Inclusively Advancing Agri-Food Systems through AI and Automation

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This document presents a subset of the full study on Inclusively Advancing Agri-Food Systems Through AI and Automation, focusing on **considerations to inclusively advance AI and automation in agri-food systems.**

INTRODUCTION

The Age of Artificial Intelligence (AI) is upon us - driven by unprecedented rates of innovation and adoption. Interest in AI has exploded as ChatGPT continues to capture the imaginations of the world. This AI technology - able to perform a wide range of language tasks at accuracies not seen before - was touted as the next frontier of AI capabilities until being achieved by OpenAI's GPT4 model. This step-change in the capability and accessibility of technology is the latest in a growing trend over the last century. In the early 1900s, the innovation and adoption of advanced agronomic practices and technologies such as high yield seed varieties, chemical inputs and mechanization led to the green revolution. The rapid growth in the capabilities of AI over the past decade is creating a new revolution in how every industry and sector around the world operates and is structured, and agriculture is no exception.

This revolution occurs at a time when the demands of the 21st century require a step change in agri-food system capabilities. The United Nations estimates that the global population will reach almost 10 billion people by 2050, with the majority living in LMICs in Africa and Asia.[1] This anticipated population boom will require a 60-70% increase in global food production by 2050.[2] The pressure on agri-food systems to produce more food to meet growing demand is compounded by the significant risks that climate change imposes on farming systems, particularly through changes in temperature and rainfall, extreme weather events and the increase in the number of pests.[3]

SSPs in LMICs, and their engagement with technology, are at the heart of whether and how this step change can occur. Although SSPs generate around one third of the world's food, they provide the vast majority of food consumed in sub-Saharan Africa and Asia – the regions where the bulk of the world's growing population will reside.[4] SSPs in LMICs are also among the poorest people in the world, with many living on less than $2 per day.[5] Even if larger, commercially oriented farmers alone were able to meet rising demand for food by adopting smart technology solutions, this would serve to further disenfranchise SSPs and the rural communities that depend on them. Enhancing the ability of SSPs to become more productive and resilient is therefore crucial, not only to global food security but to the economic and social development of LMICs.

AI and automation technologies have potential to deliver this step change due to significant advancements in their capabilities and a reduction in their costs. Foundational digital applications in agriculture are already demonstrating impact among SSPs. These include advisory services delivered through ICT rather than in-person, digital value chain payments creating an electronic record of income to better access financial services, and e-commerce platforms to procure inputs and sell products, among many others. Rapid advancements over the last decade in the capabilities of AI and digital automation technologies, with lowering barriers to entry and use, can build off this base to deliver greater value to SSPs at a much larger scale.

Despite their potential contribution, the impact that these advanced technologies among SSPs in LMICs will have is unclear. Whether they will help SSPs to improve their productivity and resilience to the extent that is required depends greatly on which value chain players the solutions are designed for; the accuracy and relevance of the solutions for SSPs; the accessibility and affordability of AI and automation and the underlying technologies; and the commercial viability of the solution providers. As with any new technologies, there are likely to be unintended consequences and risks that may limit this impact agri-food value chains are disrupted.

The full study aims to provide a compass to stakeholders navigating the complexities of these issues. As the application of these technologies among SSPs is still in the early stages, it is difficult to predict what their net impact will be, and almost impossible to do this quantitatively without significant investment in primary impact data collection. This report therefore provides a framework for considering the varied and sometimes contradictory impacts that specific AI and automation use cases may have in different contexts, and the trade-offs that need to be navigated by those working in agricultural and inclusive technology development.

This document presents four clear objectives that are required to inclusively advance AI and automation in agri-food systems. Under each objective, the study provides a number of recommended actions which will spur progress towards the set objective.

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1 United Nations, 2021, *World population projected to reach 9.8 billion in 2050, and 11.2 billion in 2100,* available here
2 GSM Association, 2022, *Assessment of smart farming solutions for smallholder farmers in low and middle-income countries,* available here
3 Mbow et al., 2019, *Food Security, Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*, available here
4 Fanzo, 2017, *From big to small: the significance of smallholder farms in the global food system*, available here
5 World Bank, 2016, *A year in the lives of smallholder farmers*, available here

METHODOLOGY

The study began with a comprehensive landscaping of AI and automation solutions in LMICs. This involved collecting information on current examples of AI and automation in agri-food systems in the twenty-three priority counties identified by the Bill and Melinda Gates Foundation (BMGF) and the US Agency for International Development (USAID).[6] Common types of applications – and their underlying AI and automation technologies – were identified in order to develop a taxonomy of use cases depending on where in the value chain they were being applied and what the core function of the technology was. This taxonomy was then used to select eight priority use cases with the greatest prevalence and potential for impacting on SSPs. The remainder of the study focused on these cases.

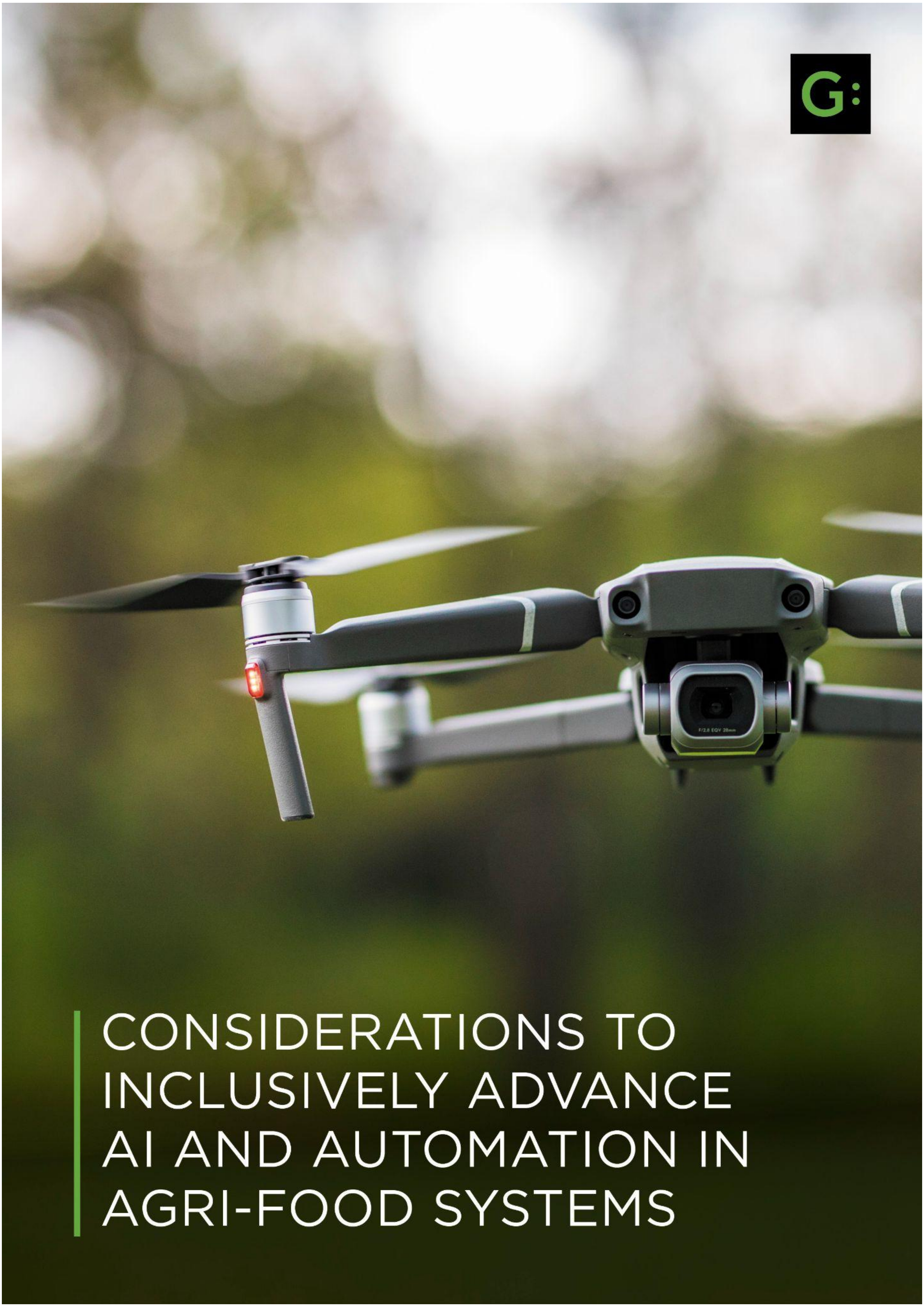
The stakeholder engagement phase collected information through targeted stakeholder interviews across the agri-food, technology and development ecosystem. These included interviews with agricultural policymakers and program officers, agricultural practitioners, impact investors, AgTech providers, and other agriculture and inclusive technology development experts. A full list of stakeholders is provided in Appendix 1. The purpose of the interviews was to uncover information on the technology requirements, delivery models and impacts of the prioritized use cases. A request for information was also issued to gauge a wider set of written responses to these questions.

