility, community-led practices, governance, and gender considerations.

- Of the 14 qualitative studies and 2 mixed-methods studies, only 4 addressed user diversity, 4 examined the digital divide, 3 discussed digital literacy, and 6 mentioned digital accessibility.

User diversity

- As AI technologies advance, it is essential to develop solutions that include various regions, cultures, and socioeconomic backgrounds. These innovations in agricultural AI should also benefit all users, regardless of their background or farm size.

Digital divide

- A fundamental way in which the digital divide manifests is through the lack of sufficient financial resources to access AI-enabled solutions (Sharma, et al. 2023)).
- Technology is largely perceived as a foreign concept and is approached with a lot of suspicion in a field heavily influenced by culture and traditional norms.
- Resistance to adapt to tech-driven changes also stems from a belief that AI tools are expensive (even when they are cost-effective).
- Despite having access to smartphones, the internet, and AI-powered agronomic advice, farmers mostly prefer traditional farming practices (Tzachor 2021).

Digital literacy

- A lack of awareness about suitable AI technology and limited technical expertise are significant barriers to the uptake of AI-enabled solutions.
- Language barriers, high illiteracy rates, and the lack of formal and informal education were among the primary barriers to integrating AI in agriculture (Tzachor 2021).

Digital accessibility issues

- Poor internet connectivity, bandwidth issues, and the absence of basic infrastructure to support these AI applications are some accessibility-related challenges (Budiman 2019)

Ethics and governance

- Evidence on ethics and governance remains limited, with studies providing few comprehensive details.

A paper titled "Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry" highlighted two policy-related barriers: (1) inadequate data governance and data rights regime, and (2) the lack of enforcement of data regulations, privacy, and transparency (Tzachor 2021)

5. Horizon mapping and recommendation

5.1 Horizon 1 – short term (1-3)

- Recognizing the current paucity of evidence regarding AI adoption bottlenecks in LICs (in Section 4.2), this study recommends prioritising research that places smallholder farmers at the centre of innovation.
- The limited evidence on AI's development, deployment, and effectiveness in smallholder settings emphasises the need for rigorous follow-up through systematic reviews or evidence gap maps
- Lack of measurable metrics and reliance on simulations rather than real-world data highlight major gaps in assessing the effectiveness of AI-enabled agricultural solutions. To address this, we recommend developing standardised operational definitions for these variables. This will ensure greater consistency and comparability in future research.

5.2 Horizon 2 – medium term (2 – 5)

- Critical socio-technical factors such as farmers' practices, technology comprehension, and adoption willingness are often overlooked in assessing tangible outcomes. Future research should integrate holistic factors into AI impact assessments.
- Given the limited evidence base, establishing enforceable regulations, ensuring transparency for smallholders, and conducting regular audits are vital for responsible AI adoption in agriculture.

5.3 Horizon 3 – long term (5 – 12)

- There is a lack of post-implementation audits to validate AI's effectiveness in real-world settings. Such audits are needed to produce generalisable evidence.

6. Conclusion

6.1 Critical gaps and paucity of evidence

- Smallholder farmers remain underrepresented in the most vulnerable low-income countries.
- Limited information available on the income brackets of existing or target users of AI-enabled solutions.
- Inadequate gender inclusivity in AI agricultural research. Female farmers have been addressed in only one study.
- As discussed in Section 4.6, only a small proportion of studies addressed issues like the digital divide, digital literacy, accessibility, and ethics and governance.
- Limited focus on scalability (6.1%) and implementation guidance (21.2%) indicates that sustainable, widespread adoption of AI interventions receives very little attention.
- Lack of shared typologies and classification of AI-enabled agricultural solutions emphasises the need for stakeholder collaboration to develop structured frameworks for comparison and evaluation.

6.2 Promising trends

- As discussed in Section 4.4, most studies report AI's potential to contribute meaningfully to agricultural development in L&MICs. However, more RCTs and quasi-experimental designs are needed to assess AI's effectiveness beyond laboratory studies.
- The increasing number of publications reflects a growing global interest in L&MICs and investment in this field.

6.3 Methodological and funding limitations

- RCT or quasi-experimental design were rated as having a high risk of bias, limiting the ability to draw robust causal conclusions. Similarly, qualitative studies often lacked rigour in exploring the sociocultural or institutional factors necessary for the success of AI-enabled solutions.
- Although the modelling/prediction studies were often high quality and assigned a low risk of bias, this does not necessarily translate to broader applicability or practical value, particularly in the context of smallholder farmers in L&MICs.
- One critical limitation of these high-quality studies is their lack of generalisability.
- Most studies are led by AI experts rather than agricultural practitioners. This creates a disconnect with farmers and restricts practical utility, because models often overlook real-world challenges such as low digital literacy, limited technology access, and socio-economic constraints in L&MICs. Bridging this gap will require interdisciplinary collaboration between machine learning experts, agricultural scientists, and farmers.

This requires supplementing with efforts to design more inclusive, accessible, and context-sensitive AI-enabled solutions.

- Nearly half of the studies reported no external funding, raising concerns about the depth of research, long-term sustainability, transparency, and potential conflicts of interest in AI for L&MICs.

6.4 Limitations of the rapid review methodology

- A rapid review sacrifices depth for speed, potentially excluding grey literature on English studies and region-specific research. This limits representation.
- In conclusion, while this RR highlights the potential of AI to transform agriculture in L&MICs, it also exposes critical gaps that must be addressed to ensure these technologies benefit the most vulnerable populations. By adopting a more inclusive, ethical, and scalable approach, the research community and stakeholders can leverage AI to address pressing agricultural challenges and contribute to sustainable development in these countries.

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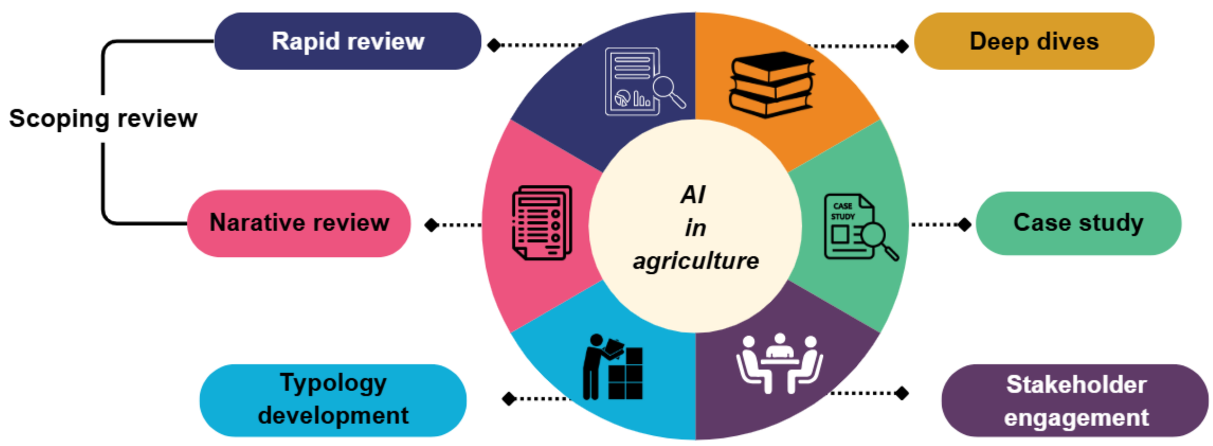
Conflicts of interest
There are no conflicts of interest.

8. Dissemination and knowledge products

To ensure an increased uptake of the findings from the RR, the research team has developed several knowledge products and dissemination efforts. These include a blog post on the RR and an evidence explainer, as well as the submission of an RR protocol, which has been accepted for publication. Additionally, the study has been selected for presentation at a conference at the University of Bath. The findings of the RR were also presented in two stakeholder engagement workshops comprised of practitioners, implementers, academicians, and relevant stakeholders. (refer to The use of artificial intelligence in food and agriculture systems)

9. Appendix

Figure 02: Mixed-methods approach



Box 1 Scope of the rapid review

Scope of AI within the rapid review

AI in this study is defined as a "family of algorithms and trained models, and processes that enable computers to solve problems and make decisions, mimicking and sometimes surpassing human capabilities" (Genesis 2023). An AI model is designed to perform a task by translating inputs such as text, audio or numerical data into an output such as a decision. For example, farmers can use AI to analyse soil data, weather patterns, and crop health to optimise resource use and increase yields with greater accuracy (Sharma and Shivandu 2024). In an L&MIC setting, AI-enabled solutions need to be scalable, cost effective, and easy to implement (Yang 2024).

Table 1: Types of AI and their sub-classifications

Base category	Subcategory
Automation and robotics	• Remote sensing and Internet of Things (IoT) including integrations with mechanisation equipment. • Applications of unmanned aerial vehicles (UAV) include surveillance or drone-assisted surveillance, land use crop cover, crop health monitoring and assessment, agricultural spraying, and livestock tracking • Application of robotics in agriculture (including but not limited to seeding and planting, spraying, inspection monitoring, harvesting, weeding, and mowing).
Machine learning	• Classification • Regression • Clustering • Ranking techniques (Gardezi 2023) that support discovery, forecasting, planning, and creation (EIT Digital 2021). These include predictive analysis for crop yields. • Optimisation
Natural language and image and video processing	• Photo recognition for diagnostics of pests and diseases, and agro-advisory processes/bots for agro-advisory processes. • Satellite image-based analysis and prediction of climate change.
Conversational chatbots	• Utilisation of large language models (LLMs) to enable rapid knowledge dissemination either to agricultural extension agents or directly to farmer end users.

Scope of agriculture within the rapid review

The RR focuses on agricultural production systems, amongst smallholder (including subsistence) and medium-scale producers. Given the scope of the RR, large-scale, intensive producers are not included.

Smallholders are defined as small-scale farmers and pastoralists, who favour the stability of the farm household system. They mainly use family labour for production, and use part of the produce for family consumption (FAO 2013). Subsistence farming, by contrast, involves small farms that rely mainly on family labour with limited or no machinery. These farms face difficulties in purchasing inputs, marketing products, and adding value to primary commodities (FAO 2015). Medium-scale producers are defined as farmers with land up to 50 hectares and a production volume of 600 tonnes.

The RR also encompasses crop production, livestock, and aquaculture activities such as commercial and municipal fisheries. Generally, fishery is an activity involving the harvesting of fish. It may involve the capture of wild fish at a commercial level, or fish farming through aquaculture (FAO 2014).

However, the capture of wild fish and other aquatic life is excluded from this RR. This decision was taken in conjunction with our experts because those involved in these activities form a distinct type of community (this also includes communities engaged with artisanal fishery). Wild capture fishery does not constitute farming and, being often offshore, is generally governed by its own policies and regulations.

This RR also excludes agroforestry applications. This is because the differences between agro-forestry and forestry are often not clear. Additionally, the reported impacts are often unreliable. Agroforestry is defined as "the collective term for land-use systems and technologies in which woody perennials (e.g., trees, shrubs, palms or bamboos) and agricultural crops or animals are used deliberately on the same parcel of land in some form of spatial and temporal arrangement" (FAO 2025). Forestry is defined as the management of forests (FAO 2020). Excluding these applications prevents potential bias in the rapid review by avoiding contentious topics.

Scope of target problem in the rapid review

This review examines the specific problems targeted by AI-enabled solutions and their corresponding potential use cases. Table 2 provides an overview of the definitions of the target problems.

Table 2: Target problem definitions

Target problem	Definitions
Forecast and prediction	This refers to the use of AI-enabled solutions for forecasting and predicting climate and weather patterns, or the optimal harvest time.
Detection	This refers to the use of AI-enabled solutions for detecting crop and livestock pests and diseases.
Differentiation	In this context, differentiation refers to AI-enabled solutions helping agricultural producers vary the size and quality of their produce to meet different market demands.
Optimisation	In the context of this report, optimisation refers to improving efficiency in irrigation, feed distribution, and nutrient application.
Capturing, interpretation, and evaluation	AI-enabled solutions capture, interpret, and evaluate data on weather patterns. The results are used to guide and assess individual farm management decisions.
Farm-level decision making	In this context, decision-making refers to the process of selecting the optimal crop variety for cultivation. The selection is based on an analysis of individual farm and household properties.

Scope of geographies in the rapid review

The RR specifically focused on L&MICs. The study has referred to the World Bank Group (2024) for the definitions of L&MICs (see Table 4 in Appendix).

Table 3: List of L&MIC countries

Economy	Region	Income group
Afghanistan	South Asia	Low-income
Burkina Faso	Sub-Saharan Africa	Low-income
Burundi	Sub-Saharan Africa	Low-income
Central African Republic	Sub-Saharan Africa	Low-income
Chad	Sub-Saharan Africa	Low-income
Congo, Dem. Rep.	Sub-Saharan Africa	Low-income
Eritrea	Sub-Saharan Africa	Low-income
Ethiopia	Sub-Saharan Africa	Low-income
Gambia, The	Sub-Saharan Africa	Low-income
Guinea-Bissau	Sub-Saharan Africa	Low-income
Korea, Dem. People's Rep.	East Asia & Pacific	Low-income
Liberia	Sub-Saharan Africa	Low-income
Madagascar	Sub-Saharan Africa	Low-income
Malawi	Sub-Saharan Africa	Low-income
Mali	Sub-Saharan Africa	Low-income
Mozambique	Sub-Saharan Africa	Low-income
Niger	Sub-Saharan Africa	Low-income
Rwanda	Sub-Saharan Africa	Low-income
Sierra Leone	Sub-Saharan Africa	Low-income
Somalia	Sub-Saharan Africa	Low-income
South Sudan	Sub-Saharan Africa	Low-income
Sudan	Sub-Saharan Africa	Low-income
Syrian Arab Republic	Middle East & North Africa	Low-income
Togo	Sub-Saharan Africa	Low-income

Uganda	Sub-Saharan Africa	Low-income
Yemen, Rep.	Middle East & North Africa	Low-income
Angola	Sub-Saharan Africa	Lower middle-income
Bangladesh	South Asia	Lower middle-income
Benin	Sub-Saharan Africa	Lower middle-income
Bhutan	South Asia	Lower middle-income
Bolivia	Latin America & Caribbean	Lower middle-income
Cabo Verde	Sub-Saharan Africa	Lower middle-income
Cambodia	East Asia & Pacific	Lower middle-income
Cameroon	Sub-Saharan Africa	Lower middle-income
Comoros	Sub-Saharan Africa	Lower middle-income
Congo, Rep.	Sub-Saharan Africa	Lower middle-income
Côte d'Ivoire	Sub-Saharan Africa	Lower middle-income
Djibouti	Middle East & North Africa	Lower middle-income
Egypt, Arab Rep.	Middle East & North Africa	Lower middle-income
Eswatini	Sub-Saharan Africa	Lower middle-income
Ghana	Sub-Saharan Africa	Lower middle-income
Guinea	Sub-Saharan Africa	Lower middle-income
Haiti	Latin America & Caribbean	Lower middle-income
Honduras	Latin America & Caribbean	Lower middle-income
India	South Asia	Lower middle-income
Jordan	Middle East & North Africa	Lower middle-income
Kenya	Sub-Saharan Africa	Lower middle-income
Kiribati	East Asia & Pacific	Lower middle-income
Kyrgyz Republic	Europe & Central Asia	Lower middle-income
Lao PDR	East Asia & Pacific	Lower middle-income

Lebanon	Middle East & North Africa	Lower middle-income
Lesotho	Sub-Saharan Africa	Lower middle-income
Mauritania	Sub-Saharan Africa	Lower middle-income
Micronesia, Fed. Sts.	East Asia & Pacific	Lower middle-income
Morocco	Middle East & North Africa	Lower middle-income
Myanmar	East Asia & Pacific	Lower middle-income
Nepal	South Asia	Lower middle-income
Nicaragua	Latin America & Caribbean	Lower middle-income
Nigeria	Sub-Saharan Africa	Lower middle-income
Pakistan	South Asia	Lower middle-income
Papua New Guinea	East Asia & Pacific	Lower middle-income
Philippines	East Asia & Pacific	Lower middle-income
Samoa	East Asia & Pacific	Lower middle-income
São Tomé and Príncipe	Sub-Saharan Africa	Lower middle-income
Senegal	Sub-Saharan Africa	Lower middle-income
Solomon Islands	East Asia & Pacific	Lower middle-income
Sri Lanka	South Asia	Lower middle-income
Tajikistan	Europe & Central Asia	Lower middle-income
Tanzania	Sub-Saharan Africa	Lower middle-income
Timor-Leste	East Asia & Pacific	Lower middle-income
Tunisia	Middle East & North Africa	Lower middle-income
Uzbekistan	Europe & Central Asia	Lower middle-income
Vanuatu	East Asia & Pacific	Lower middle-income
Vietnam	East Asia & Pacific	Lower middle-income
West Bank and Gaza	Middle East & North Africa	Lower middle-income
Zambia	Sub-Saharan Africa	Lower middle-income

Zimbabwe	Sub-Saharan Africa	Lower middle-income
Albania	Europe & Central Asia	Upper middle-income
Algeria	Middle East & North Africa	Upper middle-income
Argentina	Latin America & Caribbean	Upper middle-income
Armenia	Europe & Central Asia	Upper middle-income
Azerbaijan	Europe & Central Asia	Upper middle-income
Belarus	Europe & Central Asia	Upper middle-income
Belize	Latin America & Caribbean	Upper middle-income
Bosnia and Herzegovina	Europe & Central Asia	Upper middle-income
Botswana	Sub-Saharan Africa	Upper middle-income
Brazil	Latin America & Caribbean	Upper middle-income
China	East Asia & Pacific	Upper middle-income
Colombia	Latin America & Caribbean	Upper middle-income
Costa Rica	Latin America & Caribbean	Upper middle-income
Cuba	Latin America & Caribbean	Upper middle-income
Dominica	Latin America & Caribbean	Upper middle-income
Dominican Republic	Latin America & Caribbean	Upper middle-income
Ecuador	Latin America & Caribbean	Upper middle-income
El Salvador	Latin America & Caribbean	Upper middle-income
Equatorial Guinea	Sub-Saharan Africa	Upper middle-income
Fiji	East Asia & Pacific	Upper middle-income
Gabon	Sub-Saharan Africa	Upper middle-income
Georgia	Europe & Central Asia	Upper middle-income
Grenada	Latin America & Caribbean	Upper middle-income
Guatemala	Latin America & Caribbean	Upper middle-income
Indonesia	East Asia & Pacific	Upper middle-income

Iran, Islamic Rep.	Middle East & North Africa	Upper middle-income
Iraq	Middle East & North Africa	Upper middle-income
Jamaica	Latin America & Caribbean	Upper middle-income
Kazakhstan	Europe & Central Asia	Upper middle-income
Kosovo	Europe & Central Asia	Upper middle-income
Libya	Middle East & North Africa	Upper middle-income
Malaysia	East Asia & Pacific	Upper middle-income
Maldives	South Asia	Upper middle-income
Marshall Islands	East Asia & Pacific	Upper middle-income
Mauritius	Sub-Saharan Africa	Upper middle-income
Mexico	Latin America & Caribbean	Upper middle-income
Moldova	Europe & Central Asia	Upper middle-income
Mongolia	East Asia & Pacific	Upper middle-income
Montenegro	Europe & Central Asia	Upper middle-income
Namibia	Sub-Saharan Africa	Upper middle-income
North Macedonia	Europe & Central Asia	Upper middle-income
Paraguay	Latin America & Caribbean	Upper middle-income
Peru	Latin America & Caribbean	Upper middle-income
Serbia	Europe & Central Asia	Upper middle-income
South Africa	Sub-Saharan Africa	Upper middle-income
St. Lucia	Latin America & Caribbean	Upper middle-income
St. Vincent and the Grenadines	Latin America & Caribbean	Upper middle-income
Suriname	Latin America & Caribbean	Upper middle-income
Thailand	East Asia & Pacific	Upper middle-income
Tonga	East Asia & Pacific	Upper middle-income
Türkiye	Europe & Central Asia	Upper middle-income

Turkmenistan	Europe & Central Asia	Upper middle-income
Tuvalu	East Asia & Pacific	Upper middle-income
Ukraine	Europe & Central Asia	Upper middle-income

Note: Classification based on Gross National Income per capita.

Detailed eligibility criteria for both the quantitative and qualitative studies

Inclusive criteria

Our quantitative study eligibility criteria are as follows:

- **Setting –** Studies conducted on smallholder farms, subsistence farms, or medium-scale farms in L&MICs are included.
- **Intervention –** Field trials and simulation studies. AI-enabled solutions that are experimental (i.e., AI-enabled solutions restricted to laboratory experiments) fall outside the scope of this study. This exclusion ensures the review considers plausible applications in L&MICs that are cost-effective and scalable.
- **Comparison –** Control groups or conditions (including simulated controls) that do not use AI-enabled solutions**.**
- **Outcome –** Improvements in yield, detection of diseases, weather predictability, and other solutions.

Our qualitative study eligibility criteria are as follows:

- **Sample -** Studies conducted on smallholder farms, subsistence farms, or medium-scale farms in L&MICs are included.
- **Phenomenon of Interest –** This study focuses on assessing the impact of AI-enabled solutions in agriculture on farmers and other stakeholders. It also includes studies that examine ethical considerations and governance-related aspects associated with the implementation of such technologies.
- **Design –** Published or unpublished literature of any non-quantitative design.
- **Evaluation –** These studies are assessed on whether they help define AI, clarify its types and sub-fields, identify its position along the agricultural value chain, and specify its stage of development. They are also evaluated on whether they provide insights into ethical and equity considerations in agricultural AI, as well as the medium-, short-, and long-term trajectories of specific applications.
- **Research Type -** Case studies, qualitative research, grey literature including third sector and government reports and briefings, expert committee papers, educational theses, and conference proceedings.

Exclusion criteria

- **Language –** This review excludes studies that are not in English or Spanish.
- **Agricultural production systems –** Studies that do not focus on smallholder farms, subsistence farms, or medium-scale producers are excluded. Furthermore, studies on agroforestry, forestry, and fisheries are excluded.
- **Study design –** All study designs not included in the inclusion criteria fall outside the scope of this review.
- **Other sources –** This study excludes news articles and opinion blogs.
- **Geography –** Studies from high-income countries are excluded.

Pilot searches

To ensure a robust search strategy, pilot searches were conducted across diverse search sources. Researchers searched academic journals, dissertation catalogues, search engine repositories, and Google Scholar between 2019 and 2024. The search strategy was developed based on benchmark studies identified in high-quality journals by RR experts, content experts, and regional experts. These experts validated the electronic databases and websites utilised for the search, ensuring that no eligible studies were overlooked. Additionally, they provided feedback on the results from the pilot searches, details of the pilot search strategy, and a summary of the results (see Table 5 in Appendix).

Table 4: Number of hits from pilot searches

	Source	Search terms	Total hits yielded
Journals	Journal of Agriculture Infonomics	AI and Agriculture	25
		Artificial Intelligence and Agriculture	7
	Journal of Precision Agriculture (Accessed through Springer Link)	AI and Agriculture	50
		Artificial Intelligence and Agriculture	65
	Sociologia Ruralis	Artificial intelligence and agriculture	16
		AI and Agriculture	0
	International Journal of Agricultural Sustainability	Agriculture and artificial intelligence	6774
	Agricultural and Food Economics	Artificial intelligence and agriculture	9
		AI and Agriculture	8
		Artificial intelligence and agriculture	49

	Agricultural Systems (accessed through Science Direct)	AI and Agriculture	69
	Journal of Digital Economy (accessed through Science Direct)	Artificial intelligence and agriculture	9
		AI and Agriculture	7
	Journal of Peasant Studies	Artificial intelligence and agriculture	13
		AI and Agriculture	no relevant hits
	World Food Policy (accessed through Wiley)	Artificial intelligence and agriculture	4
		AI and Agriculture	74
	Sustainability	Artificial intelligence and agriculture	63
	Agronomy	Artificial intelligence and agriculture	49
Repositories	AgEcon	Agriculture and artificial intelligence	11
		AI and agriculture	21
	US National Agricultural Library (Agricola)	Agriculture and artificial intelligence	1722
	World Agricultural Economics and Rural Sociology Abstracts (on CABI)	Agriculture and artificial intelligence	579
	EBSCO	Agriculture and artificial intelligence	11
Dissertation Catalogues	The LILACs database	Artificial intelligence and agriculture	1
		Precision agriculture	19
		AI and agriculture	no relevant hits
	ProQuest Dissertations and Theses Global (PQDT)	Artificial intelligence and agriculture	no relevant hits
		Precision agriculture	no relevant hits
		AI and agriculture	no relevant hits
		Smart Agriculture	no relevant hits
		Small holder farming	no relevant hits
		Digital agriculture	no relevant hits
	The National Library of Australia's Trove Service	Artificial intelligence and agriculture	no relevant hits
		Precision agriculture	2276
		AI and agriculture	no relevant hits
		Smart Agriculture	906
		Small holder farming	no relevant hits
		Digital agriculture	no relevant hits
	Deutsche Nationalbibliothek	Artificial intelligence and agriculture	142
		Precision agriculture	no relevant hits

		AI and agriculture	no difference from the other results
		Smart Agriculture	468
		Small holder farming	no relevant hits
		Digital agriculture	426
	The Networked Digital Library of Theses and Dissertations (NDLTD)	Artificial intelligence and agriculture	52
		Precision agriculture	5585
		AI and agriculture	no relevant hits
		Smart Agriculture	no relevant hits
		Small holder farming	no relevant hits
		Digital agriculture	no difference from the other results
Google Scholar		"Artificial intelligence and agriculture" OR "Precision Agriculture" OR "Digital Agriculture"	17,100
		AI AND "Precision Agriculture"	22,600
		AI AND "Precision Agriculture"	22,600
		agr and Artificial intelligence ("crop production" OR "livestock" OR "machine learning" OR deep AI OR Diseases OR "irrigation" OR "neural networks")	17,600
		Artificial intelligen* or AI OR digital farm* OR remote sensor or remote sensing OR precision farm* or precision agriculture OR smart farm* or smart agriculture OR drone OR predictive farm* or predictive agriculture* OR automated or automated agriculture or automated farm*)	17,400
		agr and Artificial intelligence ("crop production" OR "livestock" OR "machine learning" OR deep AI OR Plant Diseases OR "irrigation" OR "neural networks")	17,400

Rapid review searches

Informed by the pilot searches and further consultation with rapid review experts, content experts, and regional experts, the team developed a comprehensive set of search terms such as "AI and agriculture," "precision agriculture," and "smart agriculture." These also included keyword strings combining AI- and agriculture-related keywords (see table 6 in Appendix).

