Inclusively Advancing Agri-Food Systems through AI and Automation

USAID FROM THE AMERICAN PEOPLE

BILL & MELINDA GATES foundation

DigitalFrontiers SCALING DIGITAL DEVELOPMENT

G:ENESIS UNLOCKING VALUE

CONTACT INFORMATION

Genesis Analytics (Pty) Ltd South Africa
Office 3, 50 Sixth Road Hyde
Park, Johannesburg

Genesis Analytics Ltd Kenya
4th Floor, West Park Suites, Ojijo
Close, Parklands, Nairobi

Genesis Analytics Ltd Côte d'Ivoire
Africaworks, Immeuble Le7, Rue
du 7 Décembre, Abidjan

Genesis Analytics Nigeria
3rd Floor, Maryland Mall, 350
Ikorodu Road, Maryland, Lagos

Genesis Analytics United Kingdom
WeWork Aviation House, 125 Kingsway,
London WC2B 6NH, London

www.genesis-analytics.com

Authors
Genesis Analytics

Contact us
digital@genesis-analytics.com
+27 11 994 7000

This report is made possible by the generous support of the United States Agency for International Development (USAID) and the Bill & Melinda Gates Foundation (BMGF). The contents are the responsibility of Genesis Analytics and do not necessarily reflect the views of USAID, the United States Government or BMGF.

ACKNOWLEDGMENTS

Inclusively Advancing Agri-Food Systems through AI and Automation is a project managed by the Centre of Digital Excellence at Genesis Analytics, and made possible through the support of the United States Agency for International Development and the Bill and Melinda Gates Foundation. We would like to express our gratitude to all those who contributed to the successful completion of this report.

In particular, we would like to thank Stewart Collis from BMGF and Josh Woodard from USAID for their invaluable and generous coordination, guidance, insights and other contributions. We would also like to extend our thanks to colleagues from DAI, Katie Shipley and Juliet Terrill, for their support throughout the project. We are also grateful to our technical experts, Canford Chiroro from Khanyisa Research and Consulting, Suvankar Mishra from EKUTIR, and Ernest Mwebaze from Sunbird AI, for their valued guidance and expertise.

Lastly, we would like to thank the diverse and engaging set of stakeholders who generously contributed their time and insights to key informant interviews and joint solutions workshops. Their contributions have been invaluable in shaping the outcomes of this report. A full list of these stakeholders can be found in the appendix.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

AI and automation innovation will be the most significant contributor to the transformation of agri-food systems in low and middle income countries

AI and automation solutions are transforming agri-food production and trade by completing complex physical tasks and decision-making functions usually carried out by humans. Automation is the use of technology to complete routine tasks with minimal human intervention. AI is transforming what is possible through automation by not only automating more complex physical tasks, but also functions usually associated with human intelligence. These tasks include recognizing patterns in information, operating machinery autonomously, and communicating naturally and responsively, among others. While these capabilities are still far from general human intelligence, they have advanced rapidly and can perform a variety of narrow tasks far more efficiently than humans.

OpenAI's ChatGPT application exemplifies the rapid pace of advancement in AI capabilities in the last year alone. ChatGPT is an AI chatbot developed by OpenAI. It leverages OpenAI's generative pre-trained transformer (GPT) family of large language models and has been fine-tuned using both supervised and reinforcement learning techniques.[1] The application is estimated to have reached over 100 millions users just two months after launch, making it the fastest growing software application of all time.[2]