The priority use cases were then analyzed through a framework that aimed to understand the potential impact channels – both positive and negative – and the factors likely to influence them. The framework components included economic, social, environmental and technological opportunities and risks. The most common opportunities and risks were synthesized into four key impact channels: productivity, cost saving, inclusion and climate resilience. This led to the identification of several cross-cutting trade-offs and considerations for solutioning, which need to be considered to maximize the opportunities and minimize the risks.

The cross cutting trade-offs and considerations for solutioning were then explored through several Joint Solutions workshops. The Joint Solutions methodology convenes small groups of diverse stakeholders, each of whom have a different perspective on a problem with diverse ideas on how to solve it. The purpose of the workshops was to validate the findings that emerged from our diagnostic assessment and identify potential solutions to the barriers preventing AI and automation innovation from supporting inclusive outcomes in agri-food systems.

The insights from the workshops were used to co-create policy, program and technology recommendations that can help overcome the barriers to achieving inclusive and impactful adoption of AI and automation in agrifood systems. The findings of our study, including the policy and program recommendations were presented in a public dissemination webinar on Tuesday the 4th of April 2023. The presentation outlined the key risks and opportunities of this tech-driven agricultural transformation, providing solutions to steer the ecosystem toward more inclusive outcomes.

[6] Bangladesh, Burkina Faso, DRC, Ethiopia, Ghana, Guatemala, Honduras, India, Kenya, Liberia, Mali, Madagascar, Malawi, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda and Zambia.



CONSIDERATIONS TO INCLUSIVELY ADVANCE AI AND AUTOMATION IN AGRI-FOOD SYSTEMS

Through extensive stakeholder consultations and solution workshopping, this study has identified four key objectives for the inclusive advancement of AI and automation in agri-food systems. Under each objective, we outline key actions that will make significant progress toward achieving the set objective. The objectives and actions speak directly to the application of AI and automation in agri-food systems. They do not discuss efforts to improve the general enabling environment for digital technologies, such as rural connectivity or access to finance, as these themes are addressed comprehensively elsewhere in the literature.

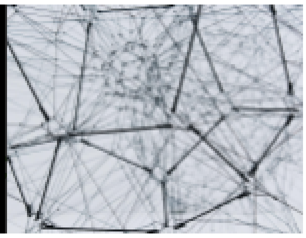
Constraints addressed by the recommendations

Poor market infrastructure	Governance and ethics gaps	Fragmented ecosystems	Capacity strengthening

Objectives and actions	Constraints addressed	Stakeholders responsible
OBJECTIVE 1: ROBUST TECHNOLOGY AND DATA INFRASTRUCTURE		
Establish an agricultural data exchange with a sustainable contributor network and a reference framework for data interoperability.	Poor market infrastructure	Donors, governments, AgTechs, NGOs, academia
Reduce on-farm hardware costs by reducing import tariffs, promoting domestic hardware recycling, and stimulating open-innovation between hardware patent holders and local innovators.	Governance and ethics gaps	Governments, AgTechs
Support white label software infrastructure developers to align development with the demands of AgTech developers.	Poor market infrastructure	Infrastructure developers, AgTechs, research/consulting services, PE/VC investors
Invest in the development of inclusive and frontier agricultural AI through research and representative data collection.	Poor market infrastructure	Donors, governments, academia, AgTechs
OBJECTIVE 2: FARMER-CENTRIC, SCALABLE AND FINANCIALLY VIABLE SOLUTIONS		
Scale the establishment of trusted intermediary networks as last-mile agents, data collectors and support staff for AgTechs.	Poor market infrastructure	Donors, governments, AgTechs
Unlock government demand for climate-smart digital extension advisory through technical assistance.	Fragmented ecosystems	Donors, governments, professional services
Strengthen the capacity of farmer organizations to facilitate bottom-up development of farm data management solutions, and act as procuring entities for purchasing costly AgTech solutions.	Capacity strengthening	Donors, governments, farmer organizations
OBJECTIVE 3: SUPPORT FOR MANAGING DIGITAL, DEMOGRAPHIC AND GREEN TRANSITIONS		
Provide vocational training and apprenticeships to equip young rural people - especially women - to take up new work opportunities in the AgTech value chain	Capacity strengthening	Donors, governments, social enterprise
Expand social support mechanisms and pathways to productive employment to support individuals affected by disruption.	Governance and ethics gaps	Donors, governments, social enterprise
Support regulators to examine the potential for digitally enabled harmful market conduct impacting agri-food systems.	Governance and ethics gaps	Donors, governments
Socialize an environmental Extended Producer Responsibility approach amongst AgTechs to shift product end-of-life responsibility upstream.	Governance and ethics gaps	Donors, governments, AgTechs
OBJECTIVE 4: ETHICAL AI AND DATA GOVERNANCE		
Develop and disseminate a domain-specific and gender-sensitive ethical impact assessment framework for the use of AI in AgTech.	Governance and ethics gaps	Donors, AgTechs, NGOs, PE/VC investors
Pilot a farmer-centric agricultural data trust that appoints an independent steward to manage AgTech data in the best interests of key stakeholders, chiefly SSPs.	Governance and ethics gaps	Donors, governments, research/consulting services, NGOs
Equip farmer co-ops, NGOs and extension service officers to support SSPs with a formalized recourse avenue in the event of opaque or otherwise unethical AI decision-making.	Capacity strengthening	Donors, governments, farmer organizations, NGOs
Establish regional AI labs to design resources and products to improve the accuracy, representativeness, explainability and failure detection capabilities of AI models in agriculture	Fragmented ecosystems	Donors, governments, AgTechs, academia

OBJECTIVE #1:

ROBUST TECHNOLOGY AND DATA INFRASTRUCTURE



The AgTech innovation ecosystem needs high-quality and locally relevant data at low costs to develop accurate solutions. Since private businesses currently collect and own much of this data, they require incentives to share their data. Targeted data collection, AI research and innovation require efforts to integrate knowledge and expertise between AI engineering and agronomy. In LMICs, infrastructure innovation is particularly important to ensure that hardware can be adapted to local conditions cost-effectively, and white label software infrastructure developers are more demand driven in tailoring their solutions to agriculture applications. The four actions described below aim to provide mechanisms to cultivate these requirements for a thriving AgTech innovation ecosystem in LMICs.

