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# What Does AI Mean for Smallholder Farmers?

## A Proposal for Farmer-Centered AI Research

**Insights**

- AI offers opportunities to solve complex problems facing smallholder farmers in the Global South. However, there is a dearth of research and resources available to organizations and policymakers for building farmer-centered AI systems.
- We propose concrete future directions for building AI solutions and tools that are meaningful to farmers and will significantly improve their lives. We also discuss tensions that may arise when incorporating AI into farming ecosystems.



Smallholder farmers make up 95 percent of the world's farmers and produce 45 percent of the world's food, 70 percent of which comes from sub-Saharan Africa, Latin America, and Southeast Asia [1]. Yet these farmers face challenges including low yields, poverty, food insecurity, climate change, and limited access to shared markets.

Artificial intelligence in agriculture promises data-informed ways to support farmers' traditional practices while mitigating the challenges. However, the drive toward precision agriculture technologies is focused on large-scale monoculture practices that are unsustainable and economically risky for farmers. This is problematic for a couple of reasons: (i) AI solutions further entrench this productivist model of farming to the exclusion of other beneficial models; and (ii) if AI solutions are targeted and priced to large farms, they will be out of reach of smallholders in the developed and Global South. The benefits will accrue to well-resourced farms, widening inequalities and threatening small-farm survival.

As HCI and social scientists who work with smallholder farmers and AI researchers, we seek in this article to take some first steps toward sharpening the blunt instrument that

is AI to support the values and practices of smallholder farmers in Southeast Asia and sub-Saharan Africa. These farmers share certain challenges, such as unreliable Internet and limited access to capital, with smallholder farmers in the developed world. They also face challenges less common in the developed world, such as low-end devices, unstable infrastructure, diverse literacy levels, and working in multiple languages. Therefore, technologists must develop AI calibrated to smallholder farmers' use cases, not simply ported over from big farms in the developed world.

## UNIQUE CONSIDERATIONS FOR RESEARCHING FARMER-CENTERED AI IN THE GLOBAL SOUTH

Drawing from our experiences, past research on smallholder farmers, and decades of research focused on social science in digital agriculture, the following sections are a first step toward mapping out the terrain of research areas for building a deeper understanding of smallholder farmers' needs, practices, value systems, and the agricultural ecosystem toward the goal of developing meaningful AI solutions and tools. We also investigate the intended and potential unintended consequences of these interventions.

***Common hardware and data constraints.*** Existing AI solutions, designed for large farms in the developed world, assume that users have reliable access to electricity, computing power, and Internet services. But many smallholder farmers in the Global South exclusively live and work in rural areas, which trail behind urban areas in terms of connectivity and digital adoption. Here are some of the common challenges and responses that farmers face:

• *Shared low-end mobile phones.* Smallholder farmers use mobile phones for verbal communication among friends and family rather than for delivering agricultural information. While device access is determined by device ownership in Western contexts, our smallholder farmers commonly share devices and access information through agriculture officials and other community members. Therefore, developers should assume that AI-based tools may be used on multiple farms across various users and device types, especially low-end smartphones.

• *Dataset availability and quality.* In our research, developers told us they encountered a "cold start problem" due to having little digitized information on potential users and the problem spaces being addressed. Many organizations and developers rely on data availability to provide personalized information and predictive services for farmers. The notable absence of reliable labeled datasets, however, hinders progress in building ML applications for smallholder farmers. Conventional Western ML applications may also be inappropriate and harmful in the Global South if they do not reflect local structures, such as poverty, infrastructures, values, and legal systems that are unique to lower-income countries. Funding to support the creation, expansion, and maintenance of publicly available labeled data in the agriculture space in the Global South is a vital step for AI development in that region.

***Build for diverse literacies and multiple languages.*** As more farmers come online, languages and digital literacies will become more critical. Without structural improvements to education, AI, whose pedagogy often assumes a degree of technical literacy, may prove daunting for smallholder farmers in the Global South. A common consequence of low literacy rates is limited access to information, which translates into lower efficiency and crop yields. From our research, we learned that lack of reliable and timely information about markets inhibits smallholders' ability to predict demand (resulting in oversupply when everyone plants the same crops) and to sell their products profitably. This traps many farmers in vicious cycles of poverty. Thus, model predictions and recommendations should translate into results that farmers of all literacy levels can use to make better decisions about their crops. Moreover, technology constraints (e.g., word-count limits for SMS on basic phones) can impede the use of information for farmers. Alternative communication mediums like audio and visual tools may help address literacy issues and reduce the digital learning curve.

Model predictions and recommendations should be *actionable* and should account for social and cultural norms and laws that are common in rural communities, such as the days on which farming activities are forbidden. Technologists should build a comprehensive understanding of these cultural norms through user experience research. AI solutions should be attuned to common cultural norms but flexible enough that farmers can adapt them to their local context.