As one key finding from the pilot searches was a paucity of evidence, these search terms were systematically applied across both academic and grey literature sources to provide broader coverage (see Table 7 in Appendix, for a full list of the resources searched for the RR). Searches were conducted in electronic databases (such as AG Econ, Scopus, and CEPAL). To include dissertations, the team extensively searched regional and university dissertation databases (such as the Center for Research Libraries, the LILACS database, and Open Access Theses and Dissertations). Further, the team hand-searched journals from the past five years to avoid overlooking recent studies delayed in indexing. According to experts' suggestions, the team searched institutional and organisational websites in incognito mode to locate grey literature (see Table 8 in Appendix for a full list of the resources searched for the RR).

The research team also searched a comprehensive set of regional databases and conducted citation searches (see Table 9 in Appendix, for a full list of the regional databases).

The researchers adhered to the search strategies outlined in the RR protocol. The protocol was led jointly by the RR expert and the content expert. The protocol was validated by 3ie and FCDO, and was accepted for publication (registration link of rapid review protocol). Please refer to this link for the protocol.

We saved the search results in Zotero, a reference management tool. We then transferred them to the Evidence for Policy & Practice Information Reviewer, a specialist systematic review tool.

Table 5: Search strings

S.no	Search Strings
1	agricultur* or agrarian or agribusiness* or agronom* or husbandry or farm* or cultivat* or planter* or smallhold* or landown* or "land own*" or outgrower* OR livestock OR crop OR crops OR pisciculture OR aquaculture OR breed* OR fish* OR "food produc*" OR floricultur* OR horticultur* OR harvest* OR OR forest* OR ("natural resource*" NEAR/1 manage*) OR agroforestry OR agriforestry OR agroecolog* OR agrifood* OR agri-food* OR plantation *)
2	Artificial intelligen* or AI OR digital farm* OR remote sensor or remote sensing OR precision farm* or precision agriculture OR smart farm* or smart agriculture OR drone OR predictive farm* or predictive agriculture* OR automated or automated agriculture or automated farm*)

Table 6: List of search sources

S. No	Search sources
1.	Electronic searches of databases
2.	Systematic review repositories (3ie, Campbell Collaboration, Cocharne, CGIAR)
3.	Databases of academic institutes (Ph.D dissertations)
4.	Hand searches of journals for the last 5 years
5.	Website site searches of institutions for grey literature
6.	Identification of seminal studies in consultation with experts
7.	Citation searches for all included studies

Table 7: List of databases

S. No.	Search sources	List of databases
1	Electronic searches of databases	AG Econ
		US National Agriculture Library (Agricola)
		World Agricultural Economics and Rural Sociological Abstracts (on CABI)
		Web of Sciences Core Collection (1900-present)
		SCOPUS
		EconLit (on EBSCO Host)
		GreenFile and Gender Studies
		Geobase (on Engineering Village)
		PAIS (on Proquest)
		Environmental Host (on EBSCO Host)
		Africa-wide information
		Business sources complete
		Instituto interamericano de cooperacion para de Agricultura
		CEPAL
2	Databases of Ph.D dissertations	The US Based center for Research Libraries (CRL)
		The LILACS database
		Open Access Theses and Dissertations (OATD)
		Proquest Dissertations and Theses Global (PQDT)
		The National Library of Australia's Trove Service
		DART-Europe
		School of Agrifood and Environment, University of Udine
		Deutsche Nationalbibliothek
		The Networked Digital Library of Theses and Dissertations (NDLTD)
		National Library of Canada's records
		Swedish University Dissertations
3	Hand searches of journals for the last 5 years	Journal of agriculture informatics
		Precision agriculture
		World Development
		Journal of Information Technology for Development
		Sociologia ruralis
		International Journal for Agricultural Sustainability
		Agriculture and Food Economics

		Agricultural Systems
		Food policy frontiers in sustainable food systems.
		Journal of Digital economy
		Journal of peasant studies
		Journal of agricultural science and technology
		Journal of artificial intelligence and research
		World Food
		Sustainability
4	Academic institutions	Artificial Intelligence for Agriculture, University of Illinois California
		School of Agriculture, Food and Ecosystem Sciences, University of Melbourne.
		Institute of agriculture, University of Sydney
		College of Agriculture and Life Sciences (CALS), Cornell University
		college of Agriculture, Purdue University.
		Institute of Digital Agriculture, Cranfield University
		School of Agrifood and the environment, University of Udine
		School of Agrifood and technology and biotechnology, The technical university of Catalonia
		Digital Science and Artificial Intelligence for Agriculture, Wageningen University & Research, Digital Science and Artificial Intelligence for Agriculture
		Institute for Food and Agriculture Sciences, University of Florida, Institute for Food and Agriculture, Institute for Food and Agriculture Sciences.
5	Website site searches of institutions for grey literature	The Campbell Library of Systematic Reviews
		3ie's impact evaluation repository / Development Evidence Portal (DEP)
		FCDO R4D
		IMMANA Grant database – ANA
		World Bank IEG evaluations
		CGIAR
		IDRC
		IFAD
		AgriPro Focus
		BMGF
		Donor Committee for Enterprise Development
		FAO
		ILO

		SNV Netherlands Development Organisation
		USAID
		IPA
		J-PAL
		USAID Development Experience Clearinghouse
		Precision for Development
		ADB
		UNEP
		African Development Bank
		GODAN Data Portal
		ICRISAT (International Crops Research Institute for the Semi-Arid Tropics)
		CIAT (International Center for Tropical Agriculture)
		IMF
		OECD
		IICA (Inter-American Institute for Cooperation on Agriculture)
		CIMMYT Knowledge Center
		FARA Knowledge Platform
		Rockefeller Digital Resources
		CATIE (Tropical Agricultural Research and Higher Education Center)
		GARDIAN (Global Agricultural Research Data Innovation & Analysis Network)
		CCAFS (Climate Change, Agriculture, and Food Security)
6	Regional sources to ensure geographical inclusion	Please see Table 11

Table 8: Regional databases

Region	Search sources	List of databases
Asia	Organisational databases	Digital AG Lab IIT Bombay
		Agro informatics IIT Bombay
		Prayog IIT Bombay
		Digital Impact Square- A TCS Foundation initiative
		Vietnam Digital Agriculture association
		Wadhwani AI
		Farm 360
		Switch ON Foundation
		Bharat Krushi Seva
		Krisiyukta
		Dvara E registry
		India AI
		IFPRI South Asia
		FICCI
		The Asia Foundation
		Niti Aayog
		The Organisation for Research on China and Asia
		Asian Productivity Organisation
		Asian Institute of technology
		The Institute for the Development of Agricultural Cooperation ...
		Asian rural institute
		Brolaug Institute of South Asia
		Digital Green
		Harvest Plus
		One Acre Fund
		Pinduoduo's Smart Agriculture Competition
		Grameen
		MS Swaminathan Foundation
		TechnoServe
		Philanthropy Asia Alliance
		Asia Productivity Organisation
		SAARC
		SEARCA
	Academic databases	NUS institute of South Asian Institute

		United Nations University
		China Agricultural University
		Asia Society Policy Institute
		Indian Institute of Science
		Shodh Ganga
		University of Agriculture, Faisalabad
		Institute of Agricultural Information, Chinese Academy of Agricultural Sciences Centre for Agricultural Resources Research,
		Chinese Academy of Science Chinese Academy of Tropical Agricultural Sciences
		Royal Agricultural University, Thailand
		Asia-Pacific Consortium on Agricultural Biotechnology and Bioresources
		Agricultural Research Funding Agency of Thailand
		National Agriculture and Food Research Organisation
		Sri Lanka Council for Agricultural Research and Policy
		Hector Kobbekeduwa Agrarian Research and Training Institute
		Borlaug Institute for South Asia
		CGIAR South Asia
		Bangladesh Agricultural Research Council
		CABI
		International Livestock Research Institute, South Asia
		Cereal Systems Initiative for South Asia
		Asian Institute of Technology
Latin America	Organisational databases	REDALYC (Network of Scientific Journals from Latin America and the Caribbean)
		LATINDEX
		FAO's Regional Office for Latin America and the Caribbean
		HortiDaily
		National Agricultural Library (USDA)
		GARDIAN - Big Data Platform by CGIAR
		INIA Biblioteca (Chile)
		INIFAP Revista Ciencias Agrícolas (Mexico)
		Inter-American Development Bank (IDB)
	Journals	American Society for Horticultural Science (ASHS) Journals
		Nature Cities

		Revista Fitotecnia Mexicana
		Revista Chapingo Serie Horticultura
Africa	Organisational databases	Farmers Organisation in Africa
		Africa wide information
		Farm africa
		African development bank
		Alliance for food prosperity in Africa
		African agricultural technology foundation
		African Crop Sciences Journal
		National Agricultural Advisory Services (Uganda)
		International African Institute (can access country specific databases/repositories)
		AGRA (Alliance for a Green Revolution in Africa)
		NEPAD (New Partnership for Africa's Development)
		African Centre for Technology Studies (ACTS)
	Academic databases	University of Zimbabwe Institutional Repository
		Makerere University Institutional Repository
		Egerton University Institutional Repository
		University of Nairobi Digital Repository
		Kenyatta University Institutional Repository
		Jomo Kenyatta University of Agriculture and Technology

Table 9: Overview of inclusion/exclusion criteria

Criteria	Inclusion criteria	Exclusion criteria
Quantitative studies: PICO framework		
Setting (population)	Studies conducted on smallholder farms, subsistence farms, or medium-scale farms in L&MICs.	Studies that do not focus on smallholder farms, subsistence farms, or medium-scale producers. Additionally, this review also excludes studies on agroforestry, forestry, and fisheries.

		Studies from high-income countries.
Intervention	Field trials and modelling/prediction studies.	All study designs not included in the inclusion criteria (e.g., news articles and opinion blogs).
Comparison	Control groups or conditions (including simulated controls) that do not use AI-enabled solutions.	N/A
Outcome	Improvements in agricultural yields, detection of diseases, weather predictability, and other solutions.	N/A
Qualitative studies: SPIDER framework		
Sample	Studies conducted on smallholder farms, subsistence farms, or medium-scale farms in L&MICs.	Studies that do not focus on small-holder farms, subsistence farms, or medium-scale producers have been excluded. Additionally, studies on agroforestry, forestry, and fisheries are excluded.

		Studies from high-income countries.
Phenomenon of interest	Assessing the impact of AI-enabled solutions in agriculture on farmers and other stakeholders. This review includes any studies considering ethical and governance-related phenomenon.	N/A
Design	Published literature of any non-quantitative design.	Studies not published between 2019 – 2025.
Evaluation	Does this study help us define AI? Does the study help us understand the types, sub-fields, position along the agricultural value chain, and stage of development of AI applications in agriculture? Does this study provide insights into ethical and equity considerations in AI applications to agriculture? Does this study provide insights into short-, medium- and long-term trajectories of specific AI applications?	N/A
Research type	Case studies, qualitative research, grey literature including third sector and government reports and briefings, expert committee papers, educational theses and conference proceedings.	All study designs not included in the inclusion criteria are excluded (e.g., news articles and opinion blogs).

Table 10: Screening tool for rapid review

Screening tool
Exclude on intervention
Exclude on year of publication
Exclude on region
Exclude on regional income
Exclude on language
Exclude on agriculture dimensions
Exclude on value chain dimensions
Exclude on publication type
Exclude on study design
Exclude on sample
Exclude on duplicates
Include for effectiveness
Include for qualitative synthesis in the RR
Include for narrative review (editorials included here)
Park for discussion
Include for Spanish studies
Include on no full text available

Details of the title and abstract screening and full-text screening

Stage 1: Title and abstract screening

Initially, the studies included from the searches were screened independently by two reviewers based on title and abstract. Blinded reviewers double-screened 10 percent of the total studies screened for title and abstract to establish inter-rater reliability. Even if only one researcher included a study, the team considered it for inclusion to ensure no studies were overlooked. Given the paucity of evidence, the team was thorough in including relevant studies. Duplicate studies were then identified and omitted. Discussions between the reviewers and the larger team of content experts resolved any disagreements.

Stage 2: Full-text screening

After title and abstract screening, studies that met the inclusion criteria were screened at the full-text level for eligibility. The Cochrane Handbook recommends completing full-text screening with the entire sample double-screened by blinded reviewers (Lefebvre 2025). However, due to the RR design and project timelines, blinded reviewers double-screened only 10 percent of the total sample to establish inter-rater reliability. Discussions between the reviewers and the larger team of content experts resolved any disagreements.

Details of data extraction and management

The data extraction tool development process was anchored by the content expert and the RR expert. The tool was developed through an iterative process guided by research questions. The team validated the coding tool by piloting 10 studies. Upon piloting, findings were presented to the experts, 3ie, and FCDO, and the extraction tool was further refined. Following expert recommendations, the team then developed a coding tool. Despite the limited evidence, the tool was open-ended to maximise data collection (see Table 12 in Appendix).

The tool consisted of 12 domains, including bibliographic characteristics such as the title, names of authors, type of publication, year of publication, and the country of study. The tool also captured descriptive and qualitative information about AI-enabled solutions and their specific AI components. It also included qualitative information on the outcome measured, information on governance, environmental and ethical issues, and overall findings.

The final data extraction was completed by two reviewers, with 10 percent of the total sample double-coded to establish inter-rater reliability. Any disagreements were resolved through discussion between the reviewers, the systematic review expert, and the wider team of content experts. The reconciliation methodology was performed by the RR expert, and the reconciliation relating to subject matter was led by the content expert. The overall quality assurance for data collection was overseen by the project director.

Table 11: Coding Tool for Data Extraction

Category	Type of data	Subcategories
Bibliographic information	Publication date	2019
		2020
		2021
		2022
		2023
		2024
	Publication type	Peer-reviewed publication
		Dissertation
		Grey literature – government document
		Grey literature – institutional document
		Grey literature – policy literature
		Grey literature – committee papers
		Grey literature – editorials (narrative review)

		Other (mention details with page number in the textbox)
	Does this study report funding information (of research, not the implementer of the intervention)?	Yes (mention details with page number in the textbox)
		Not reported
	Can the funding information (of research, not the implementer of the intervention) be accessed from other sources?	Yes (mention details with source link)
		Not reported
Information relating to the study	AI-solution: quantitative versus qualitative studies	Quantitatively analysed AI-enabled solutions (Mention details with page number in the textbox).
		Qualitative studies a. Specific region studied (mention details with page number in the textbox) b. Governance (mention details with page number in the textbox) c. Ethics (mention details with page number in the textbox) d. Gender (mention details with page number in the textbox) e. Others (mention details with page number in the textbox)
		Unclear
	If the AI-solution is quantitative, are	Specific region studied

	any of the following dimensions described or explored in the intervention of the study?	Governance
		Ethics
		Gender
		Other
		Not applicable
	Study design	Qualitative a. Ethnography and action research b. Phenomenology and process evaluations c. Grounded theory d. Case study e. Literature review f. Opinion or narrative piece g. Historical account h. Impact assessment
		Quantitative a. RCT b. Quasi-experimental c. Non-experimental d. Survey e. Field trials f. Simulation study
		Mixed-methods
	Region studied	Latin American/Caribbean (Mention details with page number in the textbox)

		South Or South East Asian (Mention details with page number in the textbox)
		Sub-Saharan Africa (Mention details with page number in the textbox)
		East Asia & Pacific (Mention details with page number in the textbox)
		Middle East & North Africa (Mention details with page number in the textbox)
		West Africa (Mention details with page number in the textbox)
		Global (Mention details with page number in the textbox) **Global will be used for studies that explore AI-dimensions (such as ethics and governance) more descriptively. This is not the appropriate code to use for an intervention-based study.*
	Region income category	Low-income
		Lower middle-income
		Upper middle-income
	Population (users)	Smallholder farmers (mention details with page number in the textbox)

		Subsistence farmers (mention details with page number in the textbox)
		Middle-scale farmers (mention details with page number in the textbox)
		Extension agents (mention details with page number in the textbox)
		Local market actors (mention details with page number in the textbox)
		Int. market actors (mention details with page number in the textbox)
		Non-human agent (mention details with page number in the textbox)
		Other (mention details with page number in the textbox)
		Not reported
	Beneficiaries	Smallholder farmers (mention details with page number in the textbox)
		Subsistence farmers (mention details with page number in the textbox)
		Middle-scale farmers (mention details with page number in the textbox)
		Extension agents (mention details with page number in the textbox)

		Local market actors (mention details with page number in the textbox)
		Int. market actors (mention details with page number in the textbox)
		Non-human agent (mention details with page number in the textbox)
		Other (mention details with page number in the textbox)
		Not reported
	Number of participants (in intervention)	
Intervention and comparator	Agriculture - dimensions	Crop production (mention details with page number in the textbox) a. Field production (mention details with page number in the textbox) b. Protected farming (mention details with page number in the textbox) c. Seasonal field crops (mention details with page number in the textbox) d. Small-scale cash crops (mention details with page number in the textbox) e. Perennial cash crop production (mention details with page number in the textbox) f. Subsistence crop production (mention details with page number in the textbox) g. Not specified

		Livestock (mention details with page number in the textbox) a. Cattle (mention details with page number in the textbox) b. Poultry (mention details with page number in the textbox) - Fattening - Eggs c. Swine (mention details with page number in the textbox) d. Fattening (mention details with page number in the textbox) e. Dairy (mention details with page number in the textbox) f. Not specified
		Aquaculture (mention details with page number in the textbox) a. Fish b. Crustaceans c. 3 types of fisheries - Commercial - Municipal - Aquaculture (brackish water, fresh water, and mariculture) e. Not specified
		Other (cross cutting) (mention details with page number in the textbox)
		Not reported
	AI categories discussed in the study intervention	Automation and robotics (mention details with page number in the textbox)
		Machine learning (mention details with page number in the textbox)

		Deep learning (mention details with page number in the textbox)
		Neural networks (mention details with page number in the textbox)
		Predictive AI (mention details with page number in the textbox)
		Generative AI: a. NPL b. LLM (mention details with page number in the textbox)
		Other (mention details with page number in the textbox)
		Not reported
	Duration of AI intervention	Duration of intervention (mention details with page number in the textbox)
		Follow-up time (mention details with page number in the textbox)
		Not reported
		Not applicable
	Value chain dimensions relating to the stage of production in study intervention	Pre-production (mention details with page number in the textbox)
		Production (mention details with page number in the textbox)

		Post-harvest (bundled) with pre-production (mention details with page number in the textbox) * *An intervention is "bundled" when it addresses both early stages of the value chain (pre-production or production) and later stages (post-harvest or consumption).*
		Distribution (bundled) with pre-production (mention details with page number in the textbox)
		Consumption (bundled) with pre-production (mention details with page number in the textbox)
		Other (mention details with page number in the textbox)
		Not reported
	Comparison	Does the paper specify a control group or control condition? a. Yes b. No *The study considers a control group or control condition to be a group or condition which does not use AI to provide a comparison for the purposes of calculating effectiveness of interventions and approaches.
		If yes. which is it (mention details with page number in the textbox)
		Not applicable
	Number of participants (in comparator)	

Target problem: categorisation based on the type of problem the solution aims to solve.		Forecast and prediction - Weather and climate - Optimal harvest time
		Detection - Crop diseases - Livestock pest disease
		Differentiation - Size and quality of produce
		Optimisation - Irrigation - Nutrient application - Feed distribution
		Capturing and interpretation and/or evaluation - Global weather patterns - Individual farm management decisions
		Decision-making - Best-fit crop variety based on individual farm and household properties
		Not specified
Organisational typology: categorisation based on the types of	Developers	NGO
		Research institutes

organisations that develop and implement AI-enabled solutions		Start-up
		Big tech.
		AgTech
		Government institutions
		Ag business
		Farmer's association
		Not specified
	Implementors	NGO
		Research institutes
		Start-up
		Big tech.
		AgTech
		Government institutions
		Ag business
		Farmer's association
		Not specified

Inclusive design and user diversity		Does the paper mention diverse demographics of farmers/users? a. Yes (mention details with page number in the textbox) b. No **Define diverse demographics: demographic diversity can come from differences in gender, ethnicity, age, class, educational background, socioeconomic status, religion, and political beliefs.*
		Does the paper discuss on digital divide issues? a. Yes (Mention details with page number in the textbox) b. No. **Define digital divide issues:* the gap between those who can and those who cannot access, meaningfully use, and benefit from digital technologies—in this study's context, specifically AI-based technologies. The divide exists between countries, regions, and individuals. Researchers traditionally distinguish between first-, second-, and third-level divides (i.e., access to infrastructure, connectivity, hardware, software, and services; literacy including both general literacy and e-literacy; and benefits such as whether access and use of digital technologies results in meaningful offline advantages). Other words to look out for: inclusivity, exclusion, equity and inequity, equality and inequality, unintended consequences, and adverse impact

		Does the paper consider digital literacy challenges? a. Yes (mention details with page number in the textbox) b. No **Define Digital Literacy: It's the ability to use digital devices and technology to access information, communicate, create and share content, solve problems, and make decisions. It's also the literacy to validate and evaluate digital technologies.*
		Does the paper focus on accessibility in AI technology adoption? a. Yes (mention details with page number in the textbox) b. No. **Define accessibility: accessibility means ensuring that all potential users, with different levels of literacy, socio-economic, racial, ethnic, gender backgrounds, can access, afford and meaningfully engage with and benefit from AI implementations.*
		Not applicable
Effectiveness **Effectiveness is defined as an AI-solution that can quantitatively improve an agricultural outcome. This includes an increase in productivity,*		Are AI-enabled solutions effective in improving outcomes related to productivity (articles must strictly use the word productivity)? a. Yes (mention details with page number in the textbox) b. No
		Are AI-enabled solutions effective in improving outcomes related to food security (articles must strictly use the word food security)? a. Yes (mention details with page number in the textbox) b. No

food security, income, and quality of livelihoods for users.		Are AI-enabled solutions effective in improving income and livelihoods (articles must strictly use the word income or livelihood)? a. Yes (mention details with page number in the textbox) b. No
		How effective are AI-enabled solutions in improving agricultural outcomes other than productivity, food security, income, or livelihoods?
		Not applicable
Outcomes		Does the study achieve to improve/solve the target problem? a. Yes b. No
Ethical and governance dimensions		Does the study discuss governance-related issues? a. Yes (mention details with page number in the textbox) b. No
		Does the study discuss ethical issues? a. Yes (mention details with page number in the textbox) b. No
		Does the study discuss barriers to the implementation of AI-enabled solutions in agriculture? a. Yes (mention details with page number in the textbox) b. No **Define barriers: barriers are challenges in implementing AI-enabled solutions. This includes opposition from key stakeholders, inadequate human or financial resources, lack of clarity on operational*

		guidelines or roles and responsibilities for implementation, and lack of infrastructure.
		Not applicable
Scalability		Does the study define scalability of AI-enabled solutions in agriculture? a. Yes (mention details with page number in the textbox) b. No
Legislation		Does the study discuss regional/national legislation of AI-enabled solutions in agriculture? a. Yes (mention details with page number in the textbox) b. No
		Not applicable
Recommendations		Does the study have recommendations on the short-, medium-, and long-run implementation of AI-enabled solutions in agriculture? a. Yes (mention details with page number in the textbox) b. No

Assessment of bias in included studies

The review team assigned a confidence rating to all included studies. The process assessed the risk of bias in the included studies and determined whether the study methods posed a high, low, or unclear risk of bias. The team employed separate tools to assess risk of bias and study confidence for quantitative, qualitative and mixed-methods evidence. For quasi-experimental designs, the team coded risk of bias as critical, serious, moderate, low, or no information. A high risk of bias undermines the reported findings by indicating serious methodological concerns that likely influenced the results and made the findings unlikely to be replicated. Conversely, a low risk of bias implies a high degree of confidence in the study's reported findings. The team assigned an unclear risk of bias where studies reported insufficient information.

Given the wide array of methodologies in this review, the team used appropriate standardised risk-of-bias according to study design. For quantitative and mixed-methods studies, researchers used PROBAST for prediction models, Cochrane RoB 2 for randomised controlled trials (RCTs), and ROBINs-I for quasi-experimental studies. The selection of the critical appraisal tool was an iterative process. The review team conducted a pilot test with two reviewers independently assessing an RCT using the Cochrane RoB 2 tool. Methodological experts selected the NICE checklist for qualitative appraisal because it better suited the review methodology.

The team applied PROBAST to prediction models. PROBAST is organised into four domains: participants, predictors, outcomes and analysis. These domains contain a total of 20 signalling questions to facilitate a structured judgment of risk of bias. This occurs when shortcomings in study design, conduct, or analysis lead to systematically distorted estimates of model predictive performance. "PROBAST enabled a focused and transparent approach to assessing the ROB and applicability of studies that develop, validate, or update prediction models for individualised predictions" (Wolff et al. 2019). For the full list of questions, see Table 13 in Appendix.

The team used Cochrane RoB 2 for RCTs. It is the recommended tool for RCTs by Cochrane because it is structured into a "fixed set of domains of bias, focusing on different aspects of trial design, conduct, and reporting". There are signalling questions to judge evidence on "low" or "high" risk of bias, or to express "some concern" within each domain (Cochrane 2025). For a full list of questions, see Table 13 of Appendix.

The researchers assessed the risk of bias in the quasi-experimental studies using the ROBINS-I tool (version 2), which is designed for non-randomised interventions. This tool evaluates seven domains with signalling questions that allow for 'strong' or 'weak' yes/no responses (Cochrane 2024).

A rapid review expert (GS) carried out the confidence rating for quantitative studies; GS has extensive experience in using these tools.