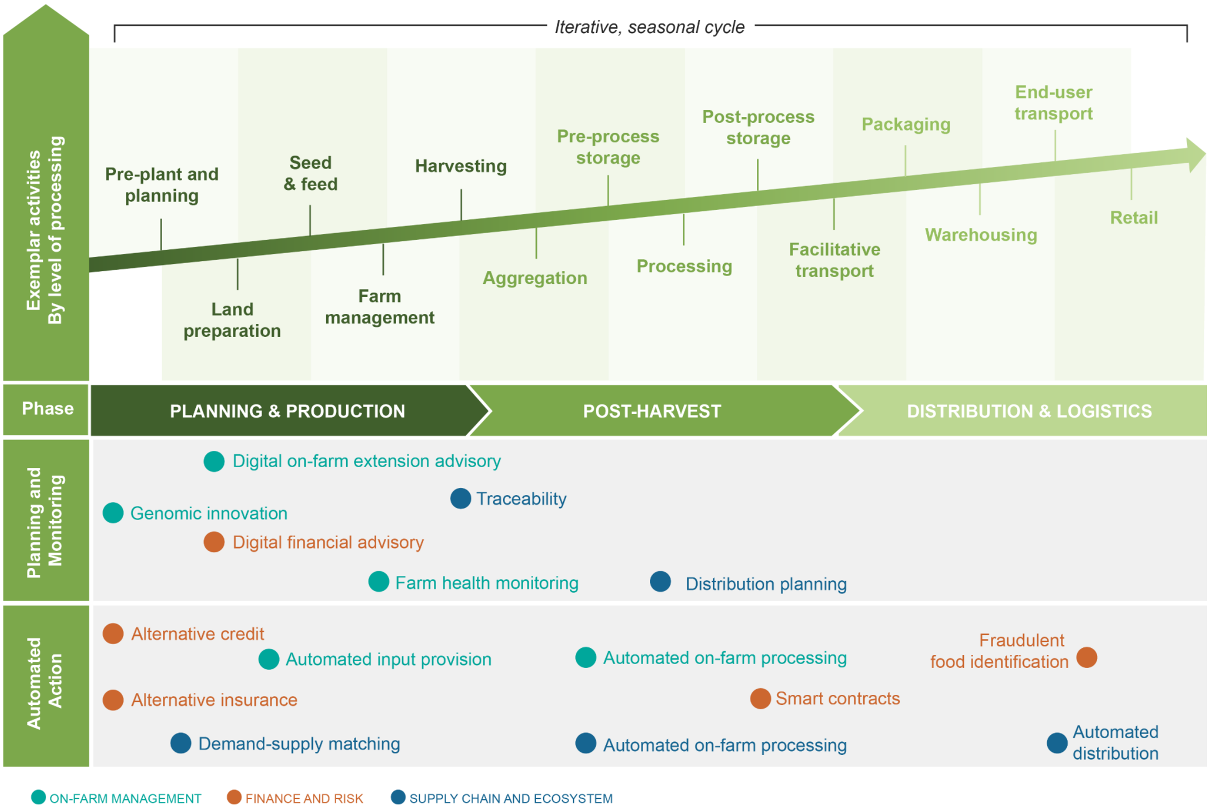
ChatGPT has received so much attention because of its ability to perform a vast array of tasks with high accuracy, ability to rapidly synthesize information into a concise, consumable form, its rapid and widespread adoption, and its exceptional design that allows for seamless interaction with people. OpenAI released the GPT-4 model only 3 years after its predecessor was released. This iteration represents another step change in AI, adding multi-modal (text, image and video) input capabilities, more factual responses, reduced hallucinations (making things up confidently) and greater alignment (i.e. guardrails to refuse to answer inappropriate or dangerous questions). However, GPT-4 does not solve these issues entirely, and it continues to reflect a disproportionately anglophone internet.

The ChatGPT algorithm is already being leveraged across a range of new applications, including apps like Spotify, Bing and Microsoft Teams and in several industries. In agri-food systems, there is great potential for it to be used for personalized digital advisory services and many other solutions, particularly if the application expands its capabilities to include languages local to small scale producers (SSPs) in low and middle income countries (LMICs).

AI and automation technologies are already being applied across agri-food value chains in LMICs, with uptake from SSPs in several cases. This study identified a broad range of use cases where AI and automation solutions are being deployed across agri-food value chains in LMICs. While this adoption is skewed towards large and more commercially oriented producers, there are many solutions where frontier technologies are applied on the back-end and delivered to SSPs using a combination of low-tech delivery channels, in-person intermediary networks and partnerships with value chain stakeholders willing to subsidize the cost of the solution. The identified use cases cover both automated planning & monitoring and automated actions across three functions:

[1] For more information on AI capabilities see Box 2; for more information on large language models see Box 3; for more information on AI learning techniques see Appendix 4.
[2] Reuters, 2023. Available here.

- Improvements in input planning, planting, harvesting and weather forecasting are facilitated by **on-farm management** solutions, such as automated input provision and digital extension advisory.
- **Finance and risk** management solutions expand the access that stakeholders like SSPs have to financial products and services like insurance and credit.
- AI and automation solutions for **supply chain and ecosystem** management facilitate seamless value chain linkages. For example, traceability solutions and demand-supply matching.



Source: Genesis Analytics, 2023

While AI and automation solution providers are highly concentrated in a handful of LMICs, improvements in the underlying technology requirements and delivery models hold promise for supporting more widespread adoptions among SSPs. Of the countries covered in this study, the majority of AI and automation solution providers operate in India, Kenya and Nigeria. While these providers do export their solutions to other LMICs, there is a large disparity in the availability of locally relevant solutions between LMICs. Even in the prominent AgTech hubs, SSPs in a low connectivity environment with low trust in technology and low ability to pay are far less likely to adopt AI and automation solutions compared to larger-scale commercial producers. Improvements in the cost and availability of the data, infrastructure and intelligence technologies required to deploy AI and automation solutions are reducing barriers to entry and stimulating innovation by AgTech developers. Innovative delivery models for these solutions are helping to address the trust, affordability and technology access barriers that prevent SSP adoption.