01 ***Establish an agricultural data exchange with a sustainable contributor network and a reference framework for data interoperability.***

A global agricultural data exchange can scale data reuse by allowing data providers and consumers to transact in a way that is mutually beneficial. A data exchange allows entities with data assets to responsibly share or sell their data with data consumers such as AgTech developers, researchers or governments. Data-driven organizations are willing to share and get returns for some of the data they collect, but do not currently have the mechanism to do so responsibly without jeopardizing their commercial incentives. The exchange needs to be operated by an independent third party to develop an interoperability framework to ensure data is classified in a way that all users understand and that consumers can receive data in their required format. The data exchange will allow consumers to post the data that they are looking for. This will provide visibility of data gaps and can be used by entities such as Lacuna fund[7] to inform data collection priorities. Visibility of the demand for data would complement the data collection activities in Solution 4 of this objective (*Invest in the development of inclusive and frontier agricultural AI through research and representative data collection*). A critical activity here would be incentivizing the reporting of underrepresented data by marginalized and less technologically connected populations. This would involve experimentation with user-centric incentives and enablers. Direct incentives can include cash payments, asset transfers or data monetization schemes, and enablers should include strengthening of data management capacity of farmer organizations (as discussed in Objective 2), alongside participatory data governance schemes (as discussed in Objective 4).

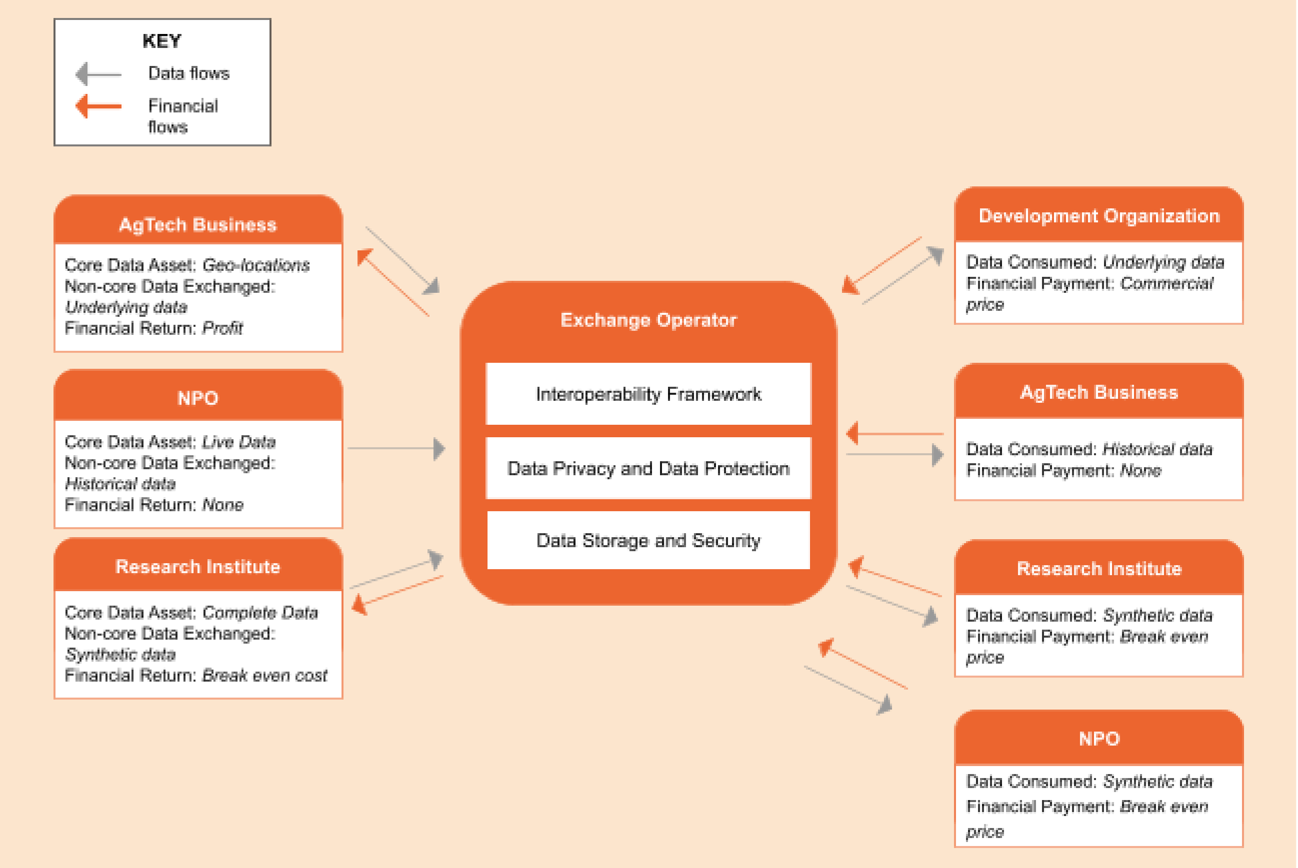
A successful data exchange is as much about technology as it is about providing incentives and creating a sustainable business model. To participate in a data exchange, commercial data asset holders will be prescriptive about who can use their data assets and what they expect in exchange. Understanding what kinds of data different organizations would be willing to share, and the return they expect, will be critical. The functionality and capabilities that data asset holders require from an agriculture data exchange platform could be determined through a grant-funded pilot. The exchange operator should become a commercially sustainable entity by collecting a fraction of each data exchange transaction's revenue. Lastly, the needs of the data subjects themselves are a key consideration - including their autonomy to determine how their data is used and monetized. To that end, the recommendations in Objective 4 (ethical AI and data governance) are material. The table below provides an indication of the exchange's participants, their role and what they would require to participate.

[7] Lacuna Fund. 2023. Available here.

Table 6: Data Exchange participants and their incentives

Role	Requirements
Exchange operator	
• Develop and market the agriculture data exchange • Develop an interoperability framework that accommodates different methods of data transformation, classification and accessibility. • Introduce internal controls to vet data providers to ensure data quality • Introduce 'dataset badges' that indicate that some of the proceeds of the sale of a dataset will be directed to the data subjects • Determine whether there are inherent limitations such as the sale of personally identifiable information	• Grant funding for the pilot and seed funding thereafter • The ability to earn revenue from a portion of transaction fees conducted through the exchange
For-profit data asset holders	
Submit data assets to the platform	• Commercial incentive to participate based on making a return on non-core data assets
Non-for-profit data asset holders	
Submit data assets to the platform	• Sharing data with no returns • Break-even cost of data collection if there are no legal challenges • In kind rewards like connections to stakeholders who could help them further their objectives
Data consumers	
Purchase data from the platform	• Ethically sourced data • Data vetted • Data extractable in desired format
Data subjects	
Submit data assets to the platform that are stored and managed through the mechanisms outlined in Objective 4	Revenue or in-kind reward- the structure of the returns would be based on the collective benefit structure of the data subjects.

BOX 11: ILLUSTRATIVE EXAMPLE OF AN AGRICULTURE DATA EXCHANGE



02

Reduce on-farm hardware costs by reducing import tariffs, promoting domestic hardware recycling, and stimulating open-innovation between hardware patent holders and local innovators.