For qualitative studies, the team used the NICE methodology checklist. The NICE qualitative checklist provides a structured framework to assess the methodological quality of qualitative research studies. It allows researchers to identify potential strengths and weaknesses in a study, ensure the reliability and validity of findings, and make more informed decisions when using qualitative evidence. It was based on five key domains: theoretical approach, study design, data collection, trustworthiness, analysis, and ethics (see Table 13 in Appendix for more information on the critical appraisal).

The principal investigator, an RR expert with extensive experience using the NICE methodology checklist, validated the confidence ratings for qualitative studies.

Figure 03: Critical appraisal tools based on study design

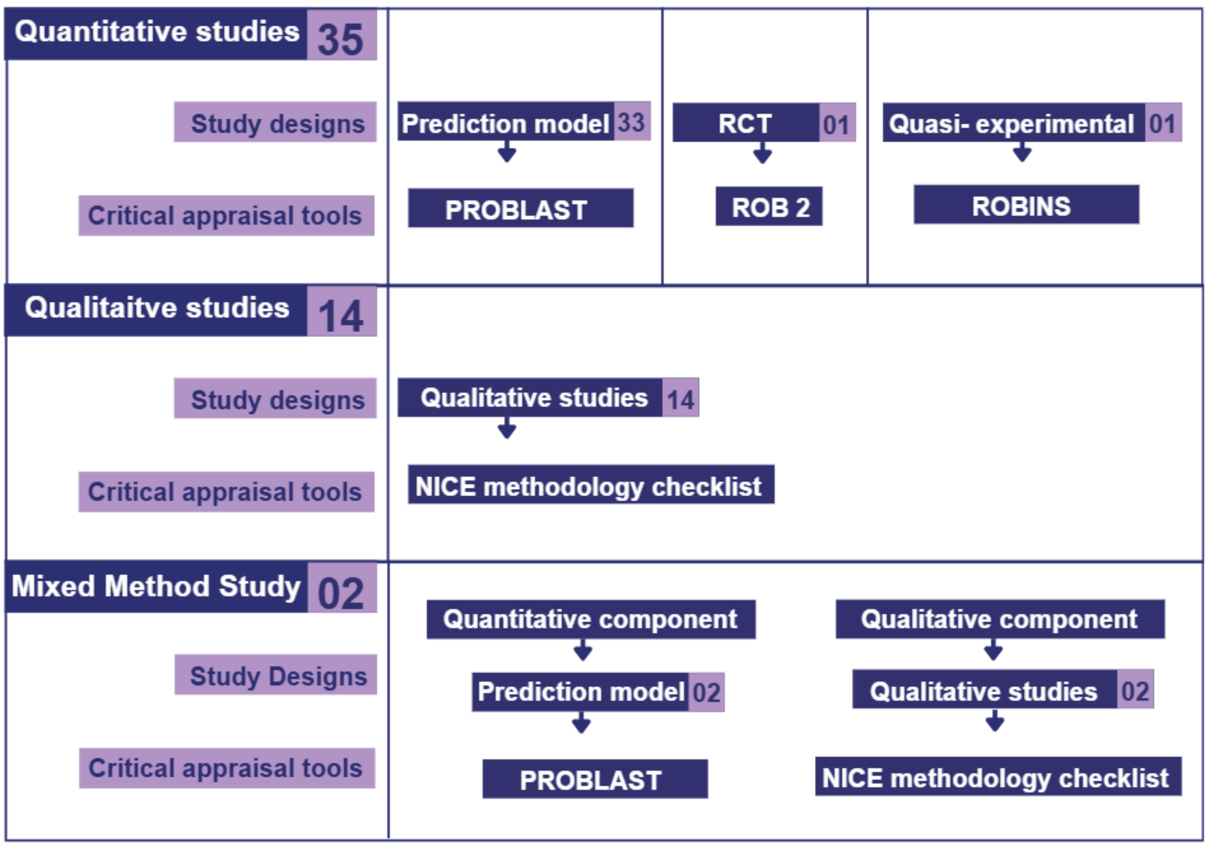


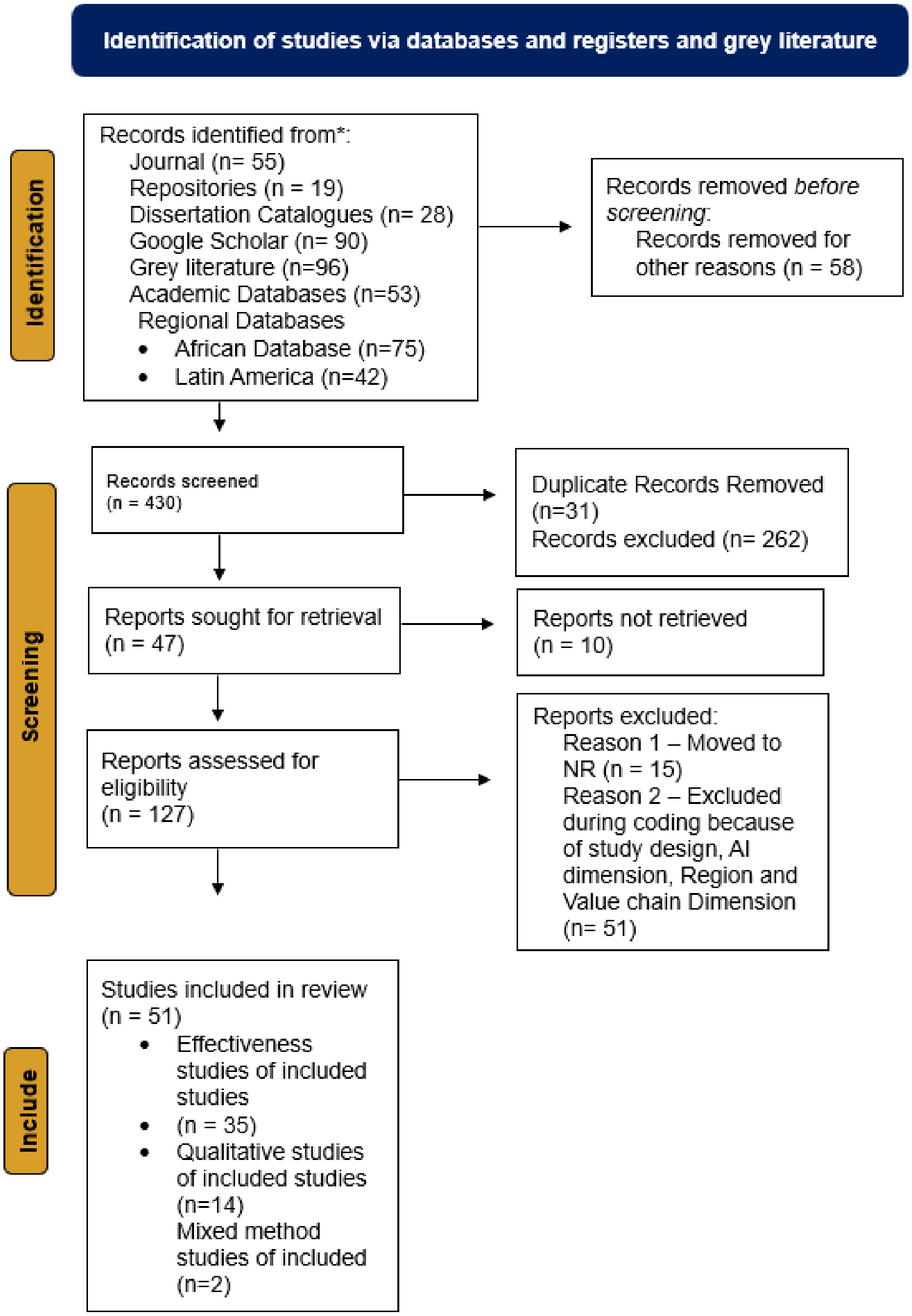
Table 12: List of tools used for critical appraisal

Methods	Tool	Links
Qualitative	NICE	https://www.nice.org.uk/process/pmg4/chapter/appendix-f-quality-appraisal-checklist-quantitative-intervention-studies
Qualitative	PROBAST (Prediction)	https://www.acpjournals.org/doi/full/10.7326/M18-1376?download=true&journalCode=aim
	ROB2	https://training.cochrane.org/handbook/current/chapter-08#section-8-1
	ROBINS I	https://drive.google.com/file/d/1LCc9_KFIpdP3_uR56M-7ngO0zppxpAMS/view

Prisma

As seen in Figure 3 the study identified 500 records from scientific databases, journals, region-specific organisational databases, repositories, academic institution-affiliated sources, and grey literature. Upon deduplication, 430 records were included for screening after refinement of the inclusion and exclusion criteria. A further 31 records were excluded as duplicates, and 47 records were sought for retrieval, out of which 10 records were not retrieved. The team excluded an additional 262 studies on the basis of the inclusion and exclusion criteria. 127 studies were coded, and yielded 51 included studies. These 51 studies comprised 35 effectiveness studies, 14 qualitative studies, and 2 mixed-methods studies. Furthermore, all included studies were critically appraised (see Section 4.3).

Figure 04: PRISMA flowchart for the rapid review



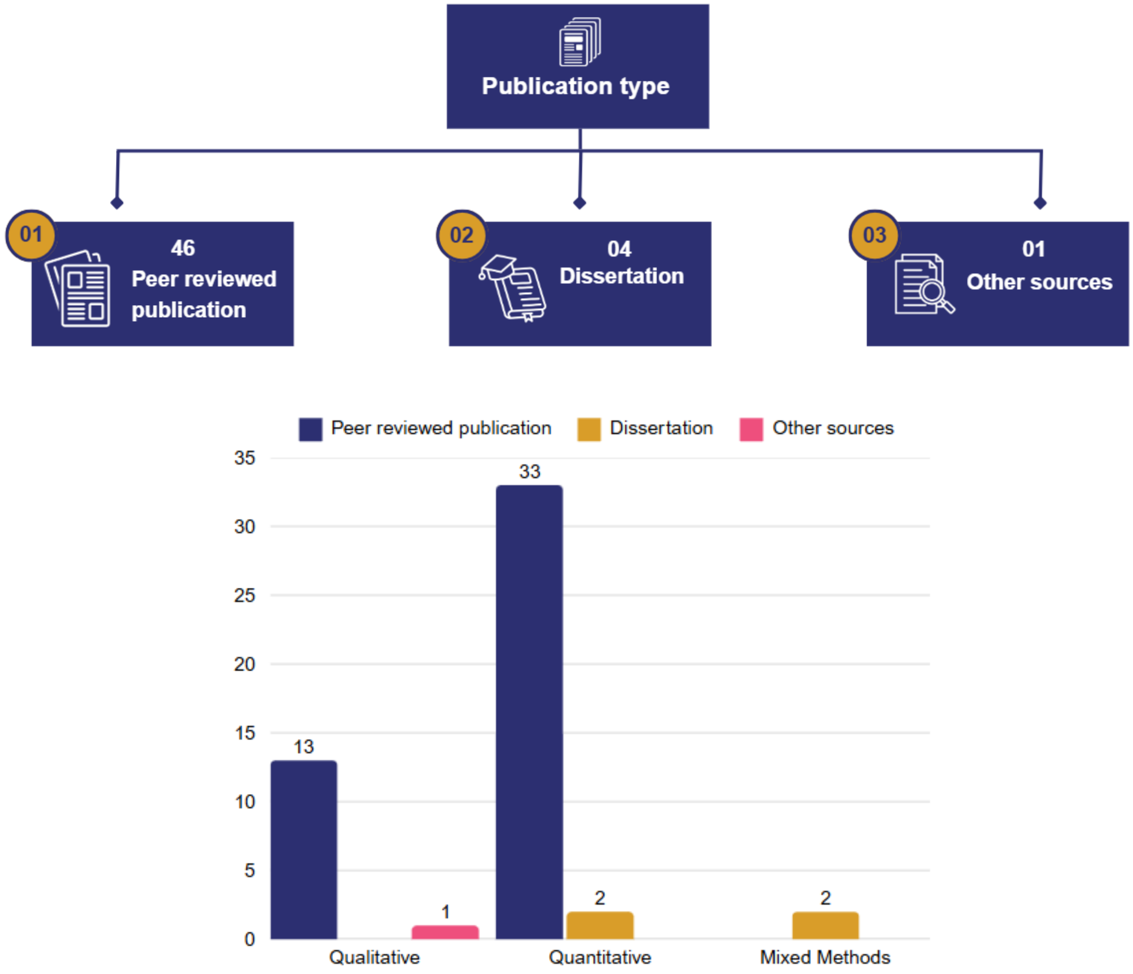
Descriptive statistics

Publication characteristics

Publication type and year

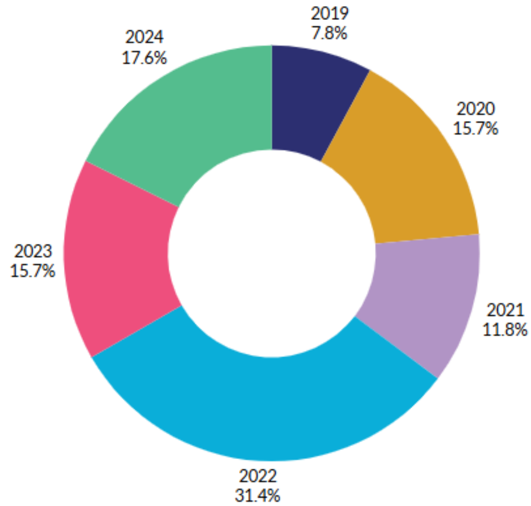
This review identified most studies (90.2%, n=46) as peer-reviewed articles and research dissertations (7.8%, n=4). These comprised 33 quantitative, 14 qualitative, and 2 mixed-methods studies.

Figure 05: Publication type and design of studies included in the rapid review



The RR included publications spanning 2019–2024. Of these, 31.4% (n=16) appeared in 2022. Fewer publications were published in later years, with 15.6% (n=8) in 2023 and 17.6% (n=9) in 2024 (see Table 17 in the Appendix).

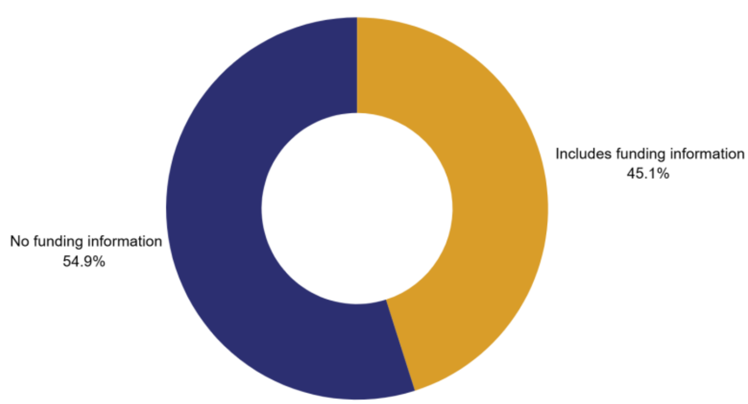
Figure 06: Year of publication reported for studies included in the rapid review



Funding

Researchers declared funding in 54.9% (n=28) of the studies. Quantitative studies accounted for 19 funded projects, while nine qualitative studies received funding. No mixed-methods studies had funders. Notable funders included the National Natural Science Foundation of China, Jawaharlal Nehru University, and the Centre for the Study of Existential Risk at the University of Cambridge. However, 45.1% (n=23) of studies reported no external funding, and additional searches revealed no further information (see Table 18 in the Appendix).

Figure 07: Funding information reported for studies included in the rapid review



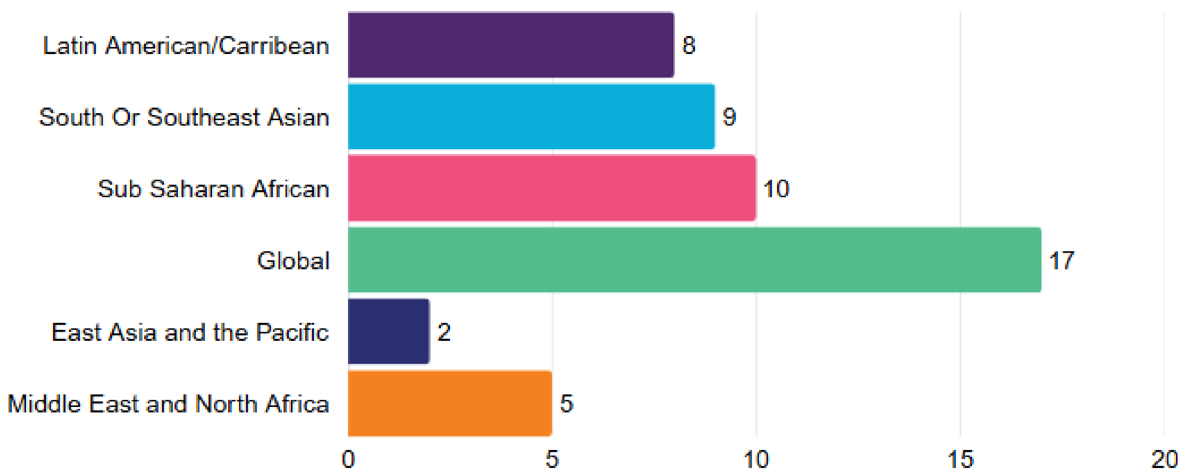
Study characteristics

Geographical representation

This review found most studies (33.3%, n=17) to be globally representative. These studies either specifically focus on L&MICs or discuss the barriers, future, and implications of AI in agriculture without focusing on specific regions.

Among region-specific studies, Sub-Saharan Africa (SSA) and South East Asia dominated representation. Sub-Saharan Africa accounted for 19.6% (n=10) of studies, while South East Asia represented 17.6% (n=9). Latin America and the Caribbean made up 15.6% (n=8). The Middle East and North Africa contributed 15.7% (n=5), and East Asia and the Pacific accounted for 3.9% (n=2) (see Table 18 in Appendix).

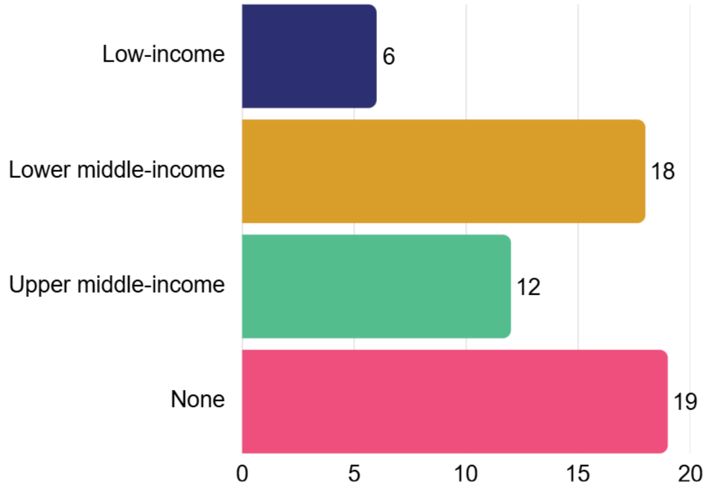
Figure 08: Regions reported for studies included in the rapid review



Income categories

Regional income categories revealed limited focus on low-income countries, with only 11.7% (n=6) of studies targeting this group. Lower-middle-income countries were represented in 35.3% (n=18) of the studies, and upper-middle-income countries in 23.5% (n=12). However, 37.3% (n=19) of studies did not specify income-related analyses.

Figure 09: Regional income category reported for studies included in the rapid review



Study design and effectiveness

Methodologies

Out of the 51 studies included in the rapid review, 35 were quantitative, 14 qualitative, and there were 2 mixed-method studies. The Quantitative studies employed diverse methodologies, including modelling and prediction (n=33), randomised controlled trials (RCTs, 2.1%, n=1), and quasi-experimental (2.1%, n=1) study design. Qualitative analyses included ethnography studies (n = 5), case studies (n=4), and qualitative impact assessment (n =4) (see Table 14 and Table15 in Appendix).

Out of the 51 studies included in the rapid review, 35 were quantitative, 14 were qualitative, and 2 were mixed-methods studies. The quantitative studies employed diverse methodologies, including modelling and prediction (n=33), randomised controlled trials (RCTs, 2.1%, n=1), and quasi-experimental (2.1%, n=1) study designs. Qualitative analyses included ethnography studies (n=5), case studies (n=4), and qualitative impact assessments (n=4) (see Table 15 and Table 16 in Appendix A).

Figure 10: Study design reported for studies included in the rapid review

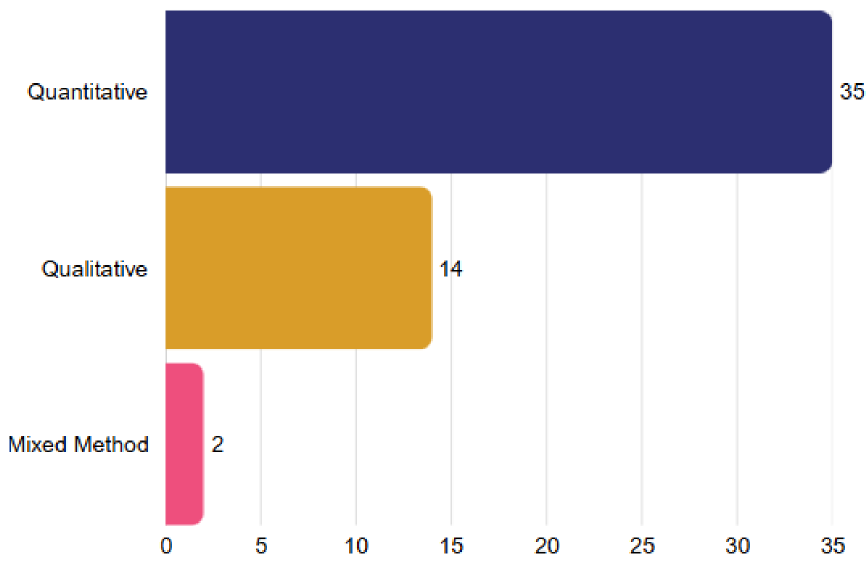


Figure 11: Qualitative study designs of the included studies in the rapid review

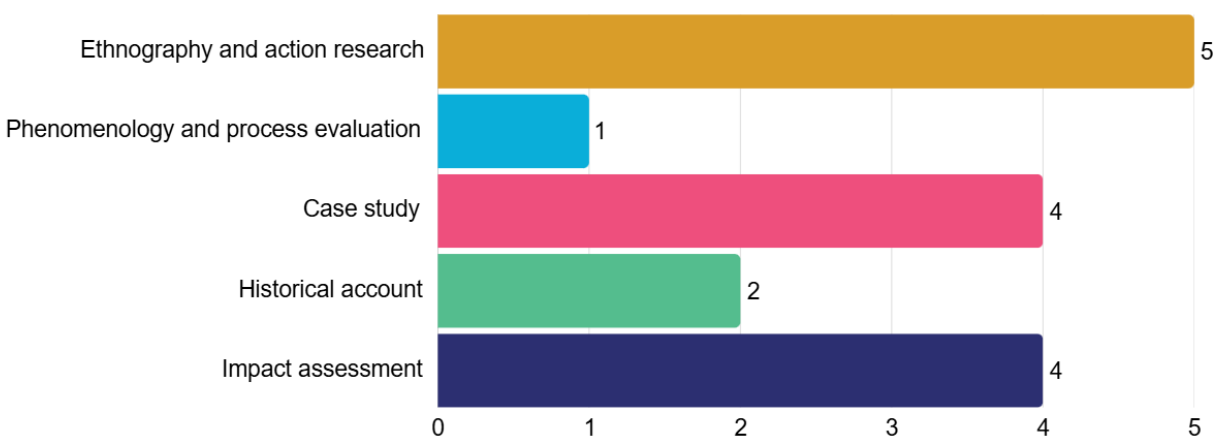
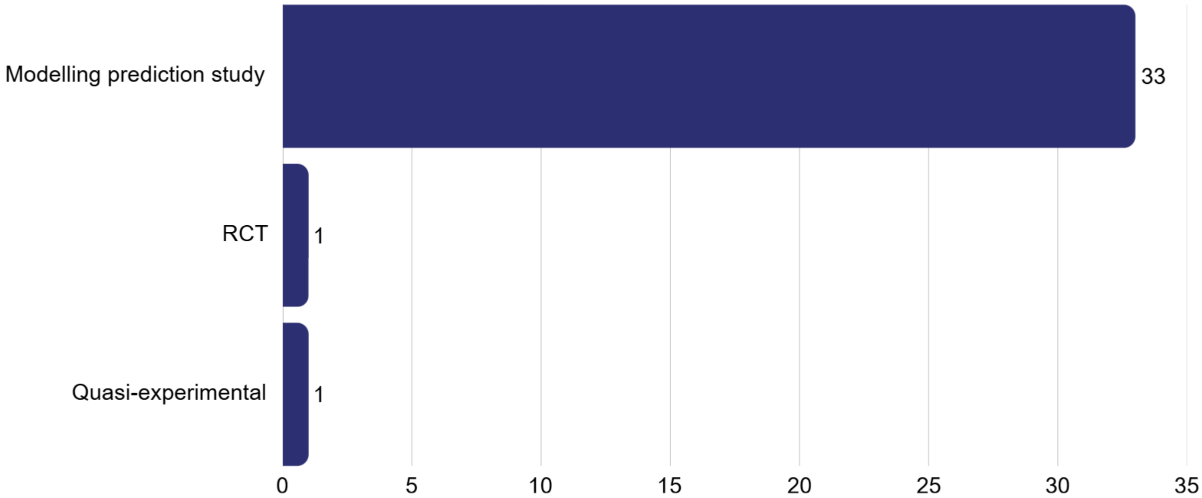


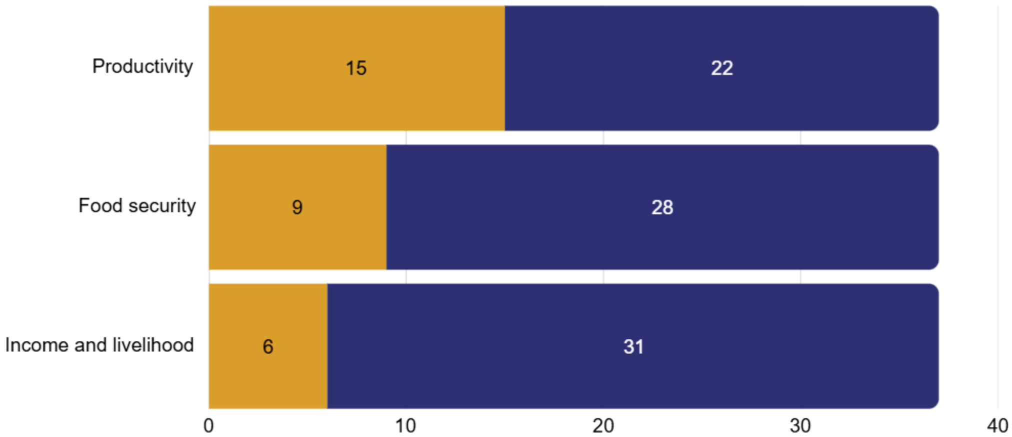
Figure 12: Quantitative study designs of the included studies in the rapid review

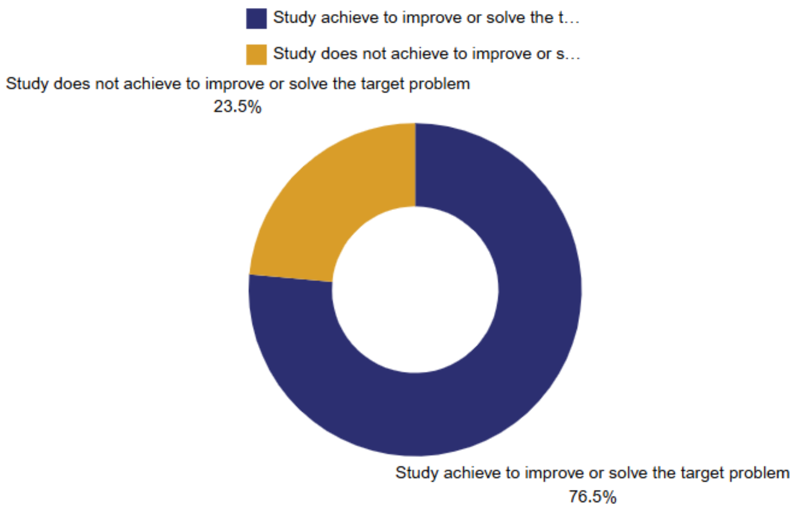


Effectiveness and outcomes

Approximately 76.5% of studies reported success in addressing their targeted agricultural challenges. Key outcomes included improved productivity (40.5%, n=15), enhanced food security (24.3%, n=9), and increased income and livelihoods (16.2%, n=6).