AI and automation solutions hold significant potential for SSPs and agri-food systems, but realizing this potential is not automatic

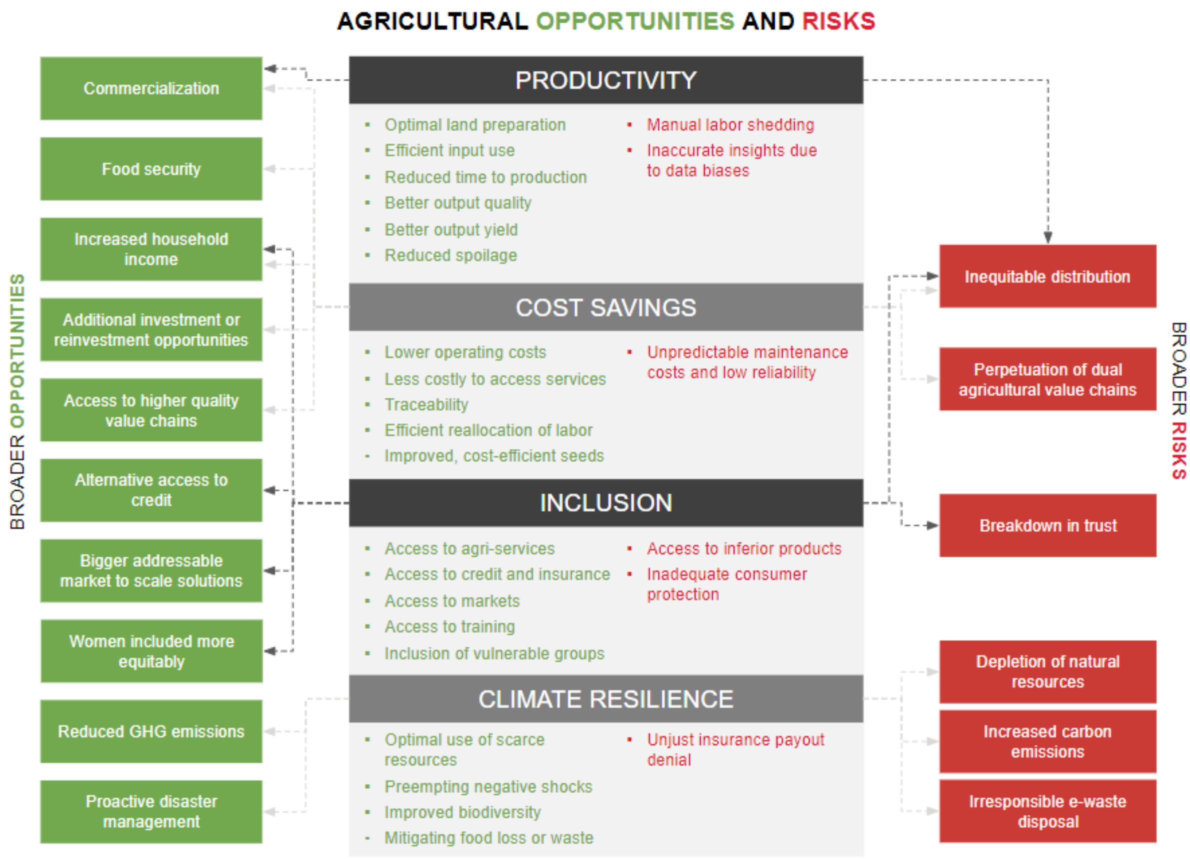
This study has identified myriad potential benefits of AI and automation solutions in agri-food systems, with the largest being significant enhancements in agricultural productivity and outputs. Data collected from sensors, satellites, or drones can help SSPs prepare and use their available land optimally. Data-generated insights can identify which farm areas are most suited to which crops, and automated input provision like automated irrigation systems can optimize resource use. AI and automation solutions can also improve extension advisory services, resulting in better, more contextualized and real-time advice for farmers, improving yields. Other solutions can predict, identify and mitigate against pests and diseases to reduce spoilage. Enhancing the improved productivity of SSPs is critical for global food security, and the economic and social empowerment of SSPs and the communities in which they live.

Indicative examples of AI and automation driving impact

Solution	*Description*	*Impact*
eFishery On-farm management	eFishery deploys in-pond sensors, artificial intelligence and automated feeders to distribute the optimal amount of feed within the pond, based on pond, fish and shrimp condition.	20% increase in profit amongst fish farmers.[3]
Apollo Agriculture Finance & risk	Apollo Agriculture is a tech start-up collecting satellite imagery of farms. The company uses predictive AI to analyze this data, to establish credit profiles for small-scale producers that would otherwise be excluded from accessing finance. The firm bundles finance with inputs, advice, insurance and market access.	2.0 - 2.5x increase in crop yields.[4]
Hello Tractor