Governments should reduce the costs of on-farm hardware like sensors, drones and mobile devices by leveraging trade, industrial policy and innovation levers. Widespread adoption of locally relevant on-farm hardware can generate significant yield and resilience benefits for SSPs. However, these technologies remain prohibitively and persistently unaffordable for most. Policymakers should pursue a threefold strategy for reducing costs. First, trade ministries should lower hardware import tariffs - in accordance with WTO bounds - to reduce the costs of purchasing international hardware for local procurers. Second, industrial policy strategies should promote the recycling of domestic hardware, through instruments such as tax rebates. Third, both governments and investors should stimulate open-innovation initiatives between patent holders of sensor hardware and local innovators; a successful example of this model is provided in the box below.

BOX 12: PHILIPS' OPEN INNOVATION ECOSYSTEM

Philips' open innovation ecosystem is a global network of innovation hubs which provide resources to small technology firms to innovate on their patented solutions. Philips collaborates with many external sources for its new products including universities, research centers, and start-ups. This accelerated research, development and commercialization of solutions makes it possible for Philips to utilize knowledge and insight from experts of various backgrounds while providing them with an inspiring research and development sandbox. In 2017, 1,733 new patent applications were filed from the Netherlands alone.

A notable product that came about from open innovation at Philips is the Airfryer, invented by Fred van der Weij.[8] The kitchen appliance division at Philips had been trying to develop a process to fry using hot air/steam for a number of years, by 2006 they had a prototype. The engineers in the division were not successful in shaping the prototype into a consumer product that was simple and inexpensive. In 2009, Fred approached Philips due to the limited resources he had at his disposal to enter the product development phase. Fred's technology was based on a similar idea but with mechanisms that resulted in a simple product with a user friendly interface. Philips provided financial resources, production facilities, market credibility and the distribution network to move the technology forward.

Philips evaluated the technology then signed a licensing agreement with Fred van der Weij in October 2009. The Licensing agreement exclusively entitled Philips to the technology in the consumer market for five years. At the end of the period, the agreement gave Philips the right to buy the technology at a predetermined price. Airfryer was initially introduced in a portion of the European market, and due to the market response the product was launched on a global scale.

Benefits to Phillips	*Benefits to the Innovator*
New technology without lengthy and costly research project	*Commercialize innovation without complementary asset investments*
Decreased time to market	*Independence to serve niche markets where Philips does not play*
If the innovation is successful, they have the option to purchase the technology	*Royalty income from Airfryer finances company growth and further research and development*
Reputation as trusted innovation partner	

03 ***Support white label software infrastructure developers to align development with the demands of AgTech developers.***

Agriculture-specific white label software infrastructure is a critical backbone of cost-effective AgTech solution development. This infrastructure is a set of tools, frameworks and other resources for software development.[9] White label infrastructure is a form of digital public good which includes "Open source software, open data, open AI models, open standards and open content that adhere to privacy and other applicable international and domestic laws, standards and best practices, and do no harm".[10] White label software infrastructure accelerates application development and generates better software applications, as AgTech solution developers can focus their resources on developing their unique value proposition and proprietary technology, instead of building underlying infrastructure for solutions. However, white label software infrastructure providers tend to develop in silos, such that the reusable infrastructure is not tailored to the demands of the application developers.

[8] European Journal of Innovation Management. 2017. *How start-ups successfully organize and manage open innovation with large companies*. Available here

[9] These resources may include re-usable code blocks, toolboxes that provide instructional documentation or software application wireframes.

[10] United Nations. 2020. Report to the secretary general: Roadmap for Digital Cooperation. Available here.

Interested parties should invest in facilitating a demand-driven approach to infrastructure innovation. This approach requires a thorough determination of AgTech data priorities, through landscape analysis, expert advice and stakeholder interviews. Any research must invest in developing feedback loops between infrastructure providers and software developers, to enable an agile, iterative response to shifting technological frontiers or developer needs. This process will prioritize software infrastructure at its inception, but will be extended to other elements of digital public goods. These efforts could be undertaken by research/consulting services firms providing technical assistance to promising infrastructure providers, funded by donors. Alternatively, PE/VC investors looking to scale their infrastructure investments could provide or commission this support themselves.

BOX 13: LACUNA FUND

Lacuna Fund is an organization that provides grants to data scientists, researchers and social entrepreneurs in LMICs to develop labeled, open-source datasets. These datasets are intended to underpin AI solutions that can address key community needs. Data priorities are determined by a steering committee, who conduct desktop research and key informant interviews with both community members, innovators and potential grant recipients.

This model could be extended to the development of software infrastructure. In this instance, infrastructure developers would periodically engage with AgTech developers and sector experts through a forum to determine which software to prioritize in their upcoming development cycle.

04 ***Invest in the development of inclusive and frontier agricultural AI through research and representative data collection.***

AI models trained specifically for the agricultural domain and local geographies will markedly improve the accuracy and applicability of AI solutions in LMIC agri-food systems. For example, limited datasets in local languages mean that many AI solutions only exist in English, limiting accessibility or resulting in incoherent language outputs from the AI system. However, building more locally relevant AI models from the ground-up would be prohibitively costly, given the massive number of data points needed to effectively train a new model. Transfer learning offers a more cost-effective solution. As discussed in Appendix 5, transfer learning leverages existing AI models and applies them to new contexts. Effective transfer learning requires good geographic and local data assets, such as an open-source local language corpus with part of speech annotations or high-resolution local crop imagery. It may also require new ways of collating and storing this data, for example through domain-specific knowledge graphs. Finally, it requires deep, technical research on how best to apply these resources to existing models.

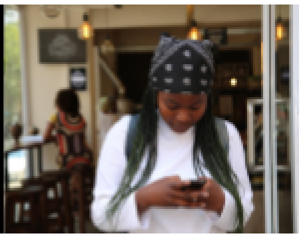
Donors and governments should invest in frontier research and data collection activities, and socialize the models developed through this process. One method would be to establish a regional network of agriculturalists, academics, AI practitioners and entrepreneurs with a mandate to strengthen collaborative efforts towards the development of AI in agriculture in LMICs. This community would also ensure that the agricultural community is at the frontier of AI research by exploring the risks and opportunities of developing an AI foundation model, and exploring how LLMs and other frontier AI technologies can be applied in the agricultural domain. This network would conduct research, host events and forums, solicit journal publications and other activities aimed at closing information silos and data gaps, advancing frontier AI in agriculture research and connecting AgTech developers to locally relevant models that can improve their solutions. Socializing the research of the community would increase the extent to which learnings are applied in large language models in the agricultural sector. These tasks could also be successfully carried out by a dedicated Agriculture AI Lab, as proposed under Objective 4.

BOX 14: OPEN SOURCE MACHINE LEARNING REPOSITORY IN HEALTHCARE

Health Catalyst launched the first open source, machine learning repository specifically for healthcare to accelerate industry-wide collaboration in the development of AI solutions for advanced healthcare outcomes, named Healthcare.AI. Before the launch of this repository the use of machine learning and predictive analytics was largely limited to data scientists within specific academic medical centers in the United States. However; subsequent to its launch, the site has provided a central platform to download algorithms and tools, read documentation, request new features, submit questions and contribute code.

OBJECTIVE #2:

FARMER-CENTRIC, SCALABLE AND FINANCIALLY VIABLE SOLUTIONS



The widespread adoption of AI and automation technologies in agri-food systems requires solutions with a deep sensitivity to local context and SSP needs. For example, many farmers can only use solutions in their local language, and will only trust technologies if delivered via a human intermediary. In addition, solutions must be both affordable to SSPs and financially viable for solution providers. Three key actions will accelerate the development and adoption of farmer-centric, scalable and financially viable solutions.