Many smallholder farming communities in the Global South are multilingual, with a combination of official, native, and trade languages. This presents interesting new challenges for natural language processing (NLP) and AI [2]. Despite the fact that Africa has more than 2,000 languages, African NLP models are severely underdeveloped. Lack of funding for translation efforts, low visibility of already scarce African language data, paucity of publicly available benchmarks, and poor reproducibility are some of the many

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problems facing machine translation of African languages [3]. India's linguistic diversity, with 22 official languages, presents a similar challenge. The funding and creation of NLP datasets to support building AI technology for farmers that is robust enough to work across linguistic diversity will facilitate its adoption. Creating multidisciplinary collaborations with sociolinguists and local language experts and identifying farmers' language needs through user-centered design early and often in the product development cycle can help identify and address the challenges that diverse literacies and multiple languages present.

***Identify barriers and pathways to building trust.*** In our fieldwork, we found *trust* to be the most critical, and difficult to achieve, element for the success of AI tools. Trust values are embedded in relationships between farmers and in their interactions with technology. Smallholder farmers have had their trust violated by technology—from insufficient recommendations about what fertilizer to use on crops to unreliable weather predictions that negatively affected the farmers' resilience. This distrust leads to skepticism about AI benefits in the Global South. AI-enabled products require trust in the automation, prediction, recommendation, and personalization capabilities of a nonhuman entity. This stands in opposition to more-established ways (i.e., face-to-face interactions) that farmers seek information and solve problems. Lack of trust also reflects established belief systems and normative roles between farmers and agribusinesses. For example, research suggests that farmers believe unequal power relations exist between farmers and large businesses; farmers then do not trust external organizations [4]. Thus, trust (or the lack thereof) may determine the success or failure of farmer-facing AI-based agriculture tools.

While AI offers a promising future for farmers in the Global South, it does not come without risks. As AI becomes more sophisticated, the growth of automation will require less human labor. For countries in the Global South, where there are few urban job opportunities and people depend on agriculture to make a living, technologies like AI that take labor out of the fields may unintentionally undermine efforts to reduce poverty and enhance development. Therefore, we need to think about ways that AI can complement, rather than replace, the capabilities of farmers.

To establish a relationship of trust between smallholder farmers and AI-based technologies, here are practices we have begun to develop:

• *Help users understand AI's capabilities.* Many agritech businesses focus on the technical components and capabilities of AI systems without careful consideration of how these might be understood and used by farmers. Corporations need to make clear the direct benefits of AI to the farmer (e.g., specifying farmers' data rights) instead of glorifying the technology. A good practice is to avoid suggestions that technology will work perfectly in high-stakes situations and to be transparent about system limitations when they do work (e.g., displaying AI model confidence).

• *Be transparent about data and privacy.* Given distrust with external organizations, farmers need assurances of privacy and security. Governments and organizations often collect data that is used without farmers' permission and knowledge, which could exploit farming communities. We argue that prior to data collection, governments and organizations should be required to collect informed consent from farmers for accessing and using their data. This will require transparent agricultural data governance to foster trust in the adoption of smart farming systems.

• *Recognize that many recommendations are high stakes.* With smallholder farms, profits are marginal and sometimes difficult to measure due to a lack of records resulting from illiteracy. Research shows that minor setbacks in a crop year could have major implications for the social and economic vulnerability of smaller farms [5]. Many AI solutions promise perfect information, but the reality is that most data-driven systems require farmers to use their own experience in conjunction with algorithmic outputs. Farmers need to understand when to trust AI and when to use their own judgment to reduce the risk of harm from an incorrect recommendation, since predictions may not account for certain unknown external factors.

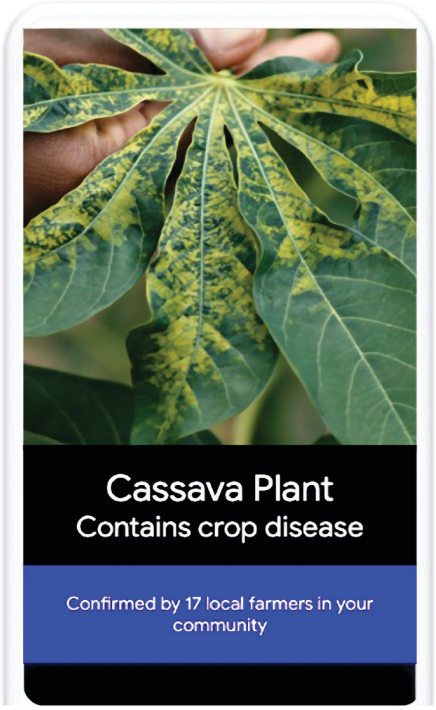


**Figure 1. A mock-up of how ML output can leverage and communicate trust through validation from the farming community.**

• *Leverage existing trusted resources.* Extension agents, input suppliers, cooperatives, and other players in the ecosystem all provide guidance for everyday decisions that farmers face. Farmers rely on word of mouth when deciding to adopt various methods and products. Given the importance of face-to-face interactions in farming communities, it is unlikely that farmers will trust an AI-based system on its own. Complementing trusted human sources, farmers with AI output can serve as an important catalyst in building trust (Figure 1).