Figure 13: Reported effectiveness from studies included in the rapid review





Population and user representation

Users and beneficiaries

Smallholder farmers constituted 19.6% (n=10) of identified users. However, 53% (n=28) of studies reported general users without specific demographic information, and 24% (n=12) did not specify users at all. Only one study explicitly targeted female farmers. Beneficiaries were sparsely detailed, with smallholder farmers accounting for just 10% (n=5) of the targeted groups (see Table 19 and Table 20 in Appendix).

Figure 14: Information relating to population – users from studies included in the rapid review

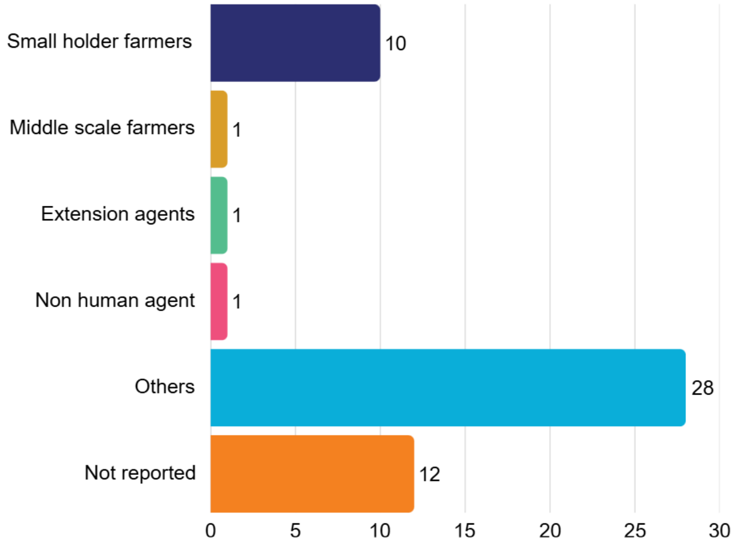
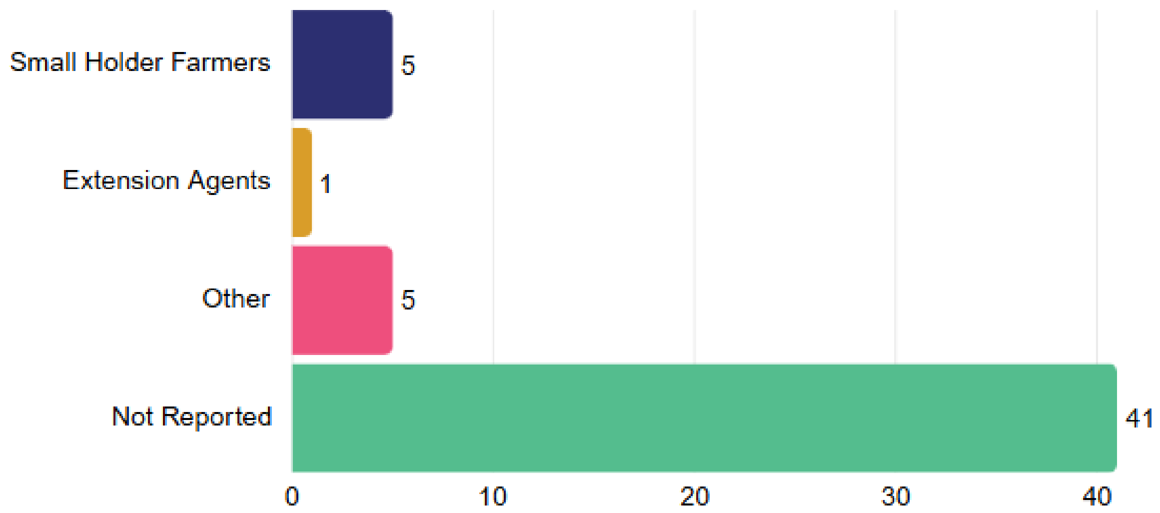


Figure 15: Information relating to population – beneficiaries from studies included in the rapid review



Agricultural dimensions and AI interventions

Agricultural activities

Most studies (81.8%, n=45) focused on crop production, with 29 examining field production and 1 analysing perennial cash crops. Livestock was represented in 7 studies, and aquaculture was not mentioned in any studies (see Table 21 in Appendix).

Figure 16: Agricultural dimensions reported from studies included in the rapid review

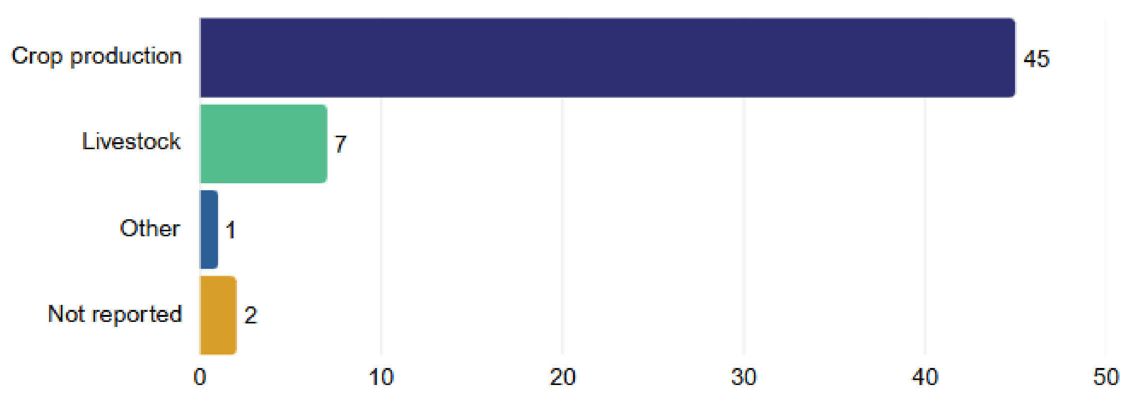
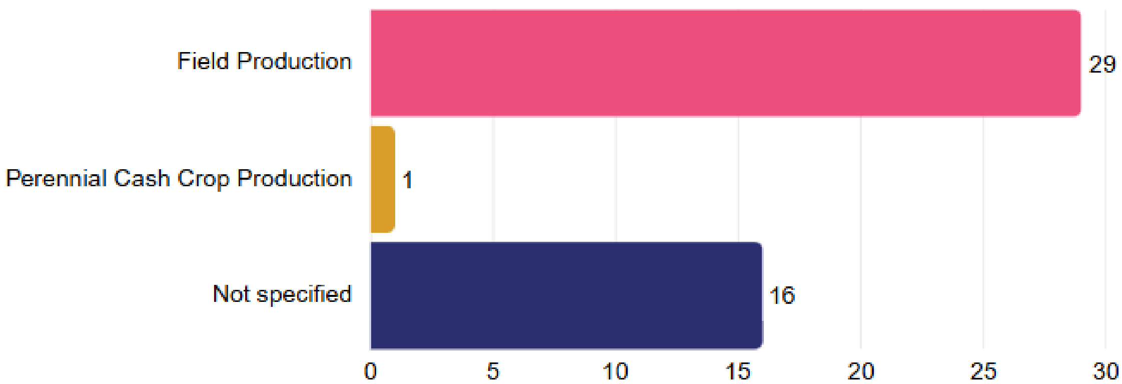


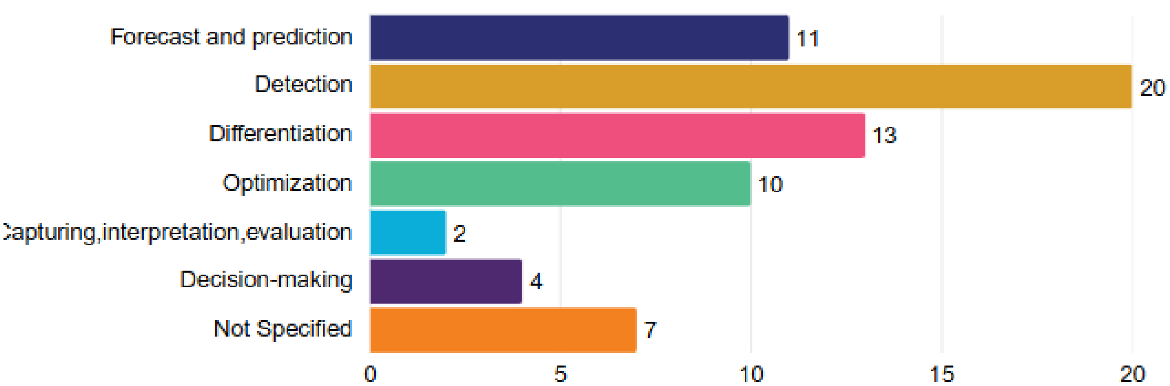
Figure 17: Agricultural dimensions within crop production



Target Problems

AI applications aimed to address six key agricultural challenges: detection (n= 20), forecast (n=11), differentiation (n=13), optimisation (n=10), decision-making (n=4), and capturing or interpretation (n=2). Detection, primarily of crop diseases, was the most common focus (see Table 23 in Appendix).

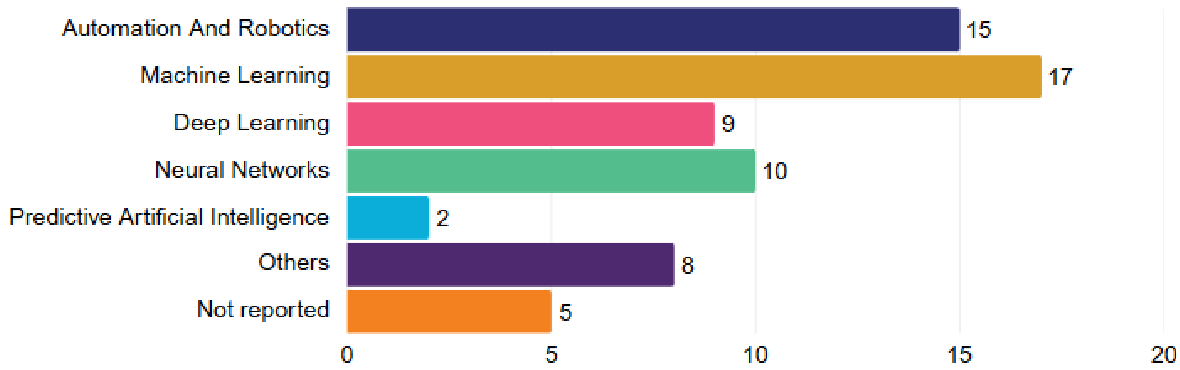
Figure 18: Target problem reported from studies included in the rapid review



AI Interventions

Machine learning was the predominant AI intervention, represented in (n= 17) studies. Other interventions included automation and robotics (n=15), deep learning (n= 9), neural networks (n=10), and predictive AI (2.4%, n=2) (see Table 23 in Appendix)

Figure 19: AI intervention implemented in studies included in the rapid review



Duration

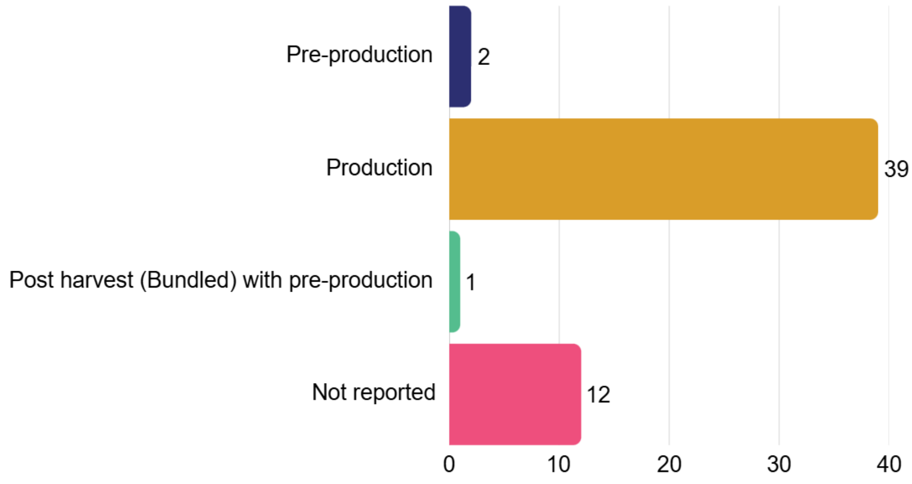
Only nine studies specified the duration of AI interventions. They ranged from one week to ten months.

Value chain dimensions and organisations

Value chain

Most interventions (76%, n=39) occurred during the production stage, while a smaller portion focused on pre-production (4%, n=2) and post-harvest stages (2%, n=1).

Figure 20: Value chain dimensions reported from studies included in the rapid review



Organisations

Information on developers and implementers was limited, with research institutes playing a prominent role in both categories. Agricultural technology entities, NGOs, and start-ups were also identified as contributors.

Figure 21: Organisational typology – developers reported from studies included in the rapid review

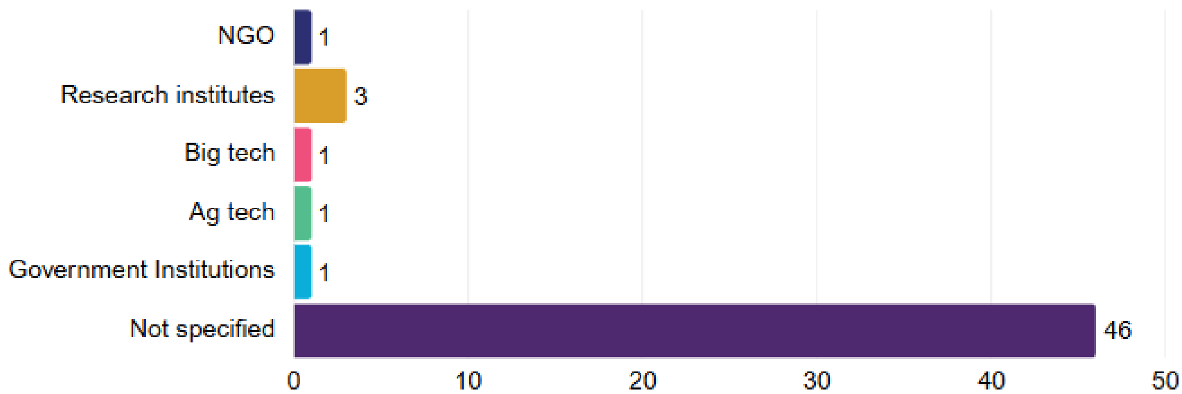
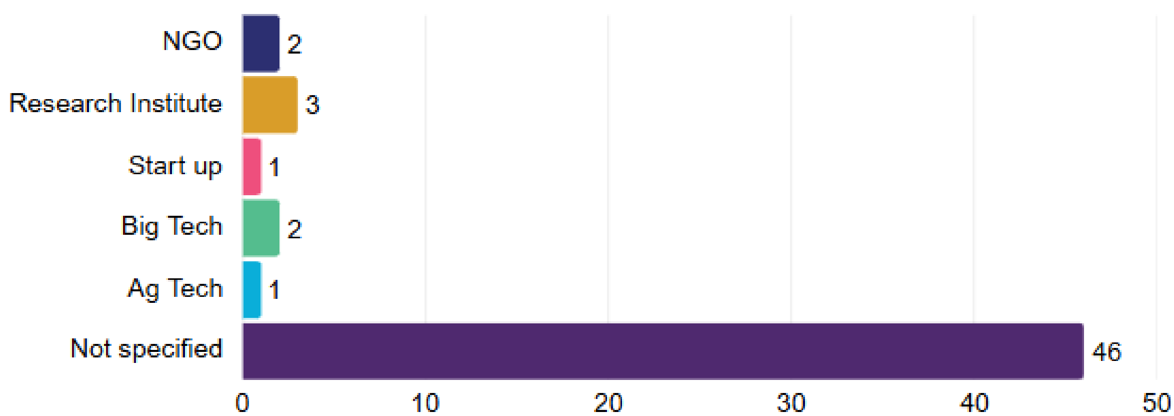


Figure 22: Organisational typology– implementers reported from studies included in the rapid review

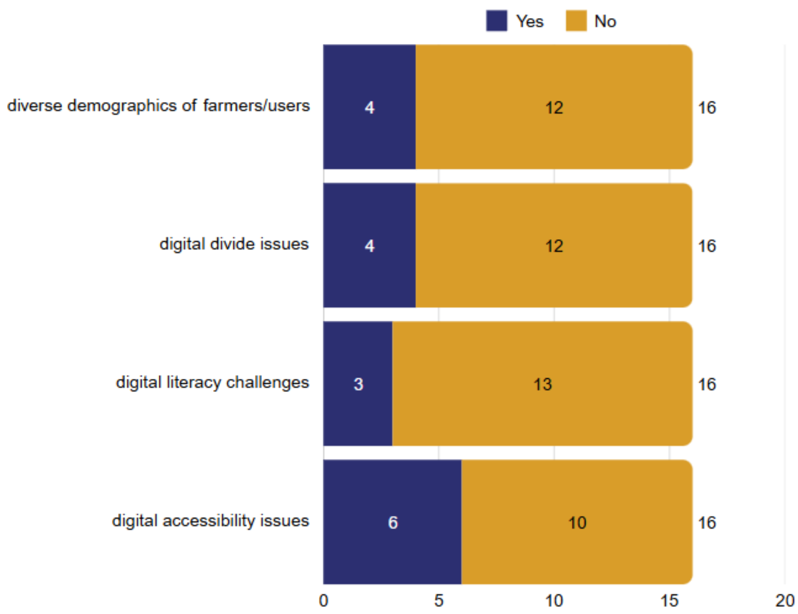


Inclusive design, ethics, and governance

Inclusivity

Only (n=4) of the studies addressed user diversity, digital divide (n=4), digital literacy (n=3), or digital accessibility (n=6).

Figure 23: Inclusive design and user diversity parameters reported from studies included in the rapid review



Scalability and implementation

Few studies addressed scalability (n=4) or provided recommendations for implementing AI-enabled solutions (n=9). Only one study mentioned regional and national legislation on AI-enabled solutions.

Figure 24: Recommendation in studies included

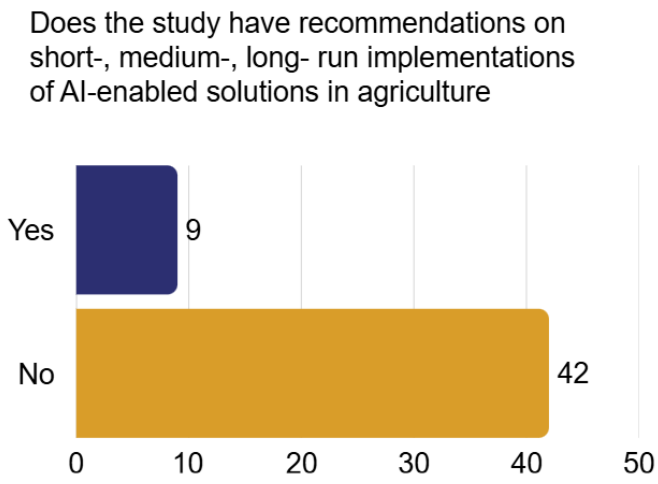
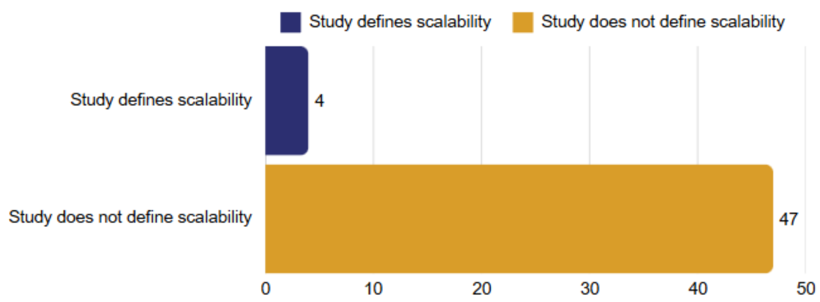


Figure 25: Scalability reported from studies included in the rapid review



Risk of bias assessment

As discussed above, the research team critically appraised all included studies and classified them as high, low, or unclear risk of bias.

For quantitative studies, researchers used the following critical appraisal tools:

1. Prediction models – PROBAST
2. RCTs – Cochrane RoB 2
3. Quasi-experimental studies – ROBINS-I

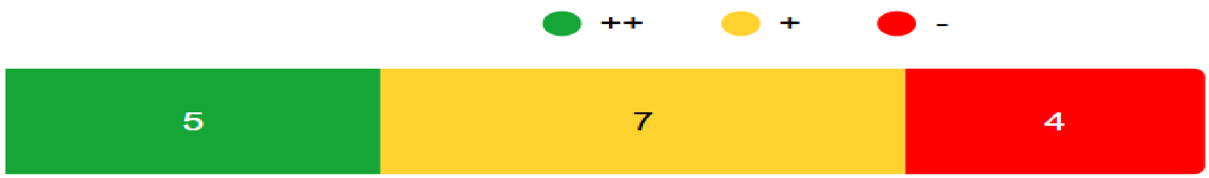
For qualitative studies, the researchers used the NICE methodology checklist.

The methodological rigour of the 35 quantitative studies varied. A majority (33) employed modelling or predictive approaches, while 1 study utilised an RCT, and another employed a quasi-experimental design. Critically, the team assessed the RCT as having a high risk of bias, and researchers judged the quasi-experimental study to be at serious risk of bias, limiting the strength of causal inferences drawn from these studies. Among the modelling and prediction studies, the risk of bias assessment revealed that 24 were at low risk, 8 at high risk, and 1 at unclear risk. This distribution suggested that while some modelling studies offer robust evidence, a substantial proportion are susceptible to biases that could affect the reliability of their findings (see Table 14 in Appendix A).

The research team assessed the 2 mixed-methods studies, which also employed modelling or prediction approaches, as having a high risk of bias, highlighting the need for more rigorous methodological approaches in this area of research.

The team conducted a critical appraisal using the NICE methodology checklist for the 14 qualitative and 2 mixed-methods studies included in the RR. According to the grading system, researchers rated 5 studies "++", meaning they met most or all of the checklist criteria, and their conclusions were very unlikely to be affected by any potential limitations. In contrast, the research team rated 7 studies "+". This indicated that while some criteria were fulfilled, any deficiencies in meeting the checklist did not significantly alter the likelihood of the conclusions being valid. The team gave 4 studies a "–" rating, suggesting that they met few or no criteria, raising concerns about their overall quality (see Table 15 and Figure 33 in Appendix A).

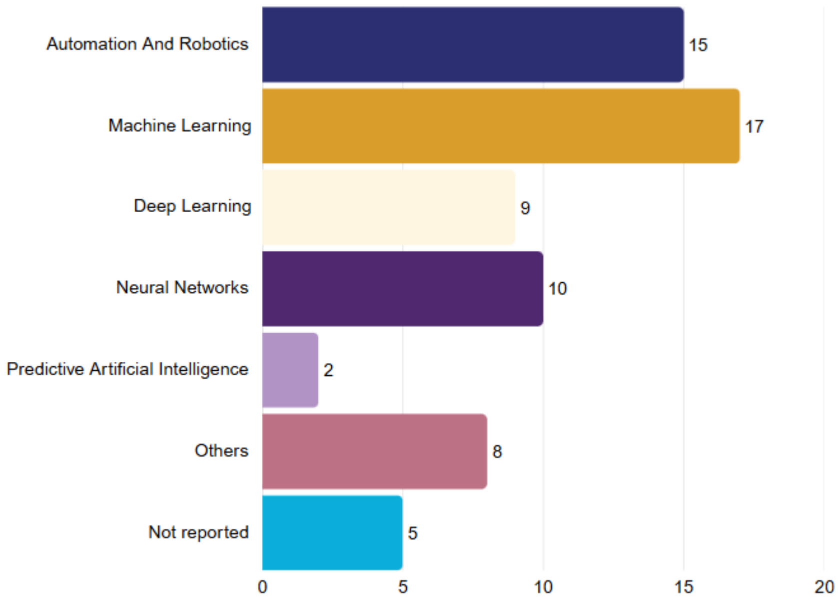
Figure 26: Critical appraisal findings of qualitative study using NICE methodology tool



Findings on AI-enabled solutions

In terms of AI, the RR showcases the growing interest in deploying AI in agriculture between 2019 and 2024. Figure 12 notes that machine learning was the predominant AI intervention, represented in 25.8% (n=17) of studies. Other interventions included automation and robotics (22.7%, n=15), deep learning (13.6%, n=9), neural networks (15.2%, n=10), and predictive AI (3%, n=2). However, none of the studies included generative AI (refer to Table 22 in Appendix).