01 *Scale the establishment of trusted intermediary networks as last-mile agents, data collectors and support staff for AgTechs.*

Shared intermediary networks with potential for commercial sustainability are a critical human interface for SSPs to adopt AI and automation solutions. AgTech solutions typically require product education, installation assistance and post-installation support, such that many SSPs will only adopt these technologies if they are provided with a human touch. Intermediary networks can also collect accurate, on-farm data for an AgTech provider; a last-mile service that is less costly than training and deploying dedicated enumerators. However, building and scaling an intermediary network is a costly and time-consuming process. As many intermediary networks already exist (as discussed under Delivery Models), a solution is to establish these networks as shared infrastructure, wherein multiple AgTechs and other organizations contribute to the costs of establishing and/or utilizing the same networks. A successful example of this model is provided by Kuza, as discussed in the box below. That said, the requirement for a human touch in delivery can lead to the exclusion of women, if delivery models are not designed to be deliberately inclusive. This is because agents are typically men, and in more conservative cultures, cultural norms or rules may dictate that women do not interact with men outside of their family.

BOX 15: THE KUZA ONE NETWORK

Kuza Rural Entrepreneur Development Incubator (REDI) sources and trains rural young people ("agripreneurs") to provide last-mile bundled service delivery to SSPs. The organization has developed a methodology for sourcing and training the agripreneurs on both soft skills and more technical agribusiness skills, such as entrepreneurship, record-keeping, climate-smart technologies, regenerative agriculture and others. Agripreneurs are equipped with small hand-held projectors for offline use to deliver advisory content in-person to SSP groups in various local languages. In providing these advisory services to SSPs, the agripreneurs are well placed to also act as sales agents, booking agents and data collectors for AgTechs, input producers and other organizations interested in engaging with SSPs.

Kuza also convenes a network of partners that leverage this intermediary network to engage with SSPs, either to sell their products and services or collect information. Kuza's model is more commercially sustainable than typical intermediary networks because these partners either offer a discount on products sold via the network, allowing Kuza to make a margin when selling them at market price, or provide funding. Both revenue sources allow Kuza to cover the operations of the network and pay a commission to the agripreneurs. This is facilitated by the *Kuza One* web platform that monitors intermediaries, matches suitable SSPs and solution providers and manages payments. Kuza's REDI has trained over 5,000 young people, who have provided services to over 750,000 SSPs across Africa and Asia.

Donors, governments and AgTechs should explore avenues to scale these shared intermediary networks in a gender-sensitive manner. One option would be to fund the creation of new networks in markets where they do not already exist, although this would be resource intensive for the reasons discussed above. An alternative is to provide support for existing network-building organizations to expand to new markets, through a combination of finance, market intelligence, technology support and industry connections. However, these organizations often do not have the capacity to expand beyond their current operations. A more sustainable option is to support the franchising of these network builders' existing IP and license this to other organizations looking to replicate the model in other markets. This IP includes the methodology for sourcing, screening and skilling the intermediaries, the content the intermediaries use to engage with farmers, and the technology platform that manages the partners and payments. Lastly, stakeholders could leverage parallel agent networks - such as those operated by mobile network operators - to perform AgTech intermediary tasks. This would require negotiated agreements between parent network operators, funders and AgTechs. Regardless of the pathway selected, funders should prioritize the promotion of female agents, which will lead to greater women's empowerment alongside greater reach for the AgTechs.

02 *Unlock government demand for climate-smart digital extension advisory through technical assistance.*

Climate change is challenging the effectiveness of traditional state-operated extension services, with significant opportunity for AgTechs. As identified under Use Cases, changing weather patterns and other climate impacts are outdating the traditional advice available to SSPs. AI-enabled and digitally delivered extension services - potentially via chatbots akin to ChatGPT - have the potential to provide climate-smart advisory at the requisite level of personalization and timeliness, at scale. Governments in LMICs typically allocate significant budgets to in-person extension advisory, and are increasingly interested in automated solutions with greater scale potential. Unlocking this government demand for climate-smart digital extension services can be an important source of revenue for AgTechs given that SSPs are generally unwilling and/or unable to pay.

Donors and governments should commission technical assistance to help policymakers procure AI-enabled climate-smart extension advisory services from AgTechs at scale. This work will help agricultural or other ministries identify which AI-enabled extension solutions are required, and which AgTechs could credibly provide them. The technical assistance must help governments develop frameworks and procedures for identifying, screening and scaling potential suppliers in a comprehensive, objective and transparent manner. Activities should include needs diagnoses and solution landscaping, and assistance drafting and evaluating RFPs. Finally, assistance must also prepare departments to work with lean, tech-enabled AgTechs by embedding new ways of working such as human-centered or iterative design principles. This transition would also require some organizational design shifts, such as appointing a dedicated innovation officer or including AI experts on procurement panels. One example model for doing this at scale - which governments and service providers could jointly evaluate and adapt according to local needs - is the *Techemerge* initiative, discussed in the box below. Technical assistance could be delivered by consultancies, NGOs or other analytical organizations.

BOX 16: TECHEMERGE

Techemerge is an IFC initiative that accelerates the development and adoption of technology solutions in the health, resilience and sustainable cooling spaces. The initiative works with organizations that have latent demand and large budgets, such as large corporations and governments, to understand where technology innovation can solve challenges. Techemerge then matches these organizations with innovators through a standardized scouting and selection process. When matched, Techemerge provides institutional support to both the innovator and the organization procuring the initiative. This support is aimed at overcoming institutional barriers to this sort of collaboration, including but not limited to ways of working.

03 *Capacitate farmer organizations to facilitate bottom-up development of farm data management solutions, and act as procuring entities for purchasing costly AgTech solutions.*

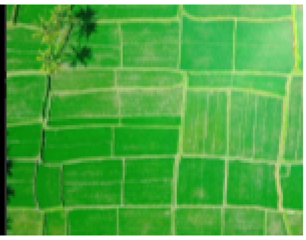
Farmer cooperatives and organizations can play a greater role in stimulating the adoption of effective AI and automation solutions by SSPs. As identified under Delivery Models, digital products that are devoid of local context and farmer autonomy are unlikely to be trusted, scalable solutions. To address this risk, digital products should be designed via a bottom-up process that includes SSPs. Farmer organizations should be important conveners, facilitating and participating in the co-creation process. While this bottom-up approach to design may be more costly for AgTech, working through farmer groups is a more cost-effective way of securing HCD inputs and ultimately leads to products that are more likely to be in-demand. In addition, many AI & automation solutions are inaccessible to SSPs due to affordability concerns. Demand aggregation ー coordinated by farmer organizations ー would facilitate lower per-product or per-SSP prices for otherwise costly solutions. This could occur either through volume discounts negotiated with AgTech providers, or asset sharing agreements amongst the SSPs.

Donors, governments and AgTechs should invest in capacity strengthening programs that empower farmer cooperatives to be part of the solution development process *and* to be effective procuring entities. To effectively contribute to the development of an AI and automation solution, farmer organizations must have sufficient digital skills to manage local data sets, which may require training on cloud-based data management platforms. Organizations also require the educational skills to be able to impart this knowledge to their SSPs, and be able to effectively solicit feedback from SSPs on whether the solutions address their needs. This includes identifying SSPs most likely to give valuable feedback, understanding what questions to ask and when, and ensuring users have the right incentives to provide honest feedback. To be an effective procuring entity, farmer cooperatives must be able identify a wide variety of SSP needs proactively and comprehensively, scout for potential solutions, and have the requisite legal and negotiation skills to deliver an fair, affordable contract for the SSPs. In addition, for asset sharing models in particular, farmer organizations must set clear expectations with respect to product use, maintenance and upgrading. Capacity strengthening programs can fill gaps in these required capabilities.Programs could be delivered through in-person or online courses and should be operationalized by NGOs, dedicated skills trainers or AgTechs. One capacity building model that could be adapted to suit the needs set out above is utilized by *AMEA*, discussed below.