***Co-designing with smallholder farmers and intermediaries.*** "Farmer-centered design" involves a dynamic understanding of farmers' changing needs and challenges to avoid parachuting solutions. Technologies must be integrated into existing sets of norms, practices, and

infrastructures. In this section, we discuss what such an approach might look like.

First and foremost, smallholder farmers' voices need to be heard throughout the machine learning development process. In our research, we heard how reliable information about preventing particular crop diseases had been expressed in ways foreign to how the farmers themselves think and talk about these diseases. Having farmers play an active role in the development process through participatory design will ensure that the results of the product, service, or experience meet farmers' needs.

We should consider how farming fits into smallholder farmers' identity. Technologists can mistakenly assume that they know what people and communities need (e.g., to increase their farms' productivity) without asking those communities what goals they aspire to. While some U.S. small-farm operators are profit motivated and eager to grow their businesses, others are committed to smallness for its perceived cultural, social, or economic value. Smallholders in the Global South have their own motivations and their own concepts of what constitutes a successful farm, beyond sheer efficiency and crop yield; understanding these motivations is key to the design of AI tools.

Aside from farmers, it is important to co-design with as many of the actors in the agriculture value chain as possible. In the Global South, efficient collaboration and cooperation across the value chain and these intermediaries is difficult to achieve due to the infrastructure challenges we mentioned earlier. Improving any part of the agriculture value chain in isolation could inadvertently result in negative outcomes. For example, an increase in yield without a corresponding increase in demand could adversely affect farmer resilience; if there is no market for the crop, the farmer will not profit.

Lastly, AI can inadvertently create tension between ecosystem actors. For example, due to rising farmer-herder conflicts in sub-Saharan Africa over the past few years, researchers are exploring how AI can understand farming patterns across a country, locate cattle herder settlements, and predict community conflict [6]. However, if the information used to develop these algorithms is prejudicial, recommendations may exacerbate tensions between these groups. Future research will need to acknowledge the existence of these tensions, understand the consequences on the respective communities, and consider solutions that result in the least amount of harm to the parties involved.

## CONCLUSION

This article seeks to start a conversation on the critical factors to consider in creating AI tools for smallholder farming communities. It is our responsibility to take a farmer-centered approach to understand how AI is perceived and adopted. We need a more inclusive frame of reference to our AI assumptions. AI is not always the right solution, as it could lead to adverse outcomes that have significant impacts on farmers' lives. By applying a farmer-centered lens to the expectations we have about AI, we hope to encourage the field to think carefully about when it is appropriate to bring AI-enabled solutions to smallholder farmers and how to do so in a way that will improve their lives and their communities.

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### ENDNOTES

1. Lowder, S.K., Sánchez, M.V., and Bertini, R. *Farms, Family Farms, Farmland Distribution and Farm Labour: What Do We Know Today?* FAO, 2019; http://www.fao.org/3/ca7036en/ca7036en.pdf
2. Sambasivan, N. and Holbrook, J.S. Toward equitable AI for the next billion users. *ACM Interactions, 26*, 1 (Jan.–Feb. 2019), 68–71.
3. Martinus, L. and Abbott, J.Z. A focus on neural machine translation for African languages. arXiv preprint arXiv:1906.05685, 2019; https://arxiv.org/abs/1906.05685
4. Jakku, E., Taylor, B., Fleming, A., Mason, C., Fielke, S., Sounness, C., and Thorburn, P. 'If they don't tell us what they do with it, why would we trust them?' Trust, transparency and benefit-sharing in smart farming. *NJAS-Wageningen Journal of Life Sciences 90* (2019); https://www.sciencedirect.com/science/article/pii/S1573521418301842
5. Steup, R., Santhanam, A., Logan, M., Dombrowski, L., and Su, N.M. Growing tiny publics: Small farmers' social movement strategies. *Proc. of the ACM on Human-Computer Interaction 2*, CSCW (2018), 1–24.
6. Okewu, E., Misra, S., Fernandez, S.L., Ayeni, F., Mbarika, V., and Damaševičius, R. Deep neural networks for curbing climate change-induced farmers-herdsmen clashes in a sustainable social inclusion initiative. *Problemy Ekorozwoju 14*, 2 (2019); http://yadda.icm.edu.pl/baztech/element/bwmeta1.element.baztech-03011668-b8c1-4f4c-ba4f-13b51fc2470c

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