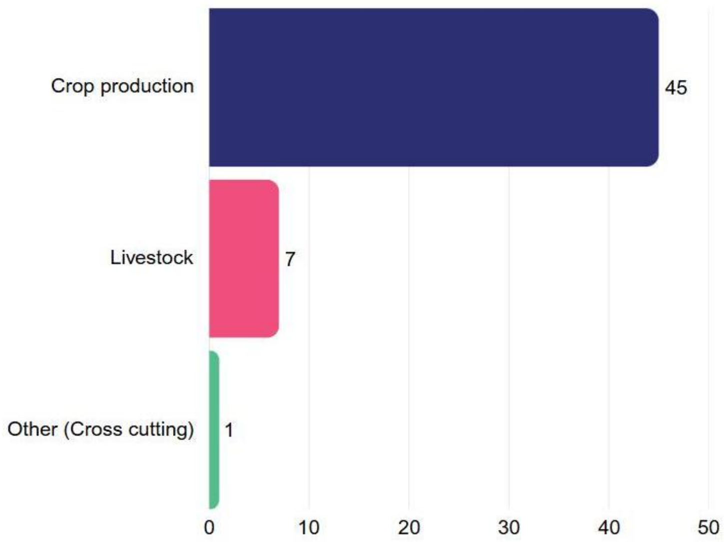
Figure 27: Types of AI-enabled solutions in agriculture



Findings on agriculture domain and target problem

The RR identified six key agricultural challenges: detection of pests and diseases (n=20), forecast of weather and climate (n=11), differentiation in terms of the quality of yield (n=12), optimisation of irrigation and yield (n=10), decision-making and farm management services(n=4), and capturing or interpretation (n=2). As referred to in Figure 13, the most common focus was primarily the detection of crop diseases. AI is also being used to predict crop yields, weather patterns, and soil conditions, empowering farmers to make informed and timely decisions (see Table 24 in Appendix).

Figure 28: Agriculture domains in the rapid review



Within the studies reviewed, crop production is the primary agricultural domain (Figure 11) (81.8%, n=45), with 29 examining field production and 1 analysing perennial cash crops. Livestock was represented in 7 studies. No studies focused on aquaculture were included. Climate-smart agriculture (CSA) technologies are among the AI-enabled solutions categorised as 'Other' (see Table 22 in Appendix A).

Figure 29: Types of target problems in the rapid review

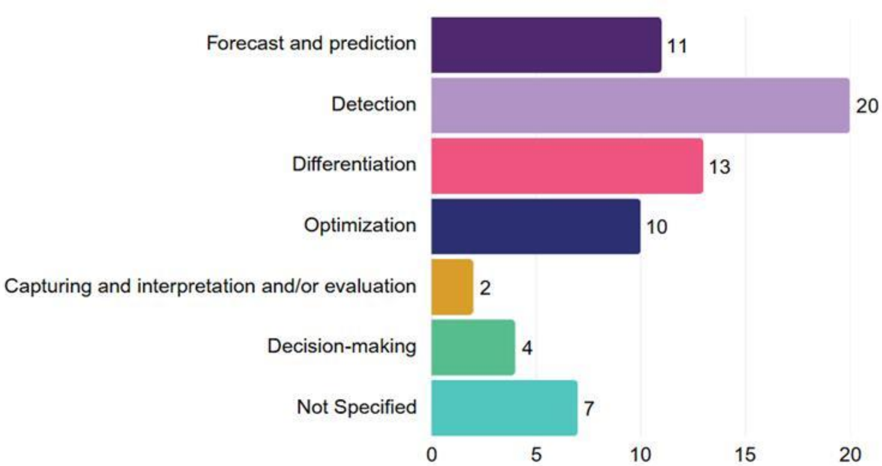
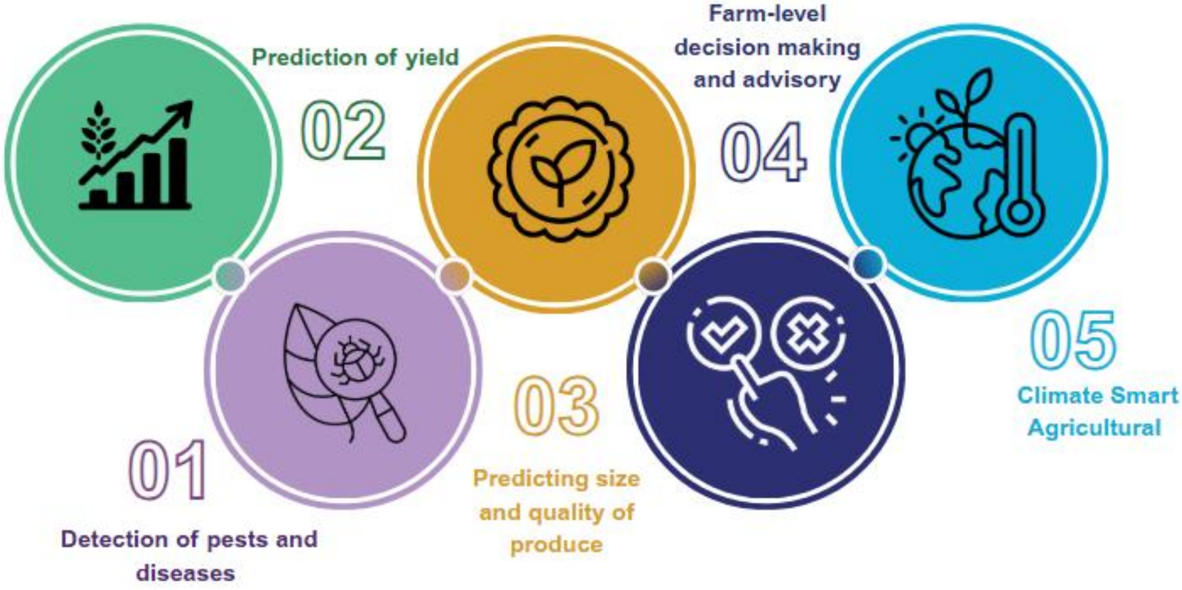


Table 3 below presents the various use cases found through the RR. Within precision agriculture, the subcategories include remote sensing and IoT services, UAVs, and field robots. Machine learning consists of classification (predicting correct labels), regression (investigating relationships between independent and dependent variables), clustering (grouping unlabelled examples based on similarities), and optimisation (adjusting models for maximum or minimum function) (IBM 2024). Deep learning consists of neural networks, while natural language processing consists of image recognition and satellite imagery, and conversational chatbots. The associated use cases across AI-enabled solutions range from weather forecasting to farm-level management services.

Often, AI-enabled solutions are provided as bundled packages. In agriculture, bundling refers to the practice of combining multiple agricultural inputs, services, or technologies into a single package. This is often done to improve access, adoption, and effectiveness for farmers, particularly smallholder farmers (Fleischer 2011). There is an urgent need for a holistic and strategic approach to scaling digital innovations (Kirina et al. 2022).

Figure 30: Primary use cases of AI-enabled solutions in agriculture



Detection of pests and diseases is a key targeted use case. An included paper in the RR utilises YOLO models in Côte d'Ivoire's cocoa plantations to classify cocoa pods, reduce manual labour for smallholders, prevent disease spread, enhance overall crop yield, and improve bean quality by detecting diseases like Phytophthora and Moniliophthora (Ferraris et al. 2023). Similarly, Convolutional Neural Networks (CNN) have been utilised to classify sugarcane leaf images as either diseased or healthy (Öğrekçi, Ünal, and Dudak 2023).

Another important use case is the prediction of yield. A study predicted agricultural yield for smallholder farmers in fourteen East African countries using advanced machine learning models (Aworka et al. 2022). Similarly, another study utilises IoT systems for predicting the yield in wolfberry plantations, a major crop in China's Ningxia province (X.-B. Jin et al. 2020). A different study employed a hybrid Random Forest and Neural Network (RNN) model to predict rice yield in Punjab, India (Lingwal, Bhatia, and Singh 2024). Their model, trained on 21 years of historical weather and agricultural data, considered key environmental factors like temperature, rainfall, and soil conditions. As an extension of yield production, some AI-enabled solutions help in predicting size and quality of produce. (Cock et al. 2023a)

Farm-level decision-making and advisory is another important use case of AI-enabled solutions in agriculture. Mokaya (2019) from the RR recommends the use of machine learning chatbots, through which multiple stakeholders can engage with farmers.

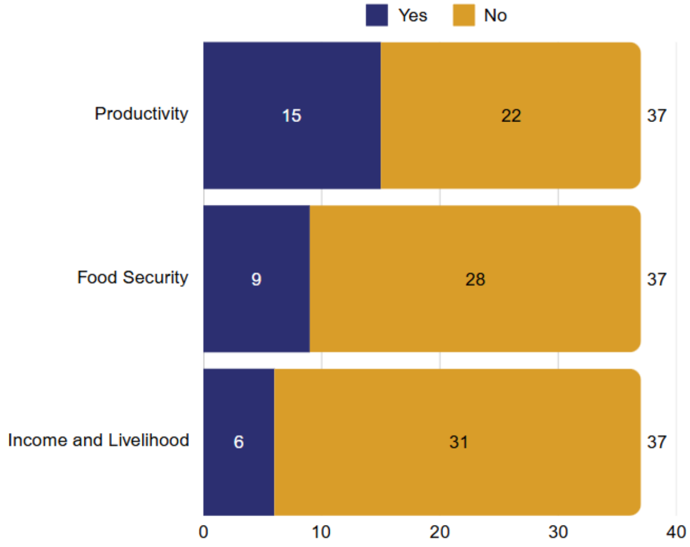
Climate-smart agricultural solutions have become increasingly important due to growing concerns about climate change. Climate-smart technologies represent a broad portfolio of services that can be provided to farmers. This includes precision agriculture solutions such as the provision of improved crop varieties, soil management practices, and crop management practices. Research highlights the increased vulnerability of smallholder farmers due to climate change. This includes impact on food security and crop damage that reduces yields (Ifeanyi-Obi et al. 2022; Budiman 2020). Some of the key challenges faced by smallholder farmers include "lack of access to good quality seeds, fertilisers, and pesticides, resource trade-offs, poor transport infrastructure, inadequate technical skills, inadequate access to post-harvest storage facilities, the provision of credit, insurance, and payment facilities" (Kirina et al. 2022). However, this varies by CSA sub-field. Practitioners supporting organic and agroecological approaches oppose using non-organic fertilisers, pesticides, and other chemicals. A study in southern Malawi demonstrated one such climate-smart solution through the USAID-funded Wellness and Agriculture for Life Advancement project. It increased maize yields by 53 percent among smallholder adopters during a drought year, showcasing the potential of CSA aid to improve food security in vulnerable, dryland regions affected by climate change (Amadu, McNamara and Miller 2024).

Understanding effectiveness

The review identified a predominantly quantitative evidence base, with 35 studies employing quantitative methodologies, alongside 2 mixed-methods studies and 14 qualitative studies. Quantitative and mixed-methods studies were evaluated for effectiveness across three key parameters: productivity, food security, and income or livelihoods. This focus on quantifiable outcomes allowed for an examination of potential measurable impacts of AI interventions within the agricultural sector.

In the RR, effectiveness was assessed for AI in agriculture across 35 studies and 2 mixed-methods studies. The parameters assessing effectiveness provided evidence on improved productivity (40.5%, n=15) (see Table 30), enhanced food security (24.3%, n=9) (see Table 31), and increased income and livelihoods (16.2%, n=6) (see Table 32 in Appendix).

Figure 31: Effectiveness frequencies



As discussed above, the review highlights methodological challenges. Quantitative studies rely on modelling over robust experimental designs, and qualitative studies lack rigour in assessing sociocultural and institutional factors.

Researchers often rated the modelling or prediction studies as high-quality with low risk of bias. However, this does not necessarily translate to broader applicability or practical value, particularly for smallholder farmers in L&MICs. One critical limitation of these high-quality studies is their lack of generalisability.

Many studies are narrowly focused, targeting specific crops, geographical regions, or climatic conditions. This specificity can lead to highly accurate models in controlled or localised settings. However, it reduces their relevance and adaptability to diverse agricultural contexts. This limitation is especially problematic in these countries, where agricultural practices, resource availability, and environmental conditions vary significantly.

Overall, studies mention little about the effectiveness regarding income and livelihood impacts. Studies briefly mention the words "productivity," "food security," "income," or "livelihood", but do not substantially measure the impact of AI-enabled solutions through these dimensions (Olivier and Ibrahim 2024; X. Jin et al. 2020; Ume and Ume 2024; Tej et al. 2024; V 2022; Amadu, McNamara, and Miller 2024)

Moreover, the findings from the rapid review display a separate metric for "effectiveness" as opposed to productivity, food security, income, and livelihoods. The metric focuses on the performance of AI in a simulation model rather than farm-level productivity or income improvement.

Studies mention future productivity gains, but they provide no measurable metrics. Although these studies demonstrate high predictive accuracy in controlled experiments, their real-world effectiveness remains uncertain.

Table 13: List classification of risk of bias for quantitative studies

S. No	Title	Study Design	Tools	Overall Bias
1	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	RCT	Cochrane ROB2	High
2	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Prediction model studies	PROBAST	High
3	A novel machine learning approach for rice yield estimation: Journal of Experimental & Theoretical Artificial Intelligence: Vol 36, No 3	Prediction model studies	PROBAST	Low
4	Plant Diseases Detection for Agricultural Management Using Machine Learning	Prediction model studies	PROBAST	Low
5	Artificial intelligence based smart and portable rainfall prediction device for precision agriculture	Prediction model studies	PROBAST	High

6	Agricultural Decision System Based on Advanced Machine Learning Models for Yield Prediction: Case of East African countries	Prediction model studies	PROBAST	High
7	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Prediction model studies	PROBAST	High
8	Precision agriculture with AI-based responsive monitoring algorithm	Prediction model studies	PROBAST	Low
9	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture	Prediction model studies	PROBAST	High
10	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Prediction model studies	PROBAST	Low
11	USING ARTIFICIAL NEURAL NETWORKS MODELS FOR PREDICTING WHEAT YIELD PRODUCTIVITY	Prediction model studies	PROBAST	Low
12	Identification of maize and wheat seedlings and weeds based on deep learning	Prediction model studies	PROBAST	Low

13	Is artificial intelligence helping to empower women in agriculture in Africa?	Prediction model studies	PROBAST	Low
14	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental Variables in an Arch Greenhouse	Prediction model studies	PROBAST	Low
15	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Prediction model studies	PROBAST	High
16	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	Prediction model studies	PROBAST	Low
17	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	Prediction model studies	PROBAST	Low
18	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	Prediction model studies	PROBAST	Low
19	Evaluating the drivers of banana flowering cycle duration using a stochastic	Prediction model studies	PROBAST	High

	model and on farm production data			
20	Sistema inteligente para el manejo de malezas en el cultivo de pia con conceptos de agricultura de precisian	Prediction model studies	PROBAST	Low
21	Aplicacian de redes neuronales convolucionales para la deteccian del tizan tardÃo Phytophthora infestans en papa Solanum tuberosum	Prediction model studies	PROBAST	Low
22	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Ca´te D'Ivoire. | EBSCOhost	Prediction model studies	PROBAST	Low
23	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Prediction model studies	PROBAST	Low
24	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Prediction model studies	PROBAST	Low
25	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Prediction model studies	PROBAST	High
26	Pattern Classification of an Onion Crop (Allium Cepa)	Prediction model studies	PROBAST	Low

	Field Using Convolutional Neural Network Models.			
27	Potato diseases detection and classification using deep learning methods	Prediction model studies	PROBAST	High
28	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data	Prediction model studies	PROBAST	Low
29	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Prediction model studies	PROBAST	Low
30	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	Prediction model studies	PROBAST	Low
31	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Prediction model studies	PROBAST	Unclear
32	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture	Prediction model studies	PROBAST	Low
33	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Prediction model studies	PROBAST	Low

34	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	Prediction model studies	PROBAST	High
35	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Prediction model studies	PROBAST	Low
36	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	Prediction model studies	PROBAST	Low
37	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Quasi-experimental studies	ROBINS-I	Serious

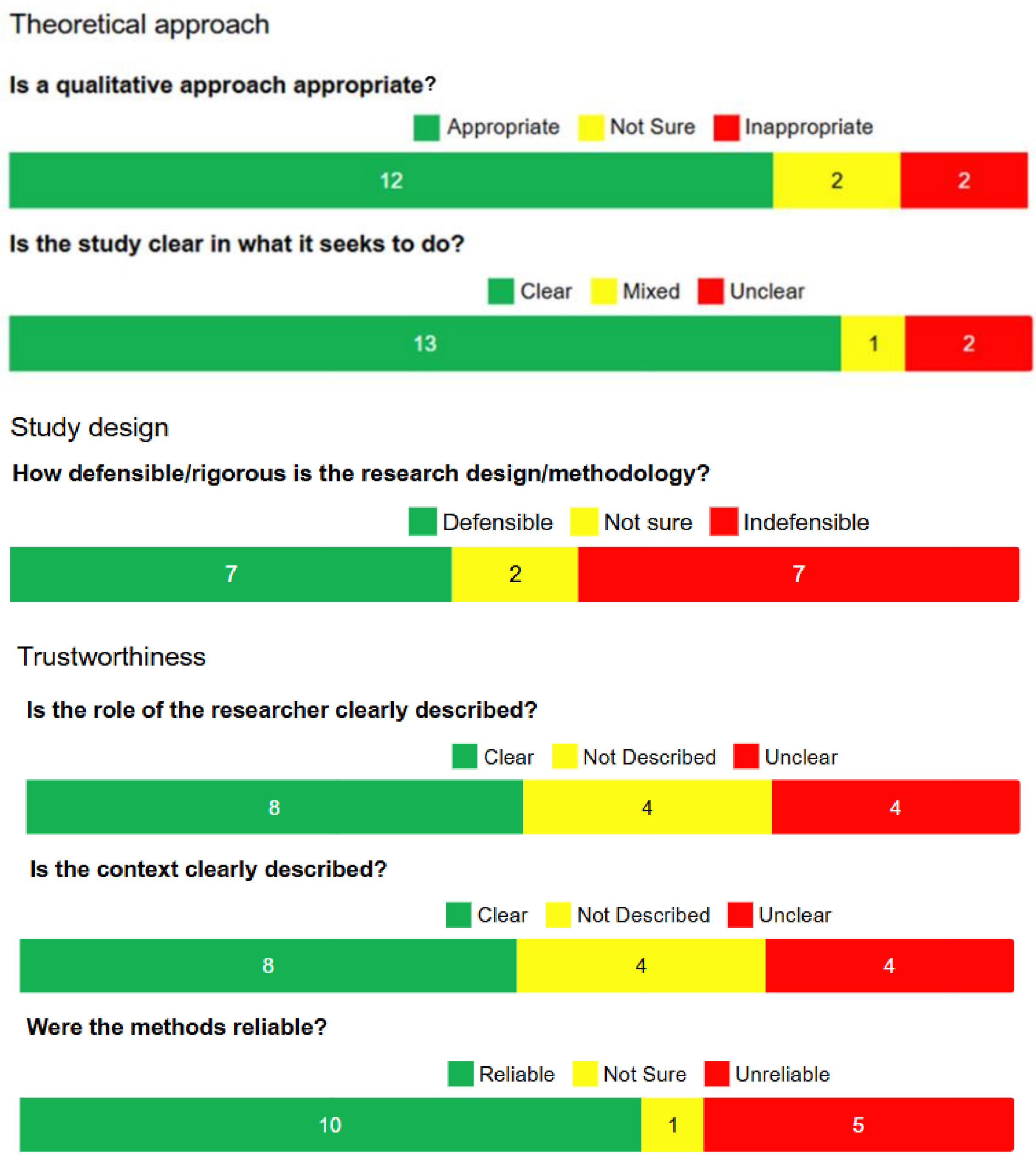
Table 14: List classification of risk of bias for qualitative studies

Title	As far as can be ascertained from the paper, how well was the study conducted? (see guidance notes)
Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	"++"All or most of the checklist criteria have been fulfilled; where they have not been fulfilled, the conclusions are very unlikely to change.
Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	"++" All or most of the checklist criteria have been fulfilled; where they have not been

	fulfilled, the conclusions are very unlikely to change.
Climate-Smart Agriculture Policy and (In)Justice for Smallholders in Developing Countries	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled or have not been adequately described, the conclusions are unlikely to change.
Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled or have not been adequately described, the conclusions are unlikely to change.
Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	"-" Few or no checklist criteria have been fulfilled, and the conclusions are likely or very likely to change.
Hacia un sistema de información sobre la producción agropecuaria	"++" All or most of the checklist criteria have been fulfilled: where they have not been fulfilled, the conclusions are very unlikely to change.
Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	"++" All or most of the checklist criteria have been fulfilled; where they have not been fulfilled, the conclusions are very unlikely to change.
Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled, or not adequately described, the conclusions are unlikely to change.
Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled, or not adequately described, the conclusions are unlikely to change.

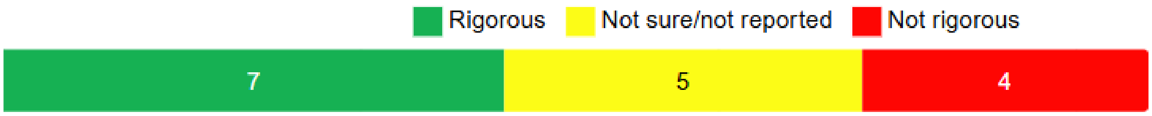
Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	"-" Few or no checklist criteria have been fulfilled, and the conclusions are likely or very likely to change.
Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	"+"Some of the checklist criteria have been fulfilled; where they have not been fulfilled, or not adequately described, the conclusions are unlikely to change.
Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled, or not adequately described, the conclusions are unlikely to change.
Role of Artificial Intelligence in Livestock and Poultry Farming	"-" Few or no checklist criteria have been fulfilled, and the conclusions are likely or very likely to change.
Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	"+" Some of the checklist criteria have been fulfilled; where they have not been fulfilled, or not adequately described, the conclusions are unlikely to change.
Robots in agriculture: prospects, impacts, ethics, and policy	"-" Few or no checklist criteria have been fulfilled, and the conclusions are likely or very likely to change.
Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	"++" All or most of the checklist criteria have been fulfilled; where they have not been fulfilled the conclusions are very unlikely to change.

Figure 33: Critical appraisal for qualitative studies using NICE tool



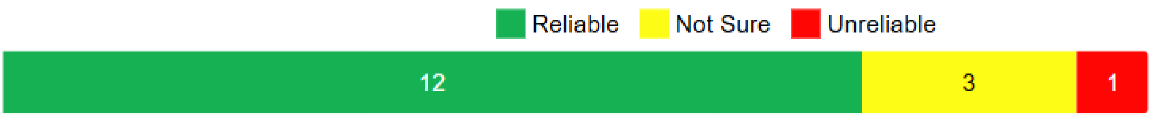
Analysis

Is the data analysis sufficiently rigorous?

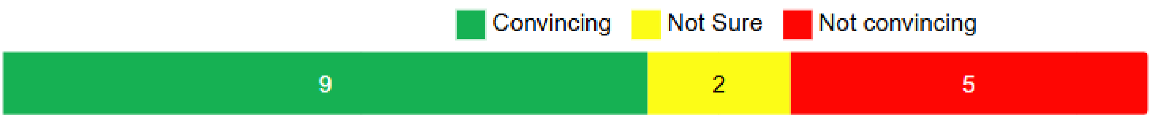


Is the data 'rich'?

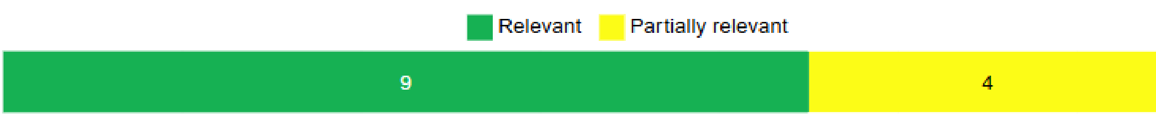
Is the analysis reliable?



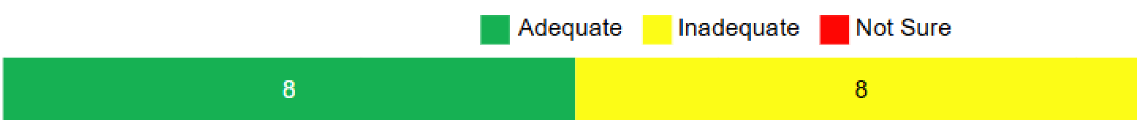
Are the findings convincing?



Are the findings relevant to the aims of the study?

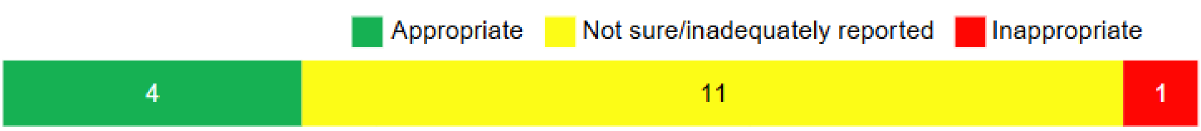


Conclusions



Ethics

How clear and coherent is the reporting of ethics?



