The Use of Artificial Intelligence in Food and Agricultural Systems

Learnings from the Stakeholder Engagement

Athena Infonomics conducted a landscape study outlining the integration of AI-enabled solutions in agriculture. The study focused on agriculture and allied sectors among smallholder farmers in low- and middle-income countries (L&MICs). The research sought to develop a comprehensive understanding of the effectiveness, and the social and equity implications of AI-enabled solutions in agriculture. Through this study, we aimed to fill a critical gap in systematically documenting evidence on the effectiveness of AI enabled solutions in agriculture.

Why Stakeholder Engagement?

This study aimed to address a critical gap by systematically documenting evidence on the effectiveness of AI-enabled solutions in agriculture, particularly those designed and implemented in L&MICs. It was an opportunity for Athena to socialize its research findings, share emerging insights from ongoing work, and address evidence gaps. These workshops significantly enriched our study by providing real-world perspectives. This added depth to the findings and enhanced their practical relevance.

Thematic Areas Explored

Theme 01
AI enabled solutions in agriculture

Theme 02
Inclusive design and user diversity

Theme 03
Sustainability of AI in agriculture

Theme 04
Need for regulatory frameworks

Theme 05
Investment, Innovation & AI Uptake

Theme 06
Horizon Mapping

Key Findings

A. Typology

Most AI innovations are still in the developmental phase. In many regions, particularly in L&MICs, the lack of infrastructure hinders the seamless scaling and adoption of AI solutions in agriculture. Additionally, while AI tools are often marketed as solutions for challenges faced by smallholder farmers, they are more commonly adopted by large-scale commercial farms.

B. Data-related Challenges

The extensive reliance on manual data collection and ground truth verification presents a significant challenge. The absence of reliable data often necessitates the use of synthetic data. While data availability is limited, the cost of manual data collection remains high. Training machine learning models requires detailed datasets, and local data is essential when working across different regions, even within the same country—due to the lack of standardized datasets for soil and other agricultural components. As a result, a major challenge for developers is that they have to compare numerous local datasets to train their AI tools. Additionally, there is a lack of trust in national-level datasets, leading to the creation of multiple locally developed regional datasets.

C. Inclusivity and Accessibility

Ensuring a participatory process to enhance the adoption of AI-led solutions is crucial. It was observed that farmers, who rely heavily on experiential knowledge, often view tech-driven solutions with skepticism. Therefore, AI-led solutions should be embedded in local knowledge to complement, rather than challenge, existing practices. Another barrier to accessibility is the high cost associated with AI-led solutions.

D. Sustainability

Developing AI tools through a participatory process that includes community experts can lead to more sustainable AI solutions. Embedding human interactions within AI-driven tools can enhance long-term impact and increase the acceptance of these solutions. The government can play a key role by establishing better frameworks, guidelines, and legislation to foster a collaborative environment. This includes supporting agri-tech companies and emerging startups in developing locally relevant solutions. Additionally, promoting digital literacy among end users of AI-led solutions is crucial for ensuring the sustained use of technology.

How to Amplify Uptake?

- Transition beyond generic AI-led solutions and design localized alternatives to increase uptake.
- Invest in digital literacy and capacity building of small-scale farmers in L&MICs.
- Ensure inclusivity in AI design from the initial stages. For example, involve gender specialists and agronomists alongside tech experts to develop well-informed AI-enabled solutions.
- Leverage traditional agricultural knowledge by engaging community champions and local farming experts.

Way Forward

- Framework development to identify key domains for measuring the effectiveness of AI in agriculture.
- Increase focus on L&MIC research to develop region-specific solutions.
- Prioritize scalable and cost-effective AI solutions with clear pathways for real-world implementation.
- Address infrastructure and connectivity gaps to enhance adoption.
- Foster an enabling environment through relevant governance frameworks.