The Use of Artificial Intelligence in Food and Agricultural Systems in Smallholder Settings

Rapid Review Blog

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Rising temperatures and erratic weather patterns are increasingly challenging global food security (WUR n.d.), and smallholder farmers face heightened vulnerability owing to these emerging threats (Touch et al. 2024). Artificial Intelligence (AI) technologies, encompassing automation, robotics, and machine learning, are frequently cited as crucial for addressing the growing need for food production while supporting vulnerable smallholder communities (Elbheri, Eskander, and Chestnove 2021).

However, there is a lack of a comprehensive and nuanced understanding of the current development and deployment of AI in agriculture. To address this gap, Athena Infonomics was commissioned by the Research Commissioning Centre (RCC) FCDO, and 3ie. This research sought to conduct a landscape review, incorporating various methodologies, including a rapid review. We aimed to synthesize the existing evidence, clarify the definition of AI within the agricultural context, explore ethical and equity considerations, and provide insights for informed investment decisions in this field.

Innovating Established Processes

Through this rapid review, we tried to strike a balance between gold standard systematic review guidelines and quick turnaround periods. This required adapting established methodologies and innovating upon them with the help of our team, which consisted of members with robust evidence synthesis expertise. We took cues from the Cochrane

systematic review guidelines and created a sound protocol for the rapid review (Higgins and Green 2008).
The pivotal idea during this project was to stay true to Athena's goal of creating a competent and high-quality product while also delivering on the client's expectations. At Athena, we acknowledge that innovation and client satisfaction are two cornerstones of staying relevant in the market.

We aimed to cover mixed methods evidence through this review by applying an adapted version of the PICO (Population, Intervention, Comparison, Outcome) framework. To ensure that the PICO framework is relevant to the review of agriculture, we replaced 'Population' with 'Setting'. The pilot coding round for the initial few studies indicated that much of the evidence will also be nested in qualitative sources. Therefore, we used the SPIDER-D (Sample, Phenomenon of Interest, Design, Evaluation, and Research Type) framework to inform the eligibility criteria of qualitative studies (opinion pieces, editorials). The SPIDER -D framework was employed as an alternative to PICO, since the former is better suited to analyse qualitative research papers. Additionally, we applied both PICO and SPIDER-D frameworks for the mixed methods evidence capture. This approach of using two different frameworks is another example of the innovation applied to established processes.

We innovated at every step, from promptly revising our strategy to adapting the PICO and SPIDER-D frameworks to align with the research requirements. Unlike typical rapid reviews, we also assessed how much confidence to place in each included study by using appraisal tools suited to its design. For the studies included, qualitative evidence was critically appraised using the NICE framework, while quantitative studies were evaluated using PROBAST, Cochrane ROB2, and ROBINS-I tools. This layered methodological approach was crucial for capturing the nuances of the evidence base.

The addition of other technical methods alongside the rapid review compounds the innovation of this study. We introduced situational examples by developing case studies and deep dives. We also engaged with stakeholders such as researchers, policymakers, and academics to both validate and enrich the study findings.

Key Findings

We identified 488 potentially relevant studies and ultimately included 51 papers. These comprised 35 effectiveness studies, 14 qualitative studies, and 2 mixed-methods studies. We searched scientific databases, journals, region-specific organizational databases, repositories, academic institution-affiliated sources, and grey literature. We screened 430 studies for full-text review after refining inclusion/exclusion criteria.

A. AI is currently in the early development stages in the agricultural sector

AI is rapidly reshaping agriculture, primarily targeting crop production through automation and machine learning. Drones are optimizing irrigation and weather forecasting, while AI-powered tools are identifying diseases, predicting yields, and providing real-time advice to smallholder farmers via chatbots and digital platforms. These solutions, often bundled for comprehensive support, are also pivotal in the transition to climate-smart agriculture. Despite the involvement of diverse stakeholders like funders and developers, there is a critical need for greater representation of smallholder farmers and low-to-middle-income countries (L&MICs) in the AI agriculture ecosystem.