As far as can be ascertained from the paper, how well was the study conducted?

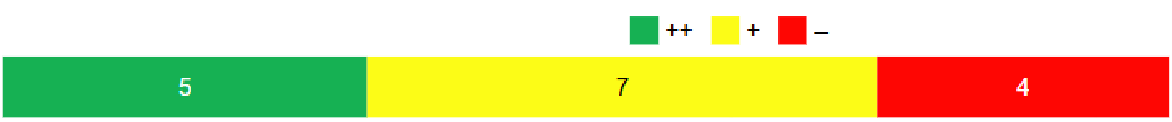


Table 15: List of studies included in the rapid review

S. No	Author	Title
1	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat
2	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System
3	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification
4	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards
5	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm
6	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.
7	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning
8	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases

9	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains
10	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming
11	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things
12	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming
13	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture
14	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy
15	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture
16	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning
17	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data
18	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing

19	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum
20	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state
21	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience
22	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers
23	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning
24	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture
25	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión
26	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria
27	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models
28	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods

29	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture
30	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity
31	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental Variables in an Arch Greenhouse
32	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia
33	Panda (2022)	Development Of Artificial Intelligent System for Identifying Crop And Vegetable Diseases
34	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation
35	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry
36	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network
37	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence
38	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things

39	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries
40	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture
41	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer
42	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons
43	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi
44	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria
45	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey
46	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?
47	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data
48	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries

49	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods
50	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria
51	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.

Table 16: Year of publication reported in studies included in the rapid review

Slno	Author	Title	Year
1	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification	2020
2	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	2023
3	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	2021
4	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	2020

5	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	2022
6	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision agriculture	2024
7	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry	2023
8	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	2022
9	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	2021
10	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	2020
11	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	2022
12	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	2021
13	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	2024

14	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	2024
15	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.	2024
16	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	2019
17	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	2022
18	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	2022
19	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	2023
20	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	2020
21	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	2023

22	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	2022
23	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	2024
24	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	2020
25	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.	2021
26	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	2019
27	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	2022
28	Cock et al. (2023)	Operations research and machine learning to manage risk and optimise production practices in agriculture: good and bad experience	2020
29	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using	2022

		Convolutional Neural Network Models.	
30	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	2022
31	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods	2024
32	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	2023
33	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	2024
34	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	2022
35	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	2022
36	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	2021
37	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and	2024

		Define Management Zones in Precision Agriculture	
38	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	2023
39	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming	2022
40	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	2022
41	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	2021
42	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	2023
43	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	2024
44	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture.	2022
45	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	2019
46	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting	2020

		Environmental Variables in an Arch Greenhouse	
47	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	2020
48	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	2023
49	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	2022
50	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	2020
51	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation	2024

Table 17: Funding descriptions reported in studies included in the rapid review

S. No	Author	Title	Funding description
1	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Brazilian Micro and Small Business Support Service (SEBRAE), and Brazilian Agricultural Research Corporation –Secretariat of Innovation and Business (EMBRAPA)
2	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry	Center for the Study of Existential Risk (CSER) at the University of Cambridge
3	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	CGIAR Trust Fund, CGIAR, and partners, including the AgriLAC Resiliente CGIAR Research Initiative on Digital Innovation
4	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Deanship of Scientific Research at King Khalid University
5	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Dutch Ministry of Foreign Affairs

6	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Empresa Brasileira de Pesquisa Agropecuária (Embrapa; Brazilian Agricultural Research Corporation), and Itaipu Binacional
7	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	CYBELE project, a European Commission research program
8	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	National Key Research and Development Program of China, Beijing Municipal Education Commission, and National Natural Science Foundation of China
9	Amadu et al. (2020)	Yield effects of climate-smart agriculture aid investment in southern Malawi	US Agency for International Development through the Borlaug LEAP Fellowship and a Feed the Future Strengthening Agriculture and Nutrition Extension project, and the US Department of Agriculture National Institute of Food and Agriculture

10	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Postdoctoral fellowship granted by the Institute of Computer Technologies and Information Security, Southern Federal University
11	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Postdoctoral fellowship granted by the Institute of Computer Technologies and Information Security, Southern Federal University
12	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Indonesia Endowment Fund for Education
13	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	Jawaharlal Nehru University, New Delhi, India
14	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Scientific and Technological Research Council of Türkiye (TÜBİTAK)

15	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	PRISM Center for Production, Robotics, and Integration Software for Manufacturing and Management at Purdue University; BARD, United States-Israel Grant; grants for development of new faculty staff, Ratch Fund, Chulalongkorn University; NSF Project Grant
16	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Research Department of the Universidad de los Llanos
17	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	African Forum for Agricultural Advisory Services (AFAAS) under the Comprehensive African Agricultural Development Programme
18	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Central Public-Interest Scientific Institution Basal Research, Technology Innovation Program of the Chinese Academy of Agricultural Sciences, and the Key Grant Technology Project of Xinxiang
19	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	Hebei North College Provincial Universities Infrastructure Scientific Research Business, the General Project of Hebei North University, and the Hebei Province Population Health Information Technology Innovation Center

20	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	National Key Research and Development Program of China, the National Natural Science Foundation of Beijing Municipal Education Commission, the Young Teacher Research Foundation Project of BTBU, and the Beijing Excellent Talent Training Support Project for Young Top-Notch Team
21	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification	This research received no external funding.
22	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire	This research received no external funding.
23	Arsaghi et al. (2022)	Potato diseases detection and classification using deep learning methods	This research received no external funding.
24	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	This research received no external funding.

25	Martinez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models	This research received no external funding.
26	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture	This research received no external funding.
27	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	This research received no external funding.
28	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	This research received no external funding.

Table 18: Region descriptions reported in studies included in the rapid review

S. No	Author	Title	Region Description
1	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	East Asia & Pacific - China
2	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	East Asia & Pacific - China
3	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Global
4	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Global
5	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	Global
6	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.	Global

7	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	Global
8	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Global
9	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Global
10	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	Global
11	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Global
12	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming	Global
13	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Global
14	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	Global

15	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	Global
16	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	Global
17	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Global
18	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Global
19	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	Global
20	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Latin America/Caribbean - Brazil
21	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	Latin America/Caribbean - North Coast of Colombia, Andes, and Mexico Sub-Saharan Africa - Ethiopia South or South East Asia - Indonesia

22	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Latin America/Caribbean - Brazil
23	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Latin America/Caribbean - Brazil
24	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Latin America/Caribbean - Brazil
25	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Latin America/Caribbean - Colombia
26	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	Latin America/Caribbean - Cuba
27	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models.	Latin America/Caribbean - Mexico
28	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods.	Middle East & North Africa - Ardebil city of Iran.
29	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture.	Middle East & North Africa - Morocco

30	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	Middle East & North Africa - Egypt
31	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental Variables in an Arch Greenhouse	Middle East & North Africa - Southeast of Iran, in Kerman Province, city of Jiroft
32	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Middle East & North Africa - Monastir region of Tunisia
33	Panda (2022)	Development Of Artificial Intelligent System for Identifying Crop And Vegetable Diseases	South or South East Asia - India
34	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation	South or South East Asia - India
35	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	South or South East Asia - India
36	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	South or South East Asia - India
37	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	South or South East Asia - India
38	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	South or South East Asia - India

39	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	South or South East Asia - India, Indonesia, and Bangladesh Africa - Malawi
40	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture	South or South East Asia – India
41	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	South or South East Asia - Pakistan
42	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Sub-Saharan Africa - Kenya, Uganda, Tanzania, and Ethiopia
43	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Sub-Saharan Africa - Malawi
44	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Sub-Saharan Africa - Nigeria
45	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Sub-Saharan Africa - Uganda
46	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Sub-Saharan Africa - 34 African countries

47	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	Sub-Saharan Africa - Cameroon
48	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Sub-Saharan Africa - 14 African Countries
49	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	Sub-Saharan Africa - Ghana and South Sudan
50	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Sub-Saharan Africa - Nigeria
51	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.	Sub-Saharan Africa - Côte D'Ivoire

Table 19: Population (users) description reported in studies included in the rapid review

Slno	Author	Title	Population (users) description
1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Middle-scale farmers
2	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	Non-human agent
3	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry	Other - farmers
4	Genaidy (2020)	Using artificial neural networks models for predicting wheat yield productivity	Other - farmers
5	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	Other - farmers
6	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and	Other - farmers

		Define Management Zones in Precision Agriculture	
7	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental Variables in an Arch Greenhouse	Other - female farmers
8	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	Other - academic context
9	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	Other - agronomists
10	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Other - farmers
11	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture	Other - farmers
12	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Other - farmers

13	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	Other - farmers
14	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	Other - farmers
15	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Other - farmers
16	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	Other - farmers
17	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Other - farmers
18	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	Other - farmers
19	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Other - farmers
20	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial	Other - farmers

		intelligence and embedded sensing	
21	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Other - farmers
22	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Other - farmers
23	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	Other - farmers
24	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Other - farmers and experts
25	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models.	Other - farmers, agronomists
26	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Other - farmers, agronomists

27	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Other - female farmers
28	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Other - farmers
29	Ferraris et al. (2023)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Smallholder farmers
30	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Smallholder farmers
31	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Smallholder farmers
32	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.	Smallholder farmers
33	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Smallholder farmers
34	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel	Smallholder farmers

		Dataset and Analysis of Deep Learning Methods	
35	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Smallholder farmers
36	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Smallholder farmers
37	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	Smallholder farmers
38	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Smallholder farmers
39	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Smallholder farmers, extension agents

Note: If the study does not specify smallholder farmers, it is categorised under 'Other.' Table 20: Beneficiary description reported from studies included in the rapid review

Table 20: Population (users) description reported in studies included in the rapid review

S. No	Author	Title	Beneficiary description
1	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Other - farmers or agronomists.
2	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Other - farmers
3	V. Ramachandran (2022)	Development Of Smart Irrigation and Recommendation System For Agriculture Using The Internet Of Things	Other - farmers
4	Mouzakitis (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Other - farmers
5	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Other - farmers

6	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Smallholder farmers
7	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Smallholder farmers
8	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Smallholder farmers
9	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.	Smallholder farmers
10	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Smallholder farmers, extension agents

Note: If the study does not specify smallholder farmers, it is categorised under 'Other.'

Table 21: Agriculture description reported in studies included in the rapid review

S. No	Author	Title	Agriculture dimension description
1	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	Crop production
2	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Crop production
3	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Crop production
4	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Crop production
5	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Crop production
6	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	Crop production
7	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Crop production
8	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation: Journal of Experimental & Theoretical Artificial Intelligence	Crop production (field production - rice yield)

9	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Crop production (field production - maize, sorghum, beans, tomatoes, onions, sunflower, cowpea beans) Livestock - poultry and dairy
10	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	Crop production (field production - pea and strawberry)
11	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Crop production (field production - sugarcane)
12	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	Crop production (field production - wheat)
13	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	Crop production (field production - wolfberry plantations)
14	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental Variables in an Arch Greenhouse	Crop production (field production - apple, blueberry, carrot, grapes, and mango crops)
15	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	Crop production (field production)
16	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture	Crop production (field production)

17	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Crop production (field production)
18	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Crop production (field production)
19	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Crop production (field production)
20	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.	Crop production (field production)
21	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Crop production (field production)
22	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	Crop production (field production)
23	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Crop production (field production)
24	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	Crop production (field production)
25	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	Crop production (field production)

26	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Crop production (field production)
27	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture.	Crop production (field production)
28	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Crop production (Field production)
29	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	Crop production (field production)
30	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Crop production (field production)
31	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	Crop production (field production)
32	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Crop production (field production)
33	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	Crop production (field production)
34	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Crop production (field production) - classify into healthy leaves, insect-damaged leaves, leaf curl, leaf viral disease,

			late blight, and early blight groups.
35	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Crop production (field production) – pineapple)
36	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	Crop production (field production) - 14 different crops, such as apple, blackberry, corn, grape, grape, peach, tomato, and potato
37	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	Crop production (field production) - banana
38	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Crop production (field production) - maize Livestock - dairy
39	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models.	Crop production (field production) - onion crop (Allium cepa)
40	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods.	Crop production (field production) - potatoes
41	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Crop production (field production) - rice
42	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Crop production (field production) - carrot

43	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	Crop production (field production), livestock
44	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	Crop production (field production), livestock
45	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Crop production (grains, fruit, horticulture), livestock (beef, pork, poultry), forestry (eucalyptus, pine, native), and other activities such as beekeeping, floriculture, aquaculture, and fish farming
46	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire.	Crop production (perennial cash crop production) - cocoa crops
47	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	Crop production, livestock
48	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	Crop production, livestock
49	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Crop production, livestock

50	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Crop production, livestock
51	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming	Livestock (cattle, poultry, dairy)

Table 22: AI dimension descriptions reported in studies included in the rapid review

S. No	Author	Title	AI dimension description
1	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Neural networks - CNN model; deep learning model: AlexNet
2	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation: Journal of Experimental & Theoretical Artificial Intelligence	Machine learning, neural network - hybrid 'RaNN' model, multiple linear regression, decision tree, random forest, SVM Regression, boosting regression, ensemble learner, and multilayer feedforward neural network
3	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	Machine learning, deep learning, neural networks - support vector machines, k - nearest neighbour algorithms, decision trees, and random forest
4	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall	Deep learning, neural network, machine learning - VGG16, Inception - V3, and Xception model; deep learning (DL) techniques such as convolutional neural

		prediction device for precision Agriculture	networks (CNNs) and recurrent neural networks (RNNs); decision tree, random forest
5	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Machine learning
6	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Automation and robotics
7	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	Automation and robotics (robotics process automation, or RPA), machine learning
8	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Not reported
9	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Deep learning (YOLO), neural networks (single-board computer implementation)

10	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Automation and robotics, deep learning, machine learning
11	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	Machine learning, deep learning (ENSO)
12	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	Automation and robotics (incorporating D-AS into the PA monitoring system)
13	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.	Other - interactive framework for visualisation based on crop pest image classification
14	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Automation and robotics - sensors (RGB, MS, and TIR)
15	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	Neural networks - feed-forward neural network (FFNN), generalized regression neural network (GRNN), and radial-basis neural network (RBNN))

16	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	Neural Networks (UNet network model and ViT classification algorithm), Deep learning
17	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	Automation and robotics - automated system for agricultural management and distribution of production
18	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Other
19	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Automation and robotics - autonomous robotic systems within arable frameworks; machine learning, deep learning Predictive AI - climate-smart predictive models for viticulture
20	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Automation and robotics sensors, robotics, 3D printing, drones
21	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental	Predictive AI (ANFIS structure to predict the temperatures of inside air and inside roof cover)

		Variables in an Arch Greenhouse	Neural Network - Binary Cascaded Convolutional Neural Network (BC CNN)
22	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Binary cascaded convolutional neural network (BC-CNN), and deploys
23	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	Deep learning model based on IoT
24	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	Deep learning, Neural networks - a deep learning neural network based IoT-enabled intelligent irrigation
25	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	Deep learning, machine learning, neural network (faster R-CNN), YOLO-V1, YOLO-V3), UAV imagery
26	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Deep learning

27	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	Machine learning, neural networks (ML algorithm-based convolutional neural networks), automation and robotics (big data information is implemented by robots)
28	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	Other (stochastic model)
29	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Automation and robotics - sensor
30	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Machine learning, neural networks - AANs, decision tree
31	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	Deep learning (deep learning model capable of recognizing late blight in potato crops by means of leaf image classification)
32	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for	Automation and robotics - GRACE NASA Mission and ERA5; network architecture (CIWA-net)

		Helping Cocoa Farmers in Côte D'Ivoire.	
33	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	Automation and robotics, drones and UAVs and machine learning
34	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Machine learning
35	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Machine learning algorithm using gradient boosting (GB) algorithm integrated into H2O ML module
36	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Machine learning
37	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming	Automation and robotics - use of robot for administering vaccine at poultry house
38	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using	Deep learning - artificial neural networks (ANNs), recurrent neural networks (RNNs),

		Convolutional Neural Network Models.	generative adversarial networks (GANs), CNNs
39	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods.	Neural networks, deep learning - CNN VGG, R-CNN
40	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Machine learning
41	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Automation and robotics - EM38-MK2 proximal soil sensor
42	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	Deep learning - 2D CNN architectures, RNNs, convolutional RNNs, and 3D CNNs
43	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	Neural networks, genetic algorithm (GA), and artificial neural network (ANN)
44	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming:	Machine learning

		Towards modern agriculture	
45	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture.	Machine learning
46	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	Automation and robotics - mobile robots
47	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Automation and robotics - remote sensing, IoT, and deep learning neural networks The proposed system is trained with different deep learning-based CNN algorithms.
48	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	Automation and robotics sensors, machine learning
49	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Machine learning
50	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Other

51	Zheng et al. (2019)	CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture	Automation and robotics, deep learning, neural networks, deep-learning-based model—especially convolutional neural networks (CNN)—for classification

Table 23: Target problem description reported in studies included in the rapid review

S. No	Author	Title	Target problem description
1	Öğrekçi et al. (2023)	A comparative study of vision transformers and convolutional neural networks: sugarcane leaf diseases identification.	Detection (crop diseases)
2	Lingwal et al. (2022)	A novel machine learning approach for rice yield estimation: Journal of Experimental & Theoretical Artificial Intelligence	Differentiation (size and quality of produce)
3	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	Detection (crop diseases) - automatic diagnosis of diseases and diseased parts present in plant leaf images, as well as in agricultural crop production
4	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall	Forecast and prediction (weather and climate) - parameters chosen are

		prediction device for precision Agriculture	temperature, relative humidity, pressure, and wind speed as independent variables
5	Aworka et al. (2022)	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries	Forecast and prediction (weather and climate), detection (crop diseases)
6	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Not specified
7	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry	Not specified
8	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Capturing and interpretation, and/or evaluation (global weather patterns)
9	Beyaz & Saripinar (2024)	Sugar Beet Seed Classification for Production Quality Improvement by Using YOLO and NVIDIA Artificial Intelligence Boards	Differentiation (size and quality of produce)

10	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	Forecast and prediction (weather and climate), differentiation (size and quality of produce), optimisation (nutrient application, irrigation)
11	Cock et al. (2023)	Operations research and machine learning to manage risk and optimize production practices in agriculture: good and bad experience	Differentiation (size and quality of produce), detection (crop diseases)
12	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	Differentiation (size and quality of produce)
13	Zhu et al. (2023)	Efficient data-centric pest images identification method based on Mahalanobis entropy for intelligent agriculture.	Detection (crop diseases and pests)
14	Fei et al. (2022)	UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat	Optimisation (irrigation)
15	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	Differentiation (size and quality of produce) - wheat yield prediction.

16	Guo et al. (2023)	Identification of maize and wheat seedlings and weeds based on deep learning	Detection (crop diseases)
17	Hernández & Marceau (2022)	Hacia un sistema de información sobre la producción agropecuaria	Forecast and prediction, decision-making (best-fit crop variety based on individual farm and household properties)
18	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria	Forecast and prediction (weather and climate)
19	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Not specified
20	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Forecast and prediction
21	Moghaddam et al. (2022)	Thermal, ANFIS, and Polynomial Neural Network Models for Predicting Environmental	Forecast and prediction (weather and climate) - predicting greenhouse climate

		Variables in an Arch Greenhouse	
22	Jawale & Malik (2024)	MPSARB: design of an efficient multiple crop pattern prediction system with secure agriculture-record-storage model via reconfigurable blockchains	Decision-making (best-fit crop variety based on individual farm and household properties)
23	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	Forecast and prediction (medium-term prediction: providing accurate predictions of temperature and humidity; long-term prediction: providing average daily temperature and humidity for the next 30 days), optimisation (irrigation)
24	Kashyap et al. (2021)	Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network	Optimisation (irrigation)
25	Khan et al. (2021)	Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer	Detection (crop diseases) - a detection and classification framework based on improved Faster R-CNN was developed to accurately identify weeds and crops in two different croplands naturally infested with weeds, with subsequent control operations required.
26	Kirina et al. (2022)	Scaling Climate Smart Agriculture in East Africa: Experiences and Lessons	Not specified

27	Kumar et al. (2022)	Role of artificial intelligence, sensor technology, big data in agriculture: next-generation farming	Forecast and prediction (weather and climate) Differentiation (size and quality of produce)
28	Lamour et al. (2020)	Evaluating the drivers of banana flowering cycle duration using a stochastic model and on farm production data	Differentiation (size and quality of produce) - important component of banana yield
29	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Optimisation (Irrigation) - alternate wetting and drying (also called controlled irrigation or intermittent irrigation) is a technique that involves the cultivation of irrigated paddy rice. It uses lesser water than the continuous irrigated rice production system.
30	López et al. (2020)	Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión	Detection (crop diseases)
31	Lozada-Portilla et al. (2021)	Aplicación de redes neuronales convolucionales para la detección del tizón tardío Phytophthora infestans en papa Solanum tuberosum	Detection (crop diseases) - the presence of late blight in potato crops directly affects plant growth and tuber development; therefore, early detection of the disease is important.
32	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa	Forecast and prediction (weather and climate) Detection (crop diseases) - detecting diseases and blocking their spread is a

		Farmers in Côte D'Ivoire.	critical activity. With open-source tools, it is possible to create a model to detect specific diseases without significant monetary or computational resources.
33	Mokaya (2019)	Future of Precision Agriculture in India using Machine learning and Artificial Intelligence	Forecast and prediction (weather and climate), differentiation (size and quality of produce), optimisation (irrigation), decision-making (best-fit crop variety based on individual farm and household properties)
34	Murugamani et al. (2022)	Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things	Detection (crop diseases) - observations of leaf disease detection optimisation (irrigation, nutrient application)
35	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	Forecast and prediction (weather and climate)
36	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	Detection (crop diseases)
37	Patel et al. (2022)	Role of Artificial Intelligence in Livestock and Poultry Farming	Detection (crop diseases and livestock pests diseases)

38	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models.	Optimisation (irrigation, nutrient application), decision-making (best-fit crop variety based on individual farm and household properties)
39	Arshaghi et al. (2022)	Potato diseases detection and classification using deep learning methods.	Detection (crop diseases) - the study examined 5 classes of potato diseases: healthy, black scurf, common scab, black leg, and pink rot. A database of 5,000 potato images was used.
40	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data.	Detection (crop diseases)
41	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	Capturing and interpretation, and/or evaluation (individual farm management decisions)
42	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	Detection (crop diseases) - the study predicts crop type and has performed reasonably well in Ghana and South Sudan. In these countries, data is limited and of poor quality due to high cloud cover, class imbalance, and lack of labels.
43	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial	Detection (crop diseases), differentiation (size and quality of produce)

		intelligence and embedded sensing	
44	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Not specified
45	Hachimi et al. (2022)	Smart Weather Data Management Based on Artificial Intelligence and Big Data Analytics for Precision Agriculture.	Optimisation (irrigation)
46	Sparrow & Howard (2020)	Robots in agriculture: prospects, impacts, ethics, and policy	Not specified
47	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	Detection (crop diseases)
48	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	Optimisation (irrigation)
49	Wei et al. (2020)	Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning	Differentiation (size and quality of produce)

50	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Differentiation (size and quality of produce)

Table 24: Digital divide issue description reported in studies included in the rapid review

S. No	Author	Title	Digital Divide Issues
1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Disadvantages of implementing precision agriculture include difficulty accessing the internet in rural areas and limited opportunities to become familiar with technology.

Table 26: Digital divide issue description reported in studies included in the rapid review

S. No	Author	Title	Digital divide issues

1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guayaba, Rio Grande do Sul state	Disadvantages of implementing precision agriculture include difficulty accessing the internet in rural areas and limited opportunities to become familiar with technology.
2	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	The digital divide is a massive multi-generational undertaking. "For a large swath of the population of farmers, technology is a foreign thing, subject to suspicion". "Erroneous but prevalent public perception that anything technical must be extremely costly, so if digital devices are sold cheap, farmers believe they are being cheated and that applications are not to be trusted. Farmers do not trust external advice".
3	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Technological innovations in climate-smart agriculture are viewed as barriers for farmers. In the case of smallholder farmers, it is viewed as something that usually cannot be integrated with traditional farming practices.

4	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	A strong technology infrastructure, including dependable internet access, data storage options, and sensor networks, is essential for precision farming (PF). Poor infrastructure in certain rural regions may make it difficult to apply precision agricultural methods effectively. Governments and technology providers should work together to increase connection and infrastructure in rural agricultural areas, and give farmers access to the resources they need for effective implementation.

Table 25: Digital literacy issue description reported in studies included in the rapid review

S. No	Author	Title	Digital literacy issues
1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	"Within the general scope of the study, it was possible to highlight that PA had a fundamental role to play in the development and transformation of agriculture." In addition, the study mentions the possibility of training farmers for their own development of technological knowledge. A practical opportunity can be observed here: that of farmers realizing the complexity involved in using technology but expressing willingness to understand and apply it.

2	Tzachor (2021)	Barriers to AI Adoption in Indian Agriculture: An Initial Inquiry.	"In the third category, education and skills, three inhibiting parameters were identified: language barrier, including high illiteracy rates; the lack of formal, non-formal, and informal education in data engineering, data analysis, and data science; and insufficient proficiency in computer science to explain (i.e., explainable AI) and correct AI misnomers, algorithmic biases, and model errors." For the parameter "language barrier, including high illiteracy rates, and the digital divide," participants referred to "over 20 major languages, written in over 10 different scripts, and spoken at over 600 dialects across India." This led participants to find the "language barrier insurmountable when explaining and endorsing big data in agriculture, digital agriculture applications including IoT, and AI systems." One group commented, "Bengali, Gujarati, and Tamil are not programming languages."

Table 26: Diverse demographics of farmers or users' description reported in studies included in the rapid review

S. No	Author	Title	Diverse demographics of farmers/users
1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	"Farmers" has been used as an inclusive umbrella term. "The field research was carried out with medium-sized farmers, in the municipality of Guaíba, in the metropolitan region of Rio Grande do Sul. Guaíba has unique logistical conditions for projects that aim to serve the Southern Common Market (Mercado Comum do Sul – Mercosul) with products and services of international quality."