BOX 17: AMEA'S BLENDED LEARNING APPROACH

AMEA is an agricultural alliance that is dedicated to advancing professionalism of farmer organizations globally. In Kenya, the organization aims to increase uptake of digitally delivered financial inclusion and extension advisory information by SSPs. To achieve this aim, AMEA led a capacity building initiative for farmer organizations.[11] This program selected 108 participants from 35 farmer organizations via a standardized selection process, which included English language and remote participation requirements. Participants took part in six modules, which included learnings on governance, financial management, marketing, and growing the member case. Modules were delivered through a combination of mobile and in-person delivery. AMEA is currently scoping potential support it can provide to farmer organizations to encourage the uptake of AgTech solutions.

[11] AMEA, 2021. Blended learning using AMEA tools. Available here.



OBJECTIVE #3:

SUPPORT FOR MANAGING DIGITAL, DEMOGRAPHIC AND GREEN TRANSITIONS

AI and automation solutions are being implemented in a fast transitioning world. The demographic transition creates an imperative to generate new work opportunities for a rapidly urbanizing young population, while providing socio-economic support for older SSPs. The green transition means that AgTech solutions must minimize their environmental impact while improving equity within societies. Lastly, the digital transition requires policymakers to be equipped to identify and address novel market risks. Four actions will provide the requisite support for these transitions.

01 *Provide accessible vocational training and apprenticeships to equip young rural people - especially women - to take up new work opportunities in the AgTech value chain*

Young people are entering the labor market in LMICs in unprecedented numbers and urbanizing rapidly, creating a development imperative to generate work opportunities at scale - particularly for rural populations. As identified under Impact Pathway 3, the implementation of AI and automation solutions creates some labor-shedding concern, but is also generating real opportunities for young people to work in AgTech enabling roles, such as intermediary agents, drone pilots or data annotators. These opportunities are unique in that they create income-earning potential for young people in rural areas, without requiring migration to urban centers. However, it is not automatic that these opportunities will be taken up, as they have novel requirements that demand capacity building across a mix of soft and technical skills.

Firms, donors and governments should invest in vocational training and apprenticeships to link suitable host enterprises with talented youth - especially women. Organizations in the AgTech value chain that are creating work opportunities should invest in sourcing, screening and training rural young people to fulfill these opportunities. This sourcing process must prioritize young women, to address workforce underrepresentation, gender wage disparities and discriminatory cultural norms that prevent women from accessing better job opportunities. In addition, a central employment accelerator (like *Harambee*, as discussed below) that facilitates the sourcing, screening, skilling and matching of young people to hiring organizations is an effective way to provide this service to multiple employers. This model has enjoyed success in other markets largely due to the demand-driven nature of the work - young people are skilled in accordance with the specific demands of the hiring organizations. In either approach, governments and donors can subsidize the costs, through instruments like wage subsidies or challenge funds, where hiring organizations or employment accelerators can apply to receive funding on the premise of creating a certain number of jobs.

BOX 18: HARAMBEE YOUTH EMPLOYMENT ACCELERATOR

Harambee Youth Employment Accelerator is a social enterprise that facilitates youth employment in Africa through sourcing and job placement initiatives. Harambee hosts a young talent database, which is populated by recruiting young people and screening them for aptitude. The social enterprise also coordinates a pool of employers that are looking to hire young talent, and investigates and documents the particular skills and capabilities that each organization requires. Harambee then automatically matches candidates to available appropriate opportunities, and provides the training and skilling required to fulfill a given position. These efforts are facilitated through Harambee's bespoke web platform called *sayouth.mobi*. In addition to managing the matching process and hosting individual and enterprise data, this data-free website is a resource hub for training courses and related resources, such as interview tips, digital skills and "how to hustle". Finally, Harambee undertakes research and advocacy activities that aim to actively create more demand for young talent in emerging markets.

02 *Expand social support mechanisms and pathways to productive employment to support individuals affected by disruption.*

The inevitable winners and losers of parallel transitions require new forms of social support. At-risk communities include casual farm laborers that are displaced due to automation, or SSPs that are unable to access AI and automation technologies, rendering them uncompetitive relative to larger, more tech-enabled producers. These individuals may face high barriers to transitioning into new industries, due to affordability constraints, distance from opportunity, health and other age-related concerns, or cultural commitments to remaining on ancestral land. In agri-food systems, rural, older farmers are most likely to be affected in this manner.

Donors, governments, NGOs and civil society organizations must invest in socio-economic support mechanisms to protect at-risk people from the most distressing socio-economic outcomes. Social support systems and the challenges they look to solve are evolving, and should be highly tailored to the country context and the needs of the beneficiaries. Further research is required to fully understand which groups are most at-risk through the AgTech transition, and which levers work best to support them sustainably. One common approach to building social resilience is the use of transfers, as discussed in the box below. Some key design choices would be whether to provide cash or in-kind transfers, the quantum of the transfer, targeted versus universal distribution, identifying the appropriate household recipient and establishing a funding mechanism for the transfers. Social support may also include mental health interventions. Some playbooks recommend a "cash+" approach, which combines cash transfers with asset transfers and upskilling.

Social support in isolation is insufficient; stakeholders must also enable new pathways to productive employment. These efforts involve upskilling, capacity strengthening and employment matching initiatives, as outlined in Box 18. These interventions are typically carried out by governments or NGOs. However, models where technology firms compensate those most affected by disruption - via social support and/or investment in new employment pathways - must also be considered. This is especially pertinent if firms leverage data provided by those who are affected to enact the disruption. This model could be operationalized via top-down regulation, where government agencies require firms to pay public interest compensation if labor disruption is expected. A complementary, more bottom-up approach would be advocacy and community work that enforces financial compensation for disruption as a prerequisite for doing business with local communities. Some firms may already see a commercial case for such investment, particularly if their business models rely on community trust and regular local engagement.

03 *Support regulators to examine the potential for harm in digital market conduct in agri-food systems.*

Regulators need to consider the new market risks created by platformication and digital transitions in agri-food systems. One potential issue is the consolidation of IP and/or data that AI and automation solutions are built upon amongst a few companies located outside LMICs. Another potential issue is anticompetitive partnerships between Big Tech and local firms, via tying & bundling or killer acquisitions.[12] In both cases, the "winner-take-all" dynamics drive higher prices and reduced consumer choice. In turn, this can stifle innovation and create uneven power dynamics between incumbent platforms and their users, and between tech-developing and tech-receiving nations. In addition, as agriculture industrializes and starts prioritizing economies of scale - a process that may be accelerated by AI and automation solutions - there is a risk of land consolidation amongst the largest farms. This would generate unequal power dynamics between the large commercial farmers and SSPs, creating real wellbeing consequences. As digital agriculture becomes more commonplace, the likelihood and potential severity of these risks increases.

