EVIDENCE EXPLAINER

The Use of Artificial Intelligence in Food and Agriculture Systems

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Key Messages

The agricultural sector has relied on traditional methods for a long time, but the shift towards modern practices through the integration of artificial intelligence (AI) is creating new opportunities for smallholder farmers to reduce losses and streamline their processes. However, the use of AI in agriculture is still in its nascent stages, with many tools currently in development or the trial phase.

Evidence of AI interventions is predominantly focused on crop production, including field crops and perennial crops, while in aquaculture, applications remain limited.

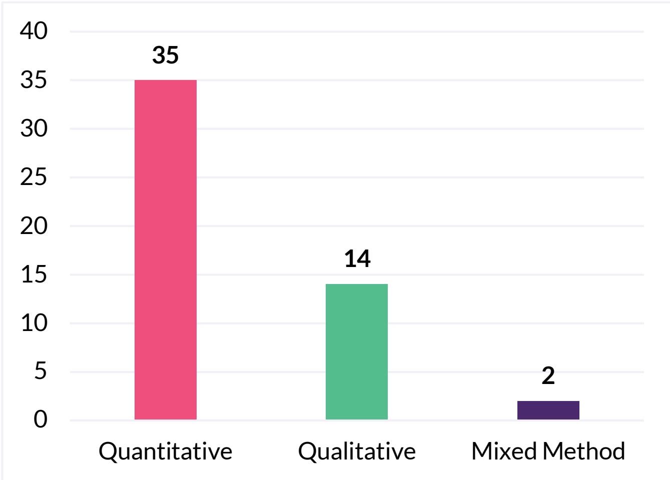
The most predominantly used AI tools in agriculture are automation, robotics, and machine learning. While the use of generative AI is rarely reported.

Evidence regarding the impact and effectiveness of AI interventions in agriculture is weak. Most studies focus solely on the accuracy of AI models, rather than providing comparable socio-economic measures of effectiveness.

There is ample evidence on challenges to inclusive AI integration, such as the digital divide, digital literacy, accessibility issues, and demographic factors. However, little evidence exists on how to effectively address these challenges.

Mapping the Evidence: Existing literature on AI in agriculture

We developed a rapid review to capture the nature of existing evidence on the use of AI in agriculture in L&MICs. Through this rapid review, we aimed to cover mixed methods evidence and hence used an adapted version of the PICO (Population, Intervention, Comparison, Outcome) framework. To make the PICO framework relevant to the review of agriculture, we replaced 'Population' with 'Setting'. We also used the SPIDER-D (Sample, Phenomenon of Interest, Design, Evaluation, and Research Type) framework as it is better suited to the analysis of qualitative research papers.



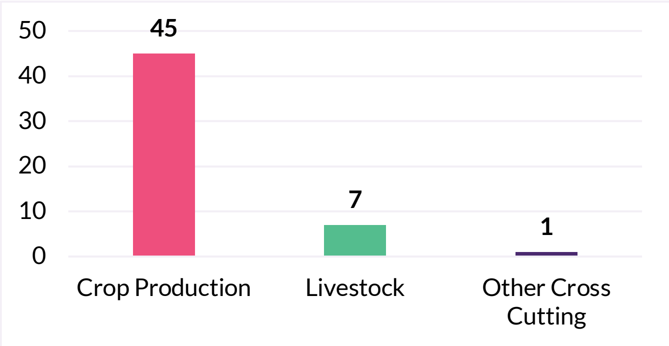
In this rapid review, we identified 488 potentially relevant studies[0] from scientific databases, journals, region-specific organizational databases, repositories, academic institution-affiliated sources, and grey literature. Out of these, we screened 430 studies for full-text review after refining the inclusion/exclusion criteria. Eventually, we included 51 papers. These were comprised of 35 effectiveness studies, 14 qualitative studies, and 2 mixed-methods studies.

The rapid review aims to answer four broad research themes

- Defining AI in the context of the agriculture sector, focusing on the specific target problems it addresses, and identifying where AI is integrated within the agricultural value chain.
- The effectiveness of these interventions was assessed based on their impact on productivity, food security, and income and livelihood
- We uncovered layered discussions on equity through 4 key parameters – the digital divide, data accessibility, digital literacy, and demography and diversity. The study also explores the importance of community-led practices, governance, and ethics to implement AI in agriculture
- Horizon mapping in the context of AI in agriculture involves exploring and identifying emerging technologies, trends, and challenges that may influence the agricultural sector both in the near and distant future.

Mapping the Evidence: Use of AI in agriculture

Agricultural production systems that rely heavily on traditional methods are increasingly facing challenges in meeting the rising global demand. To address these challenges, the sector is undergoing a broader agricultural transformation, through the integration of AI in agriculture. This aims to enhance productivity, resource efficiency, and sustainability through the adoption of modern farming practices and technologies, including digital technologies.

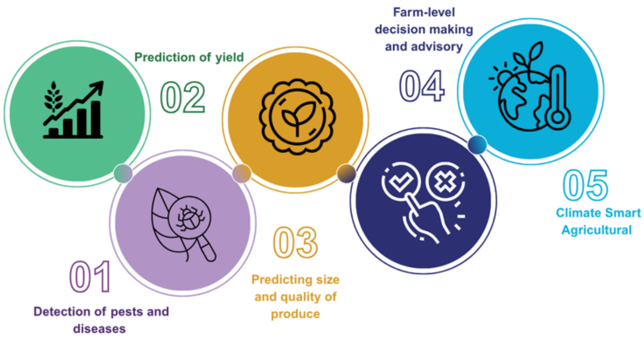


The rapid review found that most of the evidence focuses on **laboratory simulations and predictive models** to develop and optimize AI solutions for specific agricultural challenges. This reflects the **early stage of the sector, characterized by trial-and-error development and implementation** of AI integration in agriculture.