2	Ifeanyi-Obi et al. (2022)	Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria.	Farmers in Nigeria and Kenya are discussed, including a discussion on smallholders.
3	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	This governance structure needs to be reconsidered. Costs to reduce emissions in the agricultural sector are a burden for developing countries and will most likely disturb any attempts to reduce poverty. Current climate-smart agriculture threatens smallholders' access to their farms and to their basic human rights.
4	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	The initial setup expense of implementing precision farming can be a major barrier for small-scale farmers. Thus, governments and agricultural organisations should offer financial assistance, subsidies, and other rewards to promote the broad use of precision farming techniques. Continued research and development initiatives should also concentrate on creating affordable technologies and solutions that are suited for the requirements of small-scale farmers.

Table 27: Digital accessibility issues description reported in studies included in the rapid review

S. No	Author	Title	Digital accessibility issues
1	Ayres & Silva (2023)	Evaluation of farmer's perception of precision agriculture: A case study in the municipality of Guaíba, Rio Grande do Sul state	Another disadvantage of implementing precision agriculture is the difficulty of accessing the internet in rural areas. Considering the cost of implementing the precision farming system and hiring qualified people to carry out this type of activity, it is considered a disadvantage. The traditional is more accessible. "Possible ways to improve the reality of farmers who do not have large properties would be through access to smaller equipment using the same technology, improvements in connectivity and internet in rural areas, and technical development initiatives for those who still face difficulties in keeping up with advances in technology."
2	Budiman (2019)	Climate-smart agriculture policy and (in)justice for smallholders in developing countries	Farmers who cannot afford climate-smart agricultural practices should be supported by institutions and donors. The lack of operational blueprints is one key reason that explains why climate-smart agriculture development programs do not really reach poor farmers.
3	Sharma et al. (2023)	Artificial intelligence and internet of things oriented sustainable precision farming: Towards modern agriculture	Although precision farming has many advantages, its effective use necessitates a certain degree of technological knowledge and proficiency. Thus, farmers should have easy access to training programs, workshops, and instructional materials on precision farming. Precision farming practices may be encouraged and spread through partnerships between agricultural colleges, extension agencies, and industry players.

4	Mouzakitis et al. (2020)	Investigation of Common Big Data Analytics and Decision-Making Requirements Across Diverse Precision Agriculture and Livestock Farming Use Cases	Recent technological advancements in big data, AI, high performance computing (HPC), cloud services, and Internet of Things (IoT) offer new possibilities for agriculture. These technologies can help farmers overcome data management challenges, increase efficiency and productivity, and reduce input costs. However, many smallholder farmers are unaware of the available technology in the market.
5	Bofle 2020	Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers	The cost of purchasing machines, equipment, and applications, and problems with (or lack of) connectivity in rural areas were the main issues presented.
6	Sparrow 2021	Robots in agriculture: prospects, impacts, ethics, and policy	Public fears and stakeholder anxieties are often significant barriers to the development and adoption of new technologies.

Table 28: Effectiveness: productivity description reported in studies included in the rapid review

S. No	Author	Title	Effectiveness in productivity
1	Ahmed (2024)	Plant Diseases Detection for Agricultural Management Using Machine Learning	Farmers produce high-quality goods whose success depends on the growth and productivity of their plants. Therefore, in the agriculture industry, identifying plant diseases is crucial, and integration of AI in agricultural practices helps in enhancing productivity.
2	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	As with CSA adoption, there are variations in how group village headman communities affect adopter yields, reinforcing the importance of local conditions in agricultural productivity. Our results suggest that enhancing resource availability and providing institutional support can improve CSA adoption and boost yields. This includes improving access to hired labour and providing intensive extension services.
3	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture	By combining advanced imaging techniques, atmospheric sensors, and IoT sensors, the system provides farmers with accurate rainfall prediction and an automated irrigation model tailored to their crops' specific needs. With its portability, adaptability, and data storage capabilities, the system has the potential to revolutionise how farmers approach irrigation. This technology can also improve overall sector efficiency and productivity. Farmers can now leverage these advanced technologies to increase the profitability and effectiveness of their operations.
4	Bolfe et al. (2020)	Precision and Digital Agriculture: Adoption of Technologies and	The research also examined farmers' perceptions of the positive impacts achieved in their production processes from using digital

		Perception of Brazilian Farmers	technologies. These technologies were categorised into three groups: (i) images from remote sensing; (ii) field sensors, machinery, and equipment; and (iii) mobile applications, digital platforms, and software. All the impacts indicated were above 50% positive for farmers. This wide range of positive perceptions may be associated with the breadth of possibilities for the application of digital technologies throughout the production process. There was a perception of increased agricultural productivity, pointed out by 64.7% of farmers, followed by perceptions of easier marketing and better planning of daily property activities (62.7%), the reduction in production costs (62.3%), and the increase in profit obtained (60.9%). Farmers most strongly associated field sensors, machinery, and equipment with positive impacts on agricultural input optimisation, productivity, and product quality.
5	Ferraris et al. (2023)	Machine Learning as a Strategic Tool for Helping Cocoa Farmers in Côte D'Ivoire	"Overall, Arduino sensors offer an affordable and accessible way for farmers to gather valuable data, optimise their farming practices, and make informed decisions to enhance productivity and sustainability in agriculture."
6	Genaidy (2020)	Using Artificial Neural Networks Models for predicting wheat yield productivity	The study aimed to use three models of artificial neural networks in the field of wheat yield prediction and proposed potential increase in productivity
7	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	"In precision agriculture, the use of the Internet of Things system can effectively reduce the workload of farmers and increase farmers' awareness of the use of precision agricultural tools. According to our paper, long-term weather prediction can provide important guidance information for planning a reasonable growth cycle of crops."

			IoT systems for precision agriculture aim to create responsive growing environments that adapt to weather conditions like temperature and humidity changes. This approach optimises resource use—energy, space, and labour—to achieve more efficient production.
8	López et al. (2020)	Intelligent system for weed management in pineapple cultivation with concepts	The main objective of this research was to develop a prototype system for detecting weeds in pineapple crop rows using artificial vision and digital image processing. The system emulates targeted herbicide application to individual plants that require treatment. This approach aims to reduce excessive herbicide use, which provides several benefits: mitigating environmental impact, preventing labour accidents from herbicide application, and increasing economic productivity through input savings.
9	López-Martínez et al. (2024)	Pattern Classification of an Onion Crop (Allium Cepa) Field Using Convolutional Neural Network Models.	The results seek to contribute to the development of good agricultural practices. It aims to provide farmers with a technological tool that allows them to optimise the management of their onion fields. This could help them maximise their crop yield, reduce costs, and minimise production losses generated by environmental factors and the poor management of crop fields. It enables efficient crop management and increased agricultural productivity.
10	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine	CSA is a set of agricultural practices and technologies that simultaneously boost productivity, enhance resilience, and reduce GHG emissions. Although it is built on existing agricultural knowledge, technologies, and sustainability principles, it systematically

		learning: A prime exploratory survey	considers the synergies and trade-offs that exist between productivity, adaptation, and mitigation. This helps in increasing productivity.
11	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	For the agricultural community, a suggested plant disease detection system would help boost crop yields. Image processing tools may help better understand plants, allowing for early detection of leaf diseases and treatment before productivity is harmed. This will reduce the possibility of decreased productivity.
12	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data	Results point towards the potential of predictive AI in enhancing agricultural productivity. It can do so by enabling proactive pest management, reducing reliance on chemical pesticides, and supporting sustainable farming practices. The findings demonstrate the potential of AI by enabling early warnings, reducing pesticide use, and supporting more sustainable farming practices.
13	Rodrigues et al. (2023)	Remote Sensing and Kriging with External Drift to Improve Sparse Proximal Soil Sensing Data and Define Management Zones in Precision Agriculture	The increase in agricultural productivity is much needed due to the challenges of distributing food and commodities. Integrating AI into agricultural practices could potentially help increase productivity. However, it is challenged by rising debates on environmental protection and conservation, soil, fertilizer, water use regulation, and social and economic equity.

14	Sharma et al. (2022)	Enabling smart agriculture by implementing artificial intelligence and embedded sensing	"The motivation behind this work is to present a model that can monitor crop health regularly for accurate prediction of crop yield to enhance productivity. The proposed model performs well with fewer resource constraints and minimal data, thus providing optimal outcomes compared to various studies listed in the literature. The future scope of this research work will involve age prediction of various other crops to help farmers by providing smart farming recommendations with estimation of harvesting, cropping period, and productivity."
15	Lingwal (2022)	A novel machine learning approach for rice yield estimation: Journal of Experimental & Theoretical Artificial Intelligence	Machine learning learns from historical data, analyses them, and produces learning outcomes that result in healthy crop production. Forecast and prediction methods can be effectively used to increase productivity and crop yield. It can do so by capturing and interpreting data insights from global climatic changes such as moisture, precipitation, temperature, wind speed, and rainfall.

Table 29: Effectiveness: food security description reported in studies included in the rapid review

S. No	Author	Title	Food security

1	Ambildhuke (2024)	Artificial intelligence based smart and portable rainfall prediction device for precision Agriculture	“The use of precision agriculture has grown in recent years due to the need for increased food production to meet the growing demands of the population. Farmers can achieve food security and prevent water shortages by using sustainable precision irrigation management."
2	Dusadeerungsikul & Nof (2024)	Precision agriculture with AI-based responsive monitoring algorithm	"Precision agriculture is a relatively new agricultural methodology that seeks to optimize the efficiency of the agricultural system, thus enhancing economic performance and elevating the level of food security, both of which have recently gained significant attention. A crucial aspect of precision agriculture relies on the effective management of crop stress, as untreated stress can potentially escalate into disease and result in irreparable consequences.”
3	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	“If farmers are not prepared, especially women farmers, food security cannot be achieved. We believe that efforts are needed to create gender-sensitive extension advisory services that include access to technology, training and specific applications. In the same sense, gender equality is essential for agricultural development and food security. To over- come hunger and extreme poverty, we must encourage-age the empowerment of women in agriculture.”

4	Noma & Babu (2024)	Predicting climate smart agriculture (CSA) practices using machine learning: A prime exploratory survey	“To keep this positive outcome, better storage and management practices (in food security cluster) should be adopted as next or additional adaptation practices. The same could be inferred for most climate-smart agriculture cluster predictions since implementing each of them is demonstrated to result in higher yields; hence the need for better storage and management practices leading to sustainable food security. For each predicted practice, direct causal relationships with the previous ones are clear: previous practices causing predicted ones."
5	Panda (2022)	Development Of Artificial Intelligent System For Identifying Crop And Vegetable Diseases	“Global food security and sustainable agriculture depend on the effective management of plant diseases. Several recent studies have shows that deep learning-based image recognition systems improve upon already existing processes for the early detection of plant diseases. Plant leaf disease detection is a field of study that uses leaf analysis to identify the illness in a plant. Keeping an eye on a plant's health and illness is critical to a farm's effective plant production. It is possible that the endemic nature of plant diseases might have a negative impact on agricultural output and food security”.

6	Reddy K.V et al. (2024)	Predictive AI Models for Early Pest Infestation Alerts Using Climate and Soil Data	“This study contributes to the development of scalable, data-driven solutions that integrate environmental variables, enabling better pest management, and supporting global food security efforts. Pests significantly threaten global food security, causing up to 40 percent of crop losses annually, highlighting the need for proactive pest management strategies. This study contributes to the development of scalable, data-driven solutions that integrate environmental variables, enabling better pest management, and supporting global food security efforts. The integration of such models into farm management systems can provide farmers with real-time insights, improving decision-making and overall food security."
7	Rustowicz et al. (n.d.)	Semantic Segmentation of Crop Type in Africa: A Novel Dataset and Analysis of Deep Learning Methods	“Combined with developments in computer vision, there is an unprecedented opportunity to understand issues in food security through satellite imagery. Accurate crop type segmentation could help in understanding how farmers decide what crops to grow. It could also provide insight into interactions of crop types with environmental factors, give information on crop diversity and nutrition outcomes, and facilitate crop monitoring and yield estimation. Motivated to better understand cropping systems for applications in food security and other sustainable development goals, the research aimed to map crop type from space”.

8	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	"The system benefits the optimization of crop yield and profitability, which would consequently aid in fulfilling the rising demand of food supply. The suggested model estimates the crop yield by examining parameters such as rainfall, temperature, area, season, and soil type. The technique also reduces the farmer's probability of loss. IoT has driven soil-smart irrigation. Since population expansion is the biggest concern for food security, crop yield estimates may be used to aid farmers in decreasing crop failure to meet demand.".
9	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	Results demonstrate that policies and funding streams supporting CSA in low-income, dryland contexts such as southern Malawi can significantly impact food security. These interventions boost crop yields despite increasing climate uncertainty and extreme weather shocks.

Table 30: Effectiveness: Income and livelihood description reported in studies included in the rapid review

S. No	Author	Title	Income & livelihoods
1	Olivier & Ibrahim (2024)	Is artificial intelligence helping to empower women in agriculture in Africa?	Women's income positively influences their participation in household decision-making. However, women in rural areas do not have access to tools, barring them from the possibility of making more profits and earning more income.

2	Jin et al. (2020)	Deep Learning Predictor for Sustainable Precision Agriculture Based on Internet of Things System	According to the study, long-term weather prediction can provide important guidance information for planning a reasonable growth cycle of crops. Additionally, it can also help farmers manage farms. For example, a preliminary forecast and estimation of severe weather in agriculture can be conducted, so as to reduce risks and increase income.
3	Ume & Ume (2024)	Leveraging Artificial Intelligence for Sustainable Irrigated Rice Production: A case of Smart Alternate Wetting and Drying in Nigeria	Alternate wetting and drying (AWD) has been field-tested and validated by rice farmers in many developing nations. By virtue of its increased output, it has taken many farmers out of poverty. Farms using continuous irrigation, which does not incorporate water-saving measures, exhibit the highest water usage across all farms. This highlights AWD's water-saving potential and the possibility of higher profits.
4	Tej et al. (2024)	AI-based smart agriculture 4.0 system for plant diseases detection in Tunisia	"Even though hyperspectral images are an important source of data and include more information than standard photos, hyperspectral instruments are very costly, cumbersome, and hard to get for limited income farmers. As a result, developing a new dataset for the detection of pepper and tomato leaf diseases in Tunisia is a critical need to help Tunisian farmers determine the diseases of tomato and pepper, improve their income, and promote the country's economy."

5	V. Ramachandran (2022)	Development Of Smart Irrigation And Recommendation System For Agriculture Using The Internet Of Things	"Agriculture is one of the key sources of income for a large portion of India's population, and it is critical to the improvement of food production. "Smart farming" is a new approach that employs growing technology such as the Internet of Things (IoT), with the main goal of increasing production sustainably by expanding agricultural development at a low cost. Thus, the agriculture industry and the livelihood of farmers may be improved. Traditional irrigation strategies are not ideal for dealing with the paucity of irrigation water; this industry must benefit from new technological developments." "The farmer needs to locate the optimal temperature and need to understand the water level so that a suitable crop might be picked for specialized farming in precision agriculture. In the suggested approach, the authors enhance the net income of agriculture by advising the sowing of appropriate crops in that land".
6	Amadu et al. (2020)	Yield Effects of Climate-smart Agriculture Aid Investment in Southern Malawi	"This study contributes to the literature on climate adaptation and financing by building knowledge of CSA adoption and impacts in the context of foreign aid. It also contributes to food and development policy debates by showing that CSA aid can be effective in resource-poor, environmentally sensitive areas like southern Malawi and suggesting ways in which future investments might be targeted, designed, and implemented to maximize CSA adoption and yield gains to enhance income in the face of climate change and extreme weather shocks."

Box 1: Key research questions

- Defining AI
  - What are the major categories of AI-enabled solutions in agriculture?
  - What is the current stage of development of AI-enabled solutions and their deployment in the field?
  - What typology framework can be used to understand the types of AI applications in agriculture?
  - Who are the key vendors or institutions under each of these typologies?

- Understanding effectiveness of AI-enabled solutions
  - How effective are AI-enabled solutions in improving outcomes related to productivity?
  - How effective are AI-enabled solutions in improving outcomes related to food security?
  - How effective are AI-enabled solutions in improving income and livelihoods?
- Ethics and equity

1. What are the practical barriers for developing AI-enabled solutions for agriculture at scale, particularly in low-income settings?
2. How can AI-enabled solutions in agriculture be designed and implemented to maximise equity and avoid exacerbating existing inequalities?

- Horizon mapping
- What are the recommendations for AI-enabled solutions in agriculture?
- What are the (projected) short-, medium-, and long-term trajectories of specific AI-enabled solutions?

Table 31: Mapping AI categories to associated use cases

Base category	Subcategory	Associated use cases	References
Precision agriculture	Remote sensing and IoT	Weather forecast Management of agriculture processes	(Bolfe et al. 2020; Hernández and

		Optimisation of irrigation Application of pesticides and fertilizers Measuring weight of livestock and poultry	Marceau 2022; V 2022; Rodrigues et al. 2023; Ume and Ume 2024; R. Murugamani et al. 2022; Patel et al. 2022)
	Unmanned Aerial Vehicles (UAVs)	Optimisation of irrigation Imagery of farmlands for weed identification	(Fei et al. 2023; S. Khan et al. 2021; Martinez 2024a)
	Robotics	Differentiation of size and quality of produce	(Dusadeerungsikul and Nof 2024)
Machine learning	Classification	Detection of diseases and weeds Classification by quality	(Aworka et al. 2022; Murugamani et al. 2022; Martinez 2024; Ferraris et al. 2023; Lozada-Portilla, Suarez-Barón, and Avendaño-Fernández 2021; Sharma et al. 2023; K. V., Reddy, and Reddy 2024)
	Regression	Prediction of yield Detection of diseases	(Aworka et al. 2022; Lingwal, Bhatia, and Singh 2024; Wei et al. 2020; C. Murugamani et al. 2022)
	Clustering	Detection of diseases through image clustering	(Ahmed 2024)
	Optimisation	Farm management decisions	(Cock et al. 2023b; Mokaya 2019; C. Murugamani et al. 2022; R. V 2022)
Deep learning	Neural networks	Prediction of weather	(Ambildhuke 2024; Genaidy 2020; Guo et al. 2023; M. Z. Khan et al.

		Prediction of yield Detection of diseases and weeds Crop age estimation Optimisation of irrigation Identification of vegetation, soil, and humidity	2021; Martinez 2024b; R. Sharma et al. 2023; Balkis et al. 2024; Kumar et al. 2022)
Natural language and image processing	Photo recognition	Predicting quality of produce	(Ferraris et al. 2023)
	Satellite image based technology	Segmentation of farmlands	(M Rustowicz et al. 2019)
Conversational chatbots	Utilisation of LLMs	Farm management decisions	(Cock et al. 2023b)

Note: Table 3 only consists of use cases for pre-production and harvest phases. This is because post-harvest phases have been excluded from the rapid review

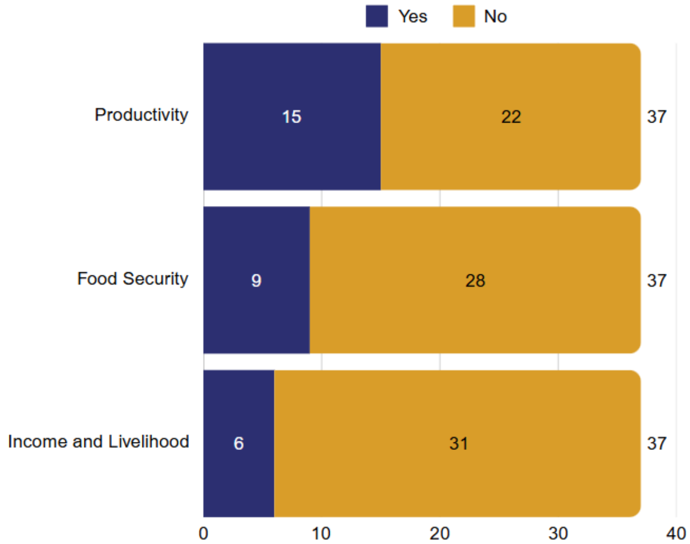
Understanding effectiveness

Effectiveness is defined as the degree to which AI-enabled solutions achieve their intended outcomes as specified by their implementers. The indicative metrics for effectiveness in this study include productivity, food security, income, and livelihoods. Effectiveness emerged as a research question with a notable paucity of evidence. As identified in the previous section, most studies concentrate on laboratory simulations, primarily reporting AI model accuracy, without addressing effectiveness in field applications.

The review identified a predominantly quantitative evidence base, with 35 studies employing quantitative methodologies, alongside 2 mixed-methods studies, and 14 qualitative studies. Quantitative and mixed-methods studies were evaluated for effectiveness across three key parameters: productivity, food security, and income or livelihoods. This focus on quantifiable outcomes allowed for an examination of potential measurable impacts of AI interventions within the agricultural sector.

Figure 19 presents an overview of the 35 quantitative and 2 mixed methods studies included in the rapid review that assessed the effectiveness of AI in agriculture. The parameters assessing effectiveness provided evidence on improved productivity (40.5%, n=15) (see Table 30), enhanced food security (24.3%, n=9) (see Table 31), and increased income and livelihoods (16.2%, n=6) **(**see Table 32 in Appendix).

Figure 31: Effectiveness frequencies



The review also highlights methodological challenges. Quantitative studies overwhelmingly relied on modelling and prediction approaches, with limited use of experimental methods like RCTs or quasi-experimental designs. Additionally, the studies that used an RCT or quasi-experimental design were rated as high risk of bias. This limits the ability to draw robust causal conclusions about the effectiveness of AI interventions. Similarly, qualitative studies often lacked rigour in exploring the sociocultural or institutional factors necessary for the success of AI-enabled solutions.

Although the modelling or prediction studies were often high-quality and rated as a low risk of bias, this does not necessarily translate to broader applicability or practical value, particularly in the context of smallholder farmers in L&MICs. One critical limitation of these high-quality studies is their lack of generalisability. Many of the studies are narrowly focused, targeting specific crops, geographical regions, or climatic conditions. While this specificity can lead to highly accurate models in controlled or localised settings, it reduces their relevance and adaptability to diverse agricultural contexts. This limitation is particularly problematic in L&MICs, where agricultural practices, resource availability, and environmental conditions vary significantly. Overall, there is little mention of effectiveness regarding income and livelihood impacts. Specifically, studies briefly mention the words "productivity," "food security," "income," or "livelihood" but do not substantially measure the impact of AI-enabled solutions in agriculture through these dimensions (Olivier and Ibrahim 2024; X. Jin et al. 2020; Ume and Ume 2024; Tej et al. 2024; V 2022, 20; Amadu, McNamara, and Miller 2024). Moreover, the findings from the rapid review display a separate metric for "effectiveness" as opposed to productivity, food security, income, and livelihoods. The metric focuses on AI performance in simulation models rather than farm-level output or income improvement. While studies mention future productivity gains, they provide no measurable metrics. Although these studies demonstrate high predictive accuracy in controlled experiments, their real-world effectiveness remains uncertain.