Donors and governments should update regulators' toolkits to future-proof against competitive risks. Leading AgTech markets that have dedicated competition regulators, such as South Africa, India and Kenya, can

[12] Killer acquisitions are purchases of small, entrepreneurial start-ups by large incumbents, where the transaction is made explicitly to discontinue innovation products of the start-up, so as to stifle the risk of future competition for the incumbent.

begin establishing pathways that other countries in the region can follow in time as these market risks unfold. These pathways should include a combination of policy, capacitation and coordination levers. For example, capacity building training to help regulators identify harmful conduct that is unique to digital markets in agri-food systems will be important. Cross-border regulatory coordination will also be critical. This can be operationalized through the secondment of digital-focused regulatory experts between regulators, or the signing of MOUs to coordinate on key cases that touch on multiple jurisdictions. Levers may also include the consultative process of establishing and socializing new competition guidelines, particularly in geographic and/or product markets that are, in the regulator's view, particularly prone to anticompetitive outcomes. Finally, these views can be informed by domain- or sector-specific market inquiries, such as agricultural or digital platform inquiries. Market inquiries - such as the one described below - allow the regulator to take a more targeted, investigative and preemptive approach to regulation.

However, regulators must be cognisant that overly onerous intervention could have consequences for innovation and technology access. For example, there are many countries where the local technology infrastructure is not well-positioned to internally generate its own AI and automation solutions. In this instance, efforts to stifle hegemonic international actors from servicing these markets as a monopoly may come at the cost of its citizens accessing key technologies. Similarly, if regulators are overly interventionist on the acquisition of start-ups by larger incumbents, this may disincentivize innovative new entrants who see acquisition as a key exit strategy. Frequent, iterative market consultations and a data-driven approach to market analysis can help strike an appropriate balance between interventionist and free market principles. At the same time, collaborative efforts amongst local private, public and civil players to strengthen capabilities for the generation of local, effective, inclusive AI and automation solutions can mitigate the need for international market entry in the first instance. In turn, this offers a non-regulatory mechanism for mitigating the binary options of a monopolistic, extractive offering or no offering at all. The efforts may include capacity strengthening at the individual or organizational level, as discussed under Objective 2 and Objective 4.

BOX 19: SOUTH AFRICAN ONLINE INTERMEDIATION PLATFORM INQUIRY (OIPMI)

The South African OIPMI is an initiative instigated by the South African Competition Commission to investigate the state of competition across digital platforms in multiple sectors, including ride-hailing, e-commerce, food delivery, software application stores and online classifieds. The inquiry was initiated because the Commission had reason to believe that there are market features that restrict competition between platforms, undermine consumer choice, create conditions for exploitative treatment of business users and reduce economic participation by MSMEs and historically disadvantaged persons. Following an initial release of a statement of issues, the Commission has undertaken several rounds of public comment, business surveys, in-person hearings, follow-up requests for information, receipt of expert reports and publication of provisional findings. If adverse findings are reached, the Commission has legal avenues to pursue remedies, which may include divestment orders, fines, price caps or other public interest conditions.

04 *Socialize an environmental Extended Producer Responsibility approach amongst AgTechs to shift product end-of-life responsibility upstream.*

Effective e-waste management can be extended by leveraging existing Extended Producer Responsibility policy tools. Extended Producer Responsibility (EPR) is an environmental policy approach which requires producers to take financial and/or physical responsibility for managing their used or end-of-life products. EPR involves establishing a take-back scheme whereby, under the producer's responsibility, consumers can return products to be reused or repaired, refurbished, remanufactured, or recycled. This shifts the burden of product end-of-life management upstream to the producer and away from local governments and taxpayers; consistent with the polluter pays principle and cost internalization. In this regard, e-waste management can be extended using an EPR policy approach. For example, recent EPR legislation enacted by the South African Department of Forestry, Fisheries and the Environment (DFFE) in May 2021 now obligates producers of electronics and electrical equipment to track their products and ensure responsible recycling and disposal of them at the end of their useful life.[13]

[13] PackagingSA. 2021. *EPR Regulations.* Available online.

Socializing AgTech developers on approaches to adhere to EPR standards will become increasingly important, as mandatory compliance could soon become the standard. As new environmental laws continue are promulgated**,** mandatory compliance of AgTech producers in the monitoring and tracking, repurposing, and safe disposal of AgTech products such as IoT sensors, drones, and robots at their end-of-life, should be encouraged. Further, as Environmental, Social and Governmenance Law continues be promulgated across the world,[14] membership for AgTech producers to EPR or PRO schemes[15] could become compulsory to meet environmental targets.

BOX 20: NIGERIA'S CIRCULAR ECONOMY PLAN FOR E-WASTE

As one of the leading importers of electrical and electronic equipment on the African continent, the Nigerian Government has taken proactive steps towards sustainable waste management through the *Circular Economy Approaches for the Electronics Sector in Nigeria* project. The project provides a detailed roadmap and implementation plan for enforcing new regulations at a global environmental standard, and further strengthens the country's Extended Producer Responsibility system, providing the legal basis for its enforcement.

[14] International Comparative Legal Guides. 2023. *Environmental, Social and Governance Law.* Available online.
[15] Existing extended producer responsibility schemes or producer responsibility organizations that aid in the ethical and effective recycling and disposal of specific materials.

OBJECTIVE #4:

ETHICAL AI AND DATA GOVERNANCE

The nascency of AI and automation AgTech solutions leaves room for ethical, social and policy issues to arise. Tailored impact assessment frameworks are necessary to pre-empt potential for discriminatory impacts, while ensuring that SSPs are able to benefit from the use of their data requires participatory governance models like data trusts. In addition, recourse avenues must be developed to ensure appropriate remedies if harm occurs. Lastly the development of AI solutions should be steered to embed ethical considerations from conception. Four key actions will advance ethical AI and data governance in agri-food systems.

01 *Develop and disseminate a domain-specific and gender-sensitive ethical impact assessment framework for the use of AI in agriculture.*

Inclusive AI solution design should be supported by an agriculture-specific ethical AI assessment framework that is gender-sensitive. Many AI solutions are experimental, such that concretely identifying all potential impacts is challenging. For example, gender-based discrimination in financing can occur where algorithms determine that women are larger credit risks than men; an outcome which reflects unrepresentative underlying data rather than genuine risk. Impact assessment frameworks provide entrepreneurs, agribusinesses, data scientists, AgTech providers and software programmers alike with a methodical approach to assessing the relative severity of the potential ethical impacts, toolkits for estimating the likelihood of their occurrence, guidance on how to consider any potential value conflicts that may arise when implementing an AgTech solution and best practice on how to implement these solutions. Whilst several ethical AI impact assessment frameworks exist, there are none that are tailored to the agriculture domain, and few that explicitly include a gender lens.

The development and implementation of this framework must include a variety of stakeholders. To begin, development should leverage impact assessment blueprints from a consortium of multidisciplinary industries including health, energy and finance.[16] This research should be supported by consultations with the end-users of AgTech solutions and AgTechs themselves. Further, AI impact assessment frameworks must incorporate guidance on how to ethically manage gender-sensitive data or data on other marginalized populations, such as peoples with disabilities, ethnic, linguistic, and religious minorities, and others. For example, this might include guidance on how to ensure that gender and other factors are systematically included as a variable in solution design and in the monitoring phase. Lastly, donors and investors should firmly encourage AgTechs to use these frameworks in the development process, by making financing conditional on proven adoption of the domain-specific, gender-sensitive impact framework.

02 *Pilot farmer-centric and participatory data governance models in agriculture.*

SSPs should have autonomy over how the data collected on them is used and commercialized. Uncertainty on who owns and benefits from data collected and stored for AgTech solutions continues to be heavily debated. In most instances, the data collector and manipulator is the de facto owner, and is able to monetize or otherwise benefit from its use, subject to data privacy laws, where they exist. These firms have financially invested in the collection process, and the data is often a core commercial asset. However, how data subjects can benefit from the commercialization of their data, while providing sufficient return to the data collectors, has yet to be determined, and top-down regulatory guidance on this matter is either slow-moving or non-existent. This status quo leaves SSPs with limited autonomy over their data.