B. Significant research gaps exist in terms of measuring effectiveness

While AI-enabled solutions in agriculture aim to enhance productivity, food security, and livelihoods, there exists a critical gap in assessing their true effectiveness because the technology is still in its early developmental stage. To address this, we examined case studies like Saagu Baagu[1], which utilizes metrics such as yield improvement, cost reduction, and income increases to quantify impact. However, significant research gaps persist in robustly measuring the effectiveness of AI solutions, highlighting the need for further investigation and standardized evaluation frameworks.

C. Significant Equity-related challenges persist

The promise of AI in agriculture is undeniable, yet its widespread adoption faces significant hurdles, particularly in relation to equity. We're seeing a stark digital divide, compounded by limitations in digital literacy and accessibility. These challenges are further intensified by structural barriers, entrenched cultural norms, and the underrepresentation of women in the sector. Critically, the potential for AI bias to exacerbate existing disparities is a major concern, especially in the absence of robust, sector-specific AI governance frameworks for agriculture. While initiatives like SciCorp[2] and Farmer.Chat[3] are making commendable efforts to address accessibility and fairness through measures like Red Teaming[4], these are insufficient. To truly realize the potential of AI in agriculture, we must prioritize equity at every stage of development and implementation. It's not just a matter of fairness; it's a matter of ensuring that this technology benefits everyone, not just a privileged few.

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[1] Saagu Baagu is an initiative by the Telangana government, in collaboration with organizations like the World Economic Forum, that aims to transform agriculture through the use of technology. Saagu Baagu intervenes by providing farmers with technology-driven solutions, including AI-powered advisory services and IoT-based monitoring, to optimize crop management and improve market linkages. (WEF, 2021)

[2]SciCrop utilizes AI to analyze diverse agricultural data, providing smallholders with precise insights on crop health and optimal resource use. This technology empowers farmers to make data-driven decisions, leading to increased yields and more sustainable farming practices (SciCorp Website, n.d.)

[3] Farmer.chat uses AI-powered chatbots to deliver instant, personalized agricultural advice and information directly to farmers via their mobile devices. This platform aims to bridge the knowledge gap by providing real-time answers to farming questions, fostering better decision-making and improved agricultural practices (Digital Green Website, n.d.).

[4] AI systems, if not carefully designed and tested, can perpetuate or even amplify existing societal biases. Red teaming, in this context, involves simulating scenarios where the AI might produce unfair or discriminatory outcomes, particularly for marginalized groups. For example, red teaming can test if a facial recognition system performs equally well across different skin tones, or if a loan application algorithm unfairly disadvantages certain demographics (Wilhelm, J., & Magnuszewski, P., 2024).

Takeaways

We find that it is essential to address the following challenges identified throughout the report:

1. Limited logistical support for smallholder farmers
2. Limited research and development funding
3. Lack of sector-specific governance frameworks
4. Gaps in regulatory compliance
5. Challenges in tracing the geographic origins of datasets
6. Difficulties in acquiring reliable and consistent local data
7. Absence of formal and standardized effectiveness measurements for AI tools

We explored the challenges of implementing AI in agriculture, particularly in L&MICs, by viewing them as opportunities for growth. Our strategy involved a phased approach: we immediately focused on building geographically representative databases, shareable data platforms, and multi-stakeholder frameworks; then, we fostered inclusive collaboration, peer-to-peer learning, and regulatory compliance; and ultimately, we supported the scaling and sustainable integration of AI solutions to drive long-term agricultural transformation.

Recommendations

So, where do we go from here? Our analysis, which paints a clear picture of AI's current footprint in L&MIC agriculture, is a call to action. We've laid the groundwork, but deeper dives – such as evidence gap maps and systematic reviews – are necessary for a nuanced understanding. Livestock and aquaculture require innovation with AI since evidence in these areas is limited. Crucially, we must build AI-enabled solutions that cater to the diversity as well as the regional challenges of the communities they serve. Bias is a real threat, and inclusivity in development is an essential component that ensures that these solutions are scalable. Finally, technology is only as good as its users. Farmers need to be empowered with the skills and knowledge to wield AI effectively. That means robust capacity building programs, leveraging the power of self-help groups, peer to peer learning, and community resource persons. The future of AI in L&MIC agriculture is bright, but it demands our continued attention, research, and collaborative spirit.

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