Further analyses: Cross-tabulations

Figure 34: Funding information across years reported in studies included in the rapid review

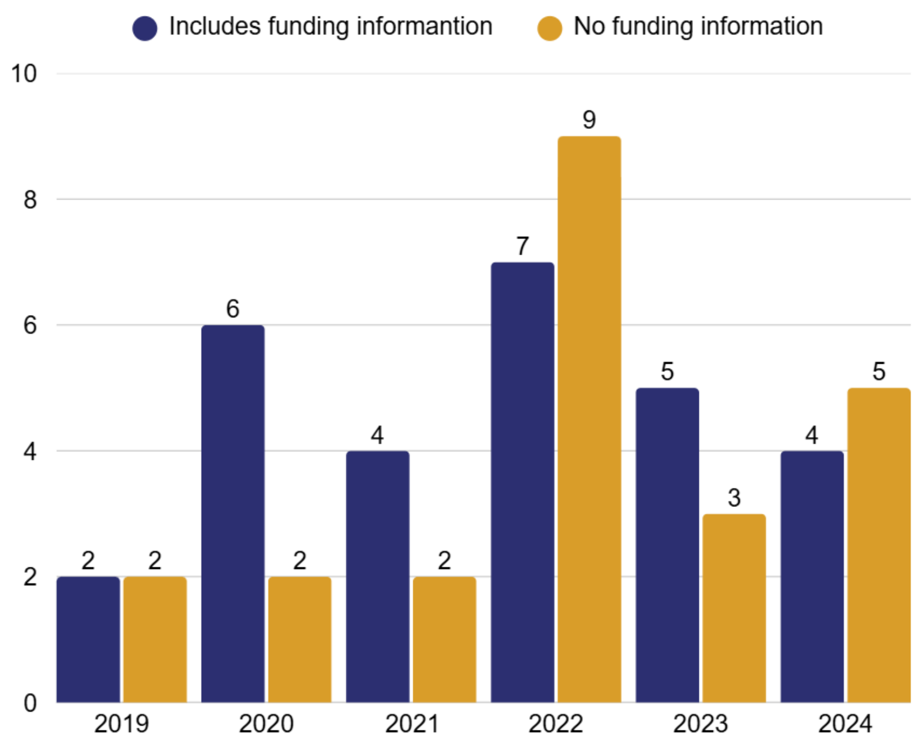


Figure 35: Agricultural dimension across years reported in studies included in the rapid review

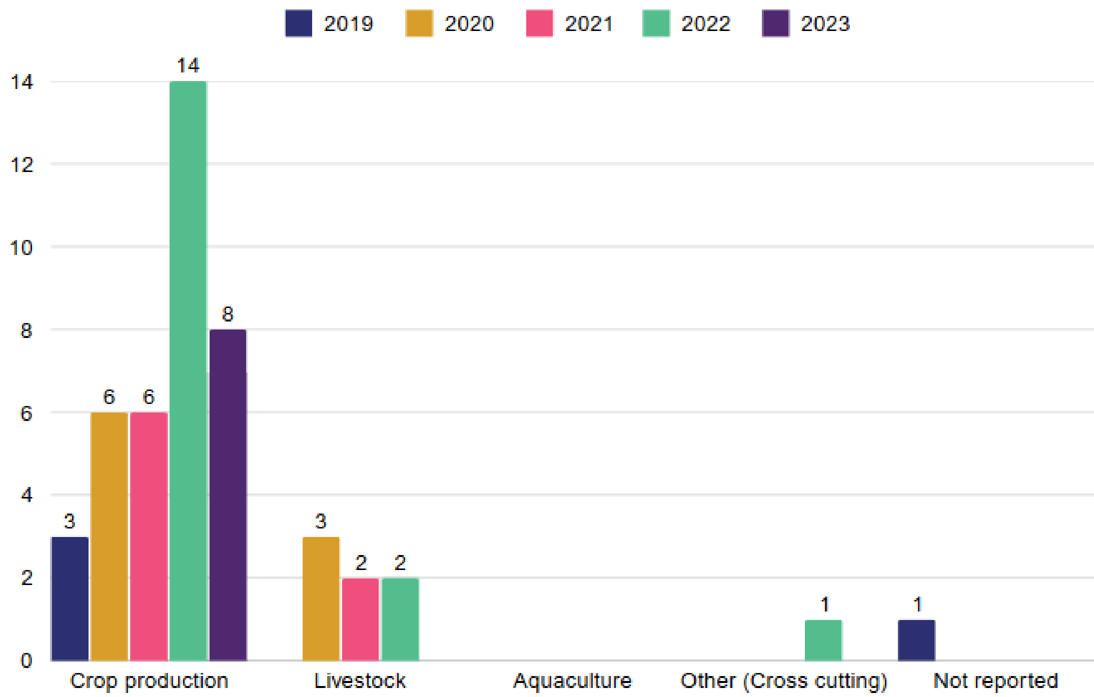


Figure 36: Agriculture dimension across funding information reported in studies included in the rapid review

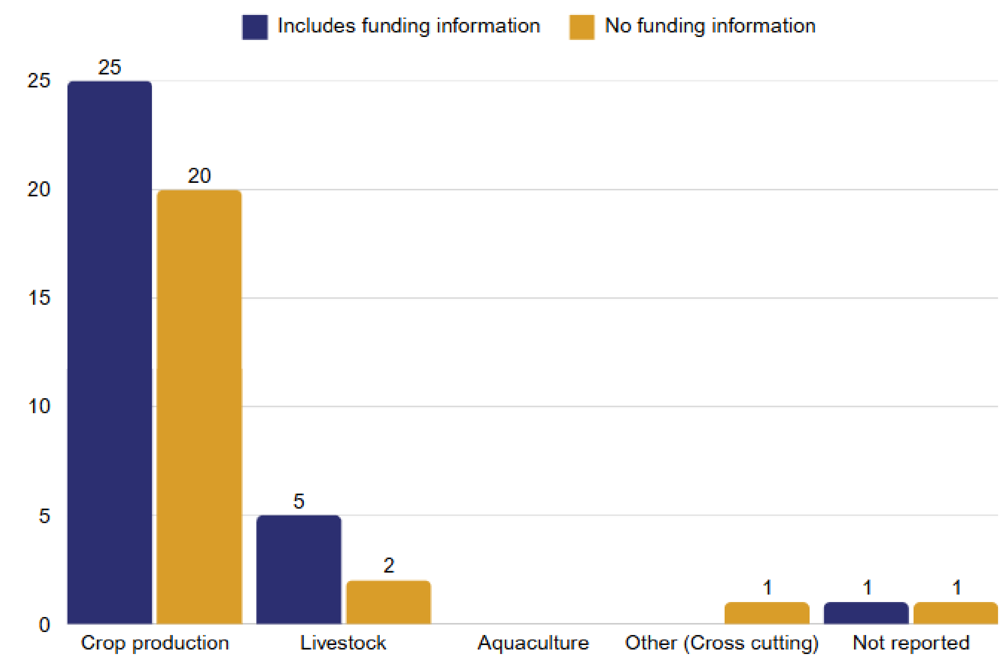


Figure 37: AI dimension across years reported in studies included in the rapid review

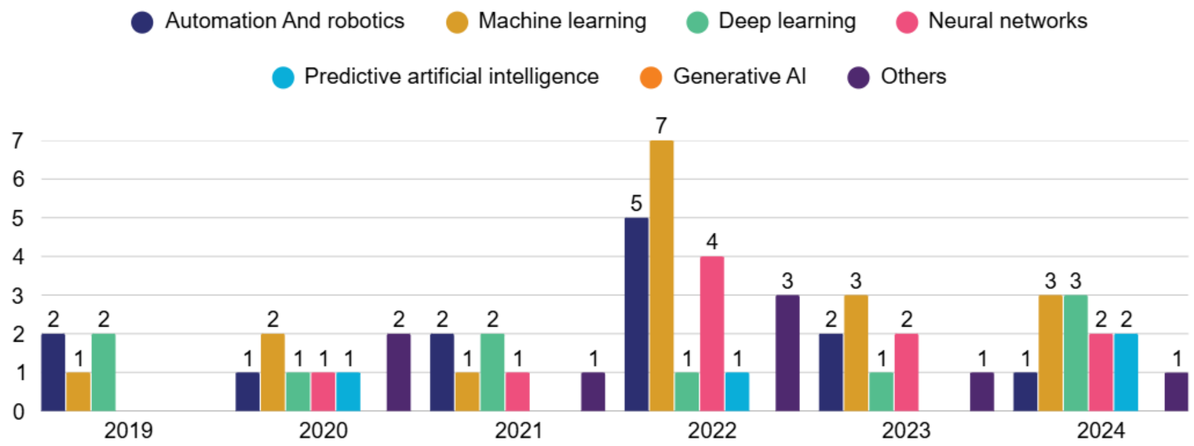


Figure 38: AI dimension across funding information reported in studies included in the rapid review

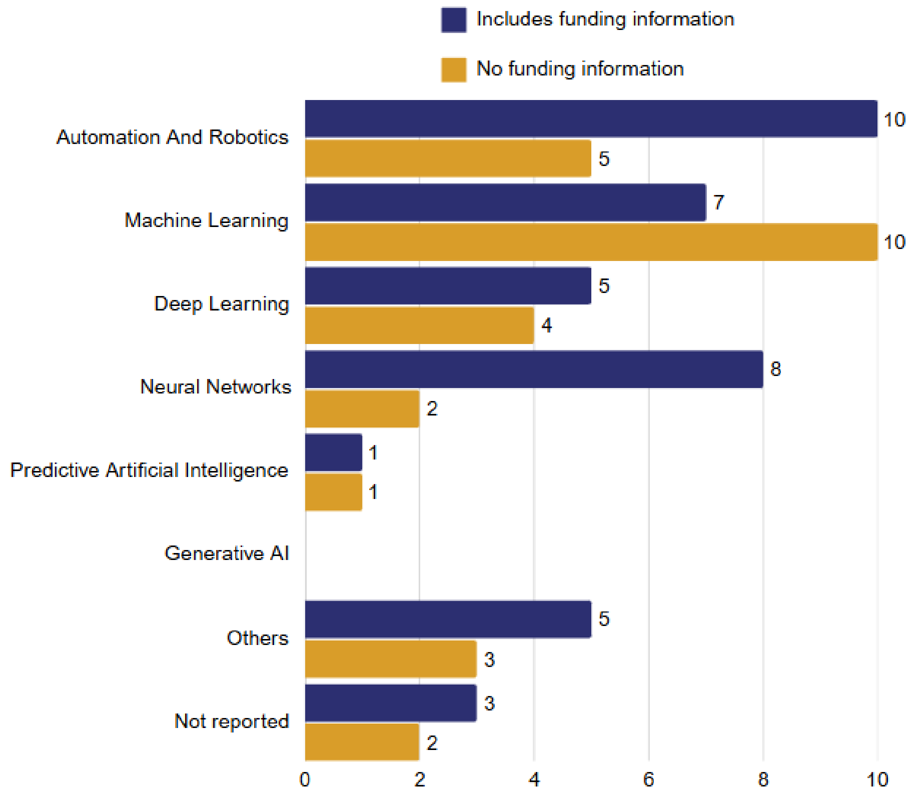


Figure 39: Agriculture dimension versus AI dimension reported in studies included in the rapid review

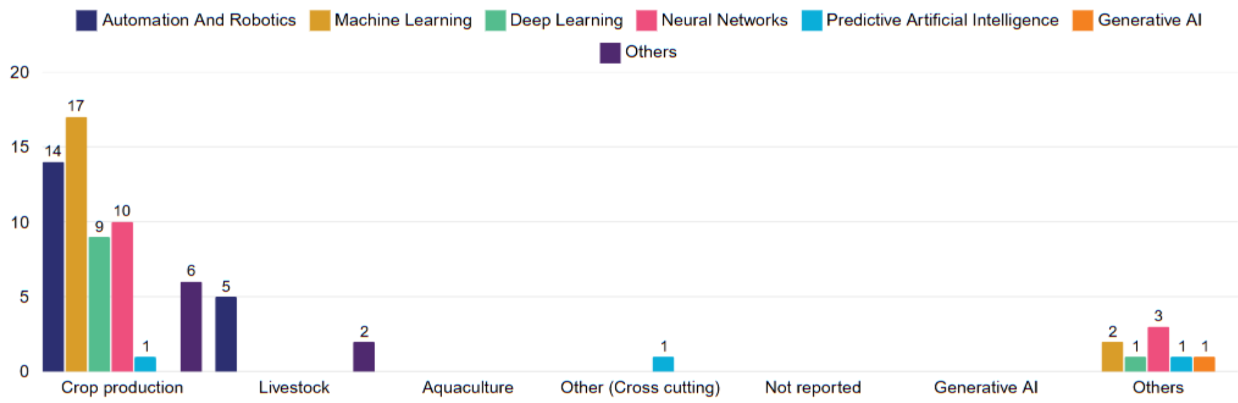


Figure 40: Target problem across years reported in studies included in the rapid review

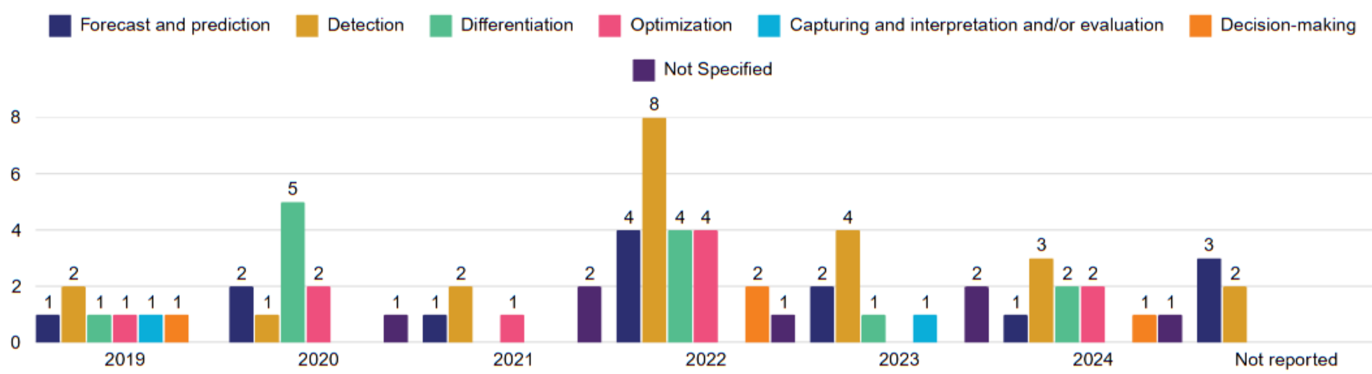


Figure 41: Target problem across funding information reported in studies included in the rapid review

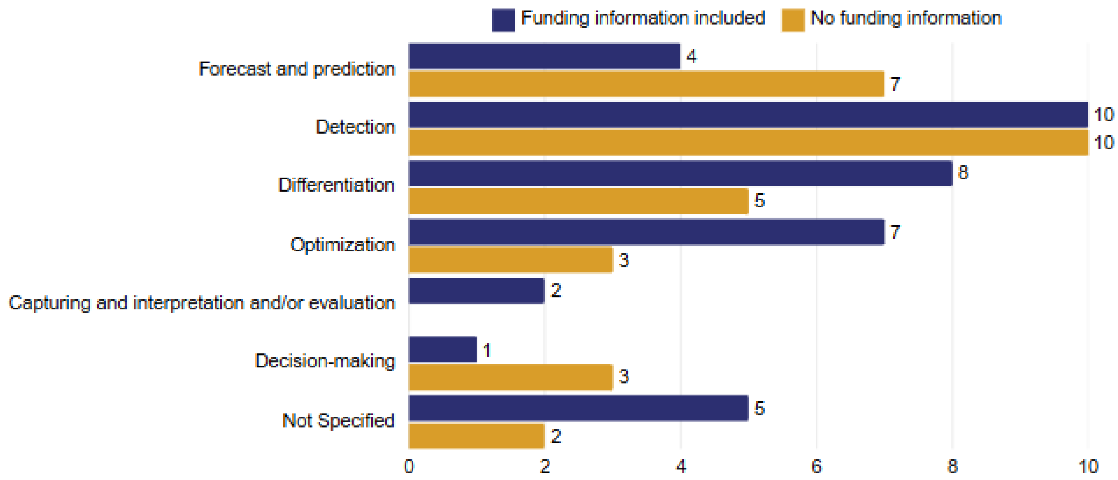


Figure 42: Target problem across agriculture dimension reported in studies included in the rapid review

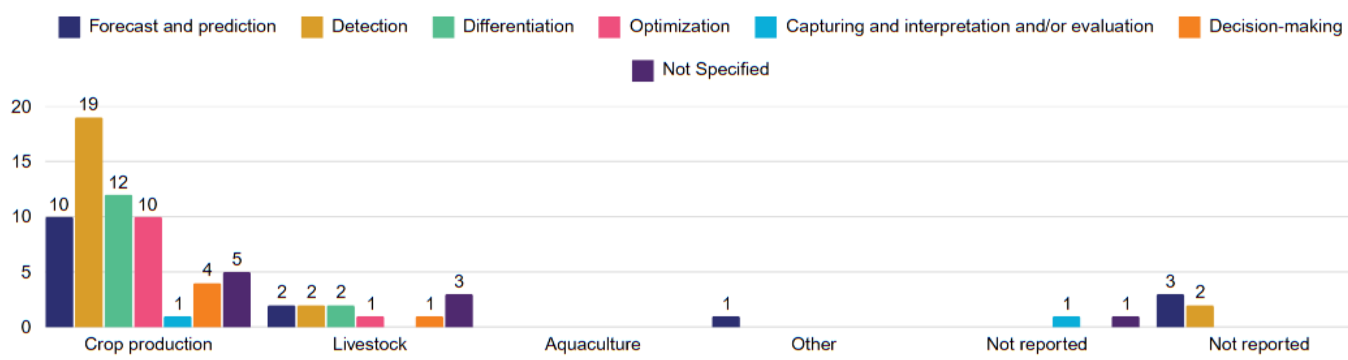


Figure 43: Target problem across AI dimension reported in studies included in the rapid review

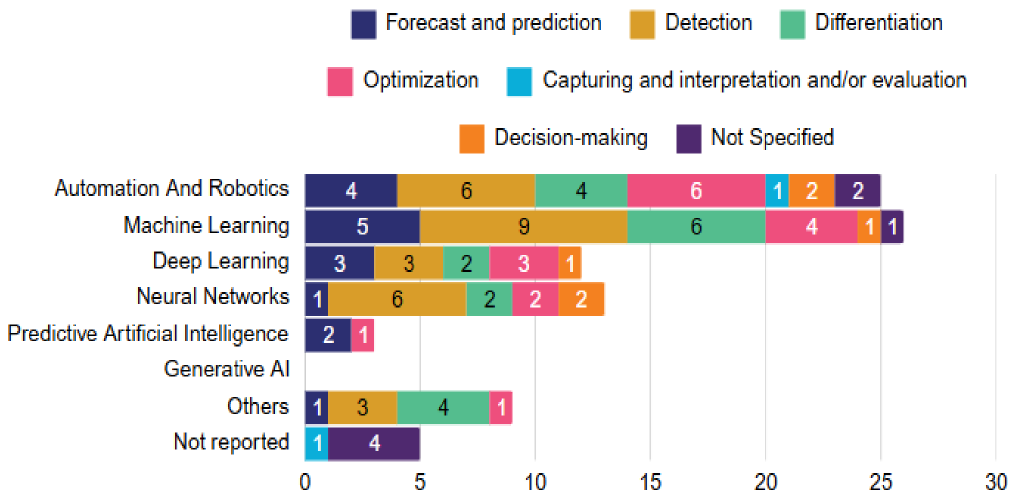


Figure 44: Region across years reported in studies included in the rapid review

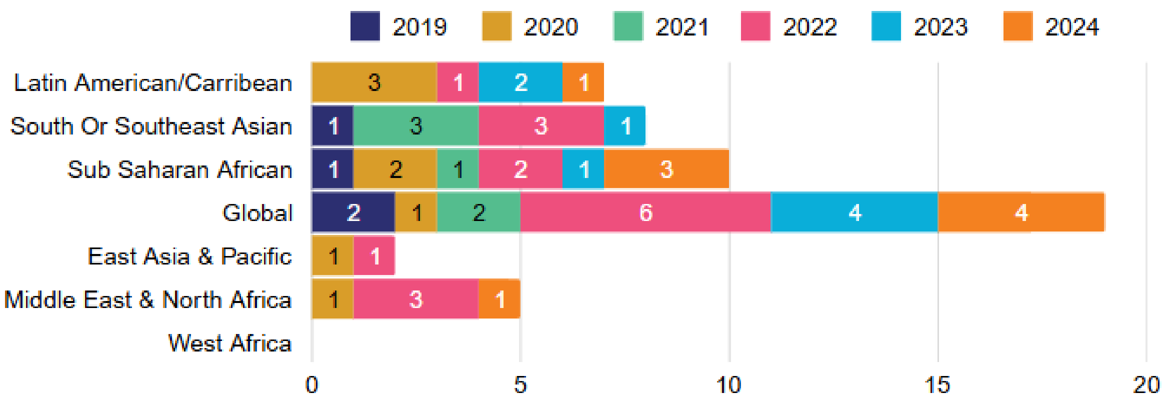


Figure 45: Regions studied across funding information reported in studies included in the rapid review

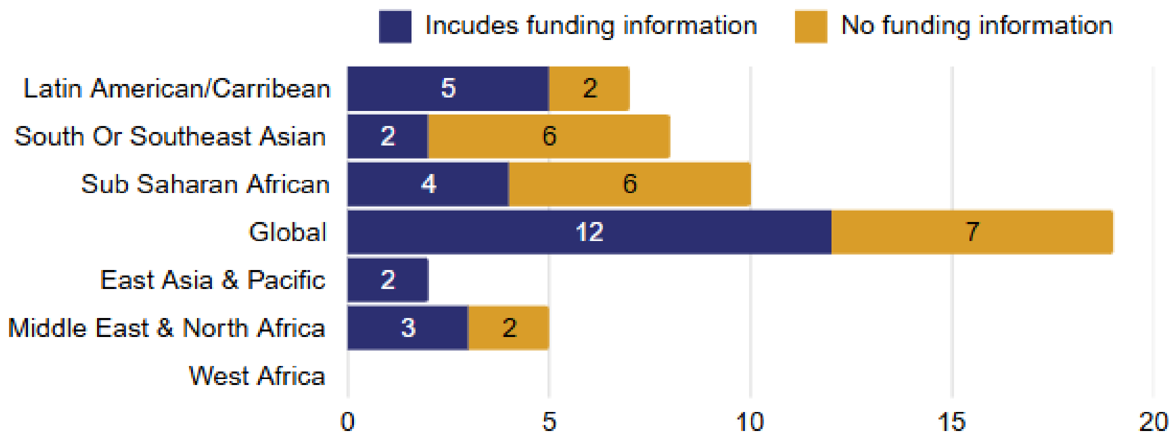


Figure 46: Region income category across funding information reported in studies included in the rapid review

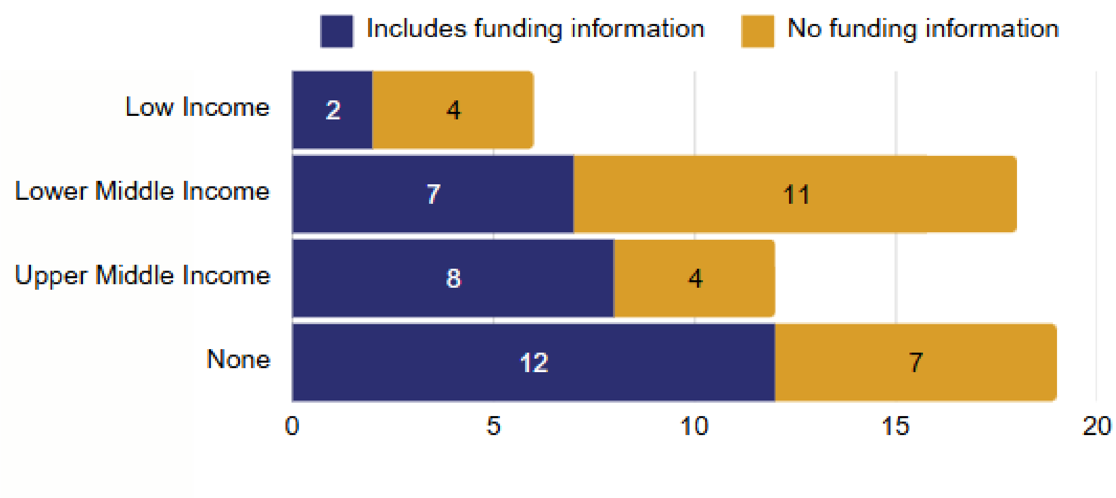


Figure 47: Population (users) across funding information reported in studies included in the rapid review

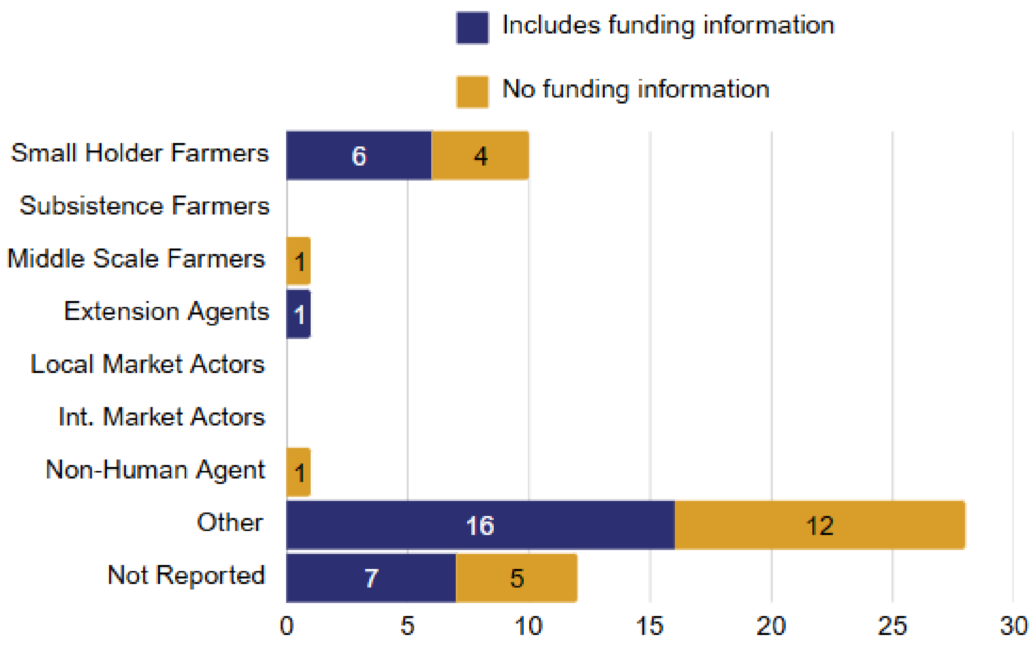
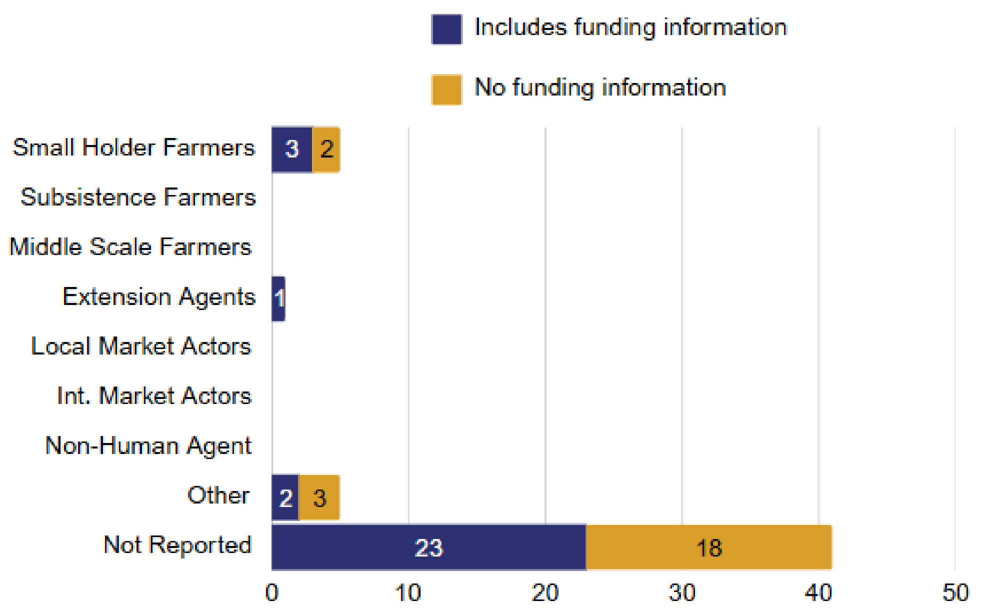


Figure 48: Beneficiaries across funding information reported in studies included in the rapid review



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