[16] Examples of these frameworks are accessible here.

Stakeholders should pilot agriculture-specific data governance models that strike a better balance between the interests of data subjects and collectors. There are various governance models that could be utilized, including data trusts, commons, collaboratives and cooperatives.[17] Data trusts offer a particularly promising approach. In this instance, a data trust appoints an independent steward with a fiduciary responsibility to manage the data in the best interests of data subjects and data collectors, usually an NGO or another independent civil society actor. It therefore provides a legal structure to manage the governance of datasets and how that data is commercialized. This structure provides data subjects with more autonomy over how their data is used and provides an opportunity to derive a benefit from the commercialization of their data. However, as mentioned, a trust is only one model - observation and co-creation of local context and culture must determine which governance model is best. There are a number of examples of innovative data governance models in the agricultural sector which are detailed in this report on farmer-centric data governance.

BOX 21: DATA TRUSTS TO ADDRESS ILLEGAL WILDLIFE TRADE

The Open Data Institute partnered with WILDLABS Tech Hub and the Office for Artificial Intelligence in 2019 to pilot a data trust to assist in combating the illegal wildlife trade in the U.K. and internationally.[18] In this pilot, data creators were researchers, academics, NGOs and conservationists; data users or providers consisted of law enforcement; and the users of the pilot included machine learning researchers and app developers. The type of data collected included image data, invoices of shipping consignments coming through border checkpoints, and acoustic and camera trap data. The pilot provided the users with improved data governance and legal and technical infrastructure for data collection and storage.

Through the pilot, it emerged that there is a genuine willingness to share data amongst various stakeholders; however, guidance on legal and technical infrastructure; improvements for information management such as digitizing hard copy data, improving data flows and breaking down data silos; guidance on standards and use of common formats to enable better access and sharing; time and funding for data cleaning and aggregation, aided by a better understanding of data protection laws was critical in addressing blockages identified during the pilot.

03 *Equip farmer co-ops, NGOs and extension officers to support SSPs with recourse in the event of opaque or otherwise unethical AI decision-making.*

Until the appropriate legal frameworks that govern agriculture-specific AI solution infractions are developed, available recourse avenues need to be formalized and sensitized among intermediaries who have the trust of SSPs. There are many conceptual frameworks under development to govern AI in agriculture, from national AI policies and strategies that prioritize the agriculture sector[19] to the potential of introducing a legal framework for small autonomous agricultural robots.[20] However, the enactment of agricultural-specific regulatory frameworks to govern unintended consequences of AI and automation in agrifood systems remains nascent. In this situation, the avenues for recourse that the SSP could pursue remain vague. This is due to the majority of AI-driven or automated decision-making systems lacking legal and policy transparency or clarity on who or which organization will be held accountable for the mismanagement, error or wrong decisions/ recommendations made by AI systems.[21]

For SSPs to feel empowered to address infractions through available recourse avenues, capacity building of intermediaries is essential. Capacity strengthening of farmer-representing organizations and intermediaries to act as first-line recourse measures can be an intermediate solution to the development of specific regulatory guidelines governing the use of AI and automation in agriculture, which will take time. As the prevalence of AgTech

[17] Development Gateway. 2023. Farmer-centric data governance models. Available here.
[18] ODI. 2019. *Illegal wildlife trade pilot: What happened when we applied a data trust.* Available here
[19] OECD. 2020. *Examples of National AI Policies.* Available online.
[20] Basu, Subhajit & Omotubora, Adekemi & Beeson, Matt & Fox, CW. 2020. *Legal Framework for Small Autonomous Agricultural Robots*. AI and Society. 35. 10.1007/s00146-018-0846-4. Available online.
[21] National Library of Medicine. 2022. *Recommendations for ethical and responsible use of artificial intelligence in digital agriculture.* Available online.

solutions becomes more pronounced, the training curriculum for extension workers and other organizations working with SSPs should be updated. Funders of AgTech solutions should prioritize funding solutions that include attainable and efficient recourse mechanisms for SSPs. These mechanisms may include giving farmer-representing organizations and intermediaries a role in the governance or ownership of AgTech solutions.

04 *Establish regional AI labs to design resources and products to improve the accuracy, representativeness, explainability and failure detection capabilities of AI models in agriculture*

An Agriculture AI Lab can address the lack of standards for bias detection for AgTech solutions, and create mechanisms for bias and accuracy detection and monitoring. AI models applied in building AgTech solutions need to be transparent and explainable to prevent SSPs experiencing adverse effects from inaccurate predictions. The Lab can be established with seed funding from donors, government or research organizations to develop resources and products to integrate responsible AI practices into AgTech solutions. The implementation of the Lab should be the responsibility of AI practitioners, with the following mandate and proposed mechanisms. The lab could be housed in an existing institution such as Microsoft with the Microsoft Africa Research Institute (MARI).[22] MARI has "Democratizing AI" as a research theme where they work on low resource languages and domains to open up new markers for small businesses in Nairobi, Kenya. Alternatively, it could work alongside or under more experimental start-ups networks, such as Mozilla.ai. In either instance, the AI lab would have a strong regional focus, to enable it to dive deeply into the constraints preventing effective, ethical AI solutions in that region. As an indicative example, availability of AI solutions in a widely spoken language may be a key binding constraint in the Sahel, which is less likely to be the case in Anglophone East Africa.

Table 7: Proposed Agriculture AI Lab mandates and mechanisms

Agriculture AI Lab mandate	Mechanism to fulfill mandate
Define the bounds, causes and consequences of bias in agriculture	Targeted research based on case studies of AI in agriculture solutions being implemented
Provide guidelines on enhancing the explainability of AI solutions.	Host a challenge fund to promote multilateral development of agriculture specific model cards and explainability 360 products.
	Promote the use of model cards and explainability 360 products adapted to agriculture.
Prevent models from being trained on limited datasets.	Collate unbiased testing datasets and make them available for experimentation and model testing
Develop a product to test the bias and robustness of AI models.	Use the testing data to develop an AI model/ algorithm that can automatically discern the accuracy of an AI solutions

BOX 22: AI MODEL BIAS PRODUCTS IN HEALTHCARE

The health sector is at the forefront of AI explainability and failure monitoring. The bounds and implications of bias from AI model recommendations in the health sector have been explored. Additionally, health institutes typically own proprietary, large and unbiased datasets which they can use to train AI models. The NHS[23] and the Mayo Clinic[24] have used their datasets to develop products that test the robustness of AI models before these models are used in solutions that may compromise the wellbeing of patients.

The NHS AI lab worked with a research group to develop a validation process that tested how accurately AI

[22] Microsoft. 2023. *Microsoft Africa Research Institute (MARI)*. Available online

[23] Healthcare IT News. 2022. *NHS creates blueprint for testing bias in AI models*. Available online

[24] Mayo Clinic News Network. 2022. *By eliminating bias in AI models and offering access to deidentified data, Mayo Clinic Platform aims to transform health care*. Available online

models detected positive and negative COVID-19 cases. The validation process used data from medical images across different patient subgroups e.g. age, ethnicity and sex. The validation process was run on five AI models using data from the National COVID-19 Chest Imaging Database (NCCID) to determine whether they could be used by the NHS.

The Mayo Clinic has developed a platform called "Validate" which evaluates AI model accuracy, efficacy, and its susceptibility to bias. The product was developed by Mayo Clinic Platform, an ecosystem that orchestrates collaborations with health technology innovators. Validate can be used by developers to ensure model accuracy and clinicians who can be certain that the AI models they are considering adapting to their practices have been evaluated for accuracy and bias.

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