The studies reviewed reveal that the integration of AI in agriculture is primarily focused on crop production, followed by livestock management. However, there is a lack of evidence supporting the use of AI in aquaculture.

Evidence of AI interventions was **primarily focused on crop disease detection**, followed by applications in **predicting crop yields, weather patterns, and soil conditions**. These empower farmers to make more informed, data-driven decisions.

Most of the evidence demonstrated that the AI tools predominantly used in agriculture were based on **automation and robotics, along with machine learning and deep learning**. In contrast, very few studies examined interventions that focused on AI tools such as **generative AI and predictive AI.**



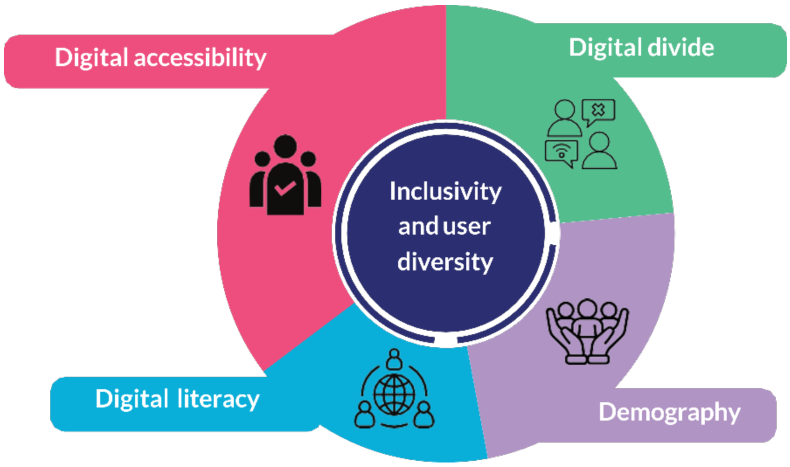
Mapping the Evidence: Effectiveness, Equity and Ethics

There is a notable paucity of studies analyzing the effectiveness of AI interventions in terms of productivity, food security, and income or livelihoods. Most of the **included studies are simulation-based, focusing primarily on the accuracy of the models rather than exploring deeper effectiveness variables** at this stage. When effectiveness is discussed, it is generally in terms of the **potential for increased productivity, improved income and livelihoods, and enhanced food security**. However, concrete evidence of these outcomes is rarely provided.

Current evidence provides **inadequate details on measuring the effectiveness** of AI solutions, highlighting the need for further investigation and standardized evaluation frameworks.

“The study aimed to use models of artificial neural networks in the field of wheat yield prediction and proposes a potential increase in productivity.”

The rapid review reveals there is substantial evidence on challenges intensified by structural barriers, digital divide, demographic diversity, digital accessibility, and digital literacy. It emphasizes the **need to develop inclusive solutions that account for regional, cultural, and socioeconomic differences.** Additionally, it is crucial to ensure that all users, **regardless of their background or farm size, can equally benefit from innovations in agriculture**.

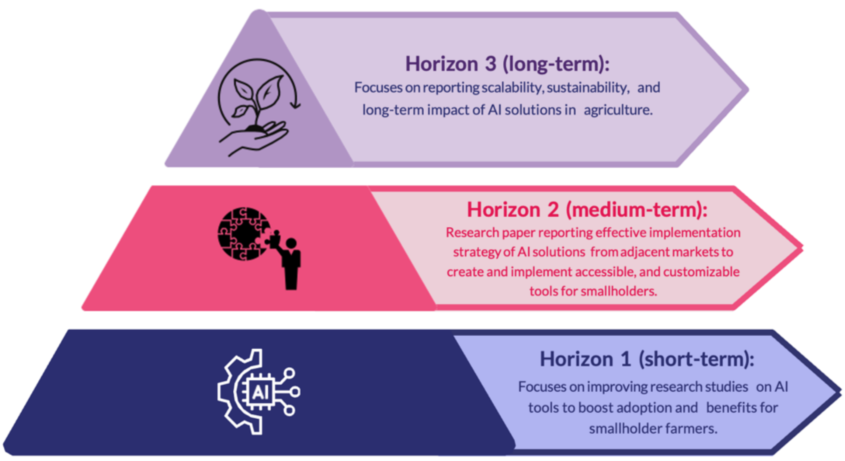


The evidence from the rapid review states **the importance of women's participation in adopting AI-enabled tools,** with a focus on digital advisory services and market access as key use cases. However, women, particularly in smallholder settings, often have limited decision-making power. This increases their vulnerability and results in poor data availability. Recommendations emphasize **developing training programs and women-centric projects to ensure their inclusion in the era of smart agriculture.**

“A disadvantage of implementing precision agriculture is the difficulty of accessing the internet in rural areas, especially the opportunity to be familiar with technology.”

Horizon Mapping of the Evidence and Recommendations

Given the limited evidence from existing literature, our rapid review assessed the potential impacts of AI technologies at different stages of adoption and mapped short-, medium-, and long-term trajectories for AI integration in agriculture.



The rapid review identifies a paucity of studies addressing the effectiveness, ethics, and equity of AI interventions in agriculture. This indicates the need for holistic assessments to demonstrate how these interventions impact smallholder farmers and strengthen agricultural support systems. Additionally, more experimental research is needed, especially randomized controlled trials, to address evidence gaps and understand AI's impact in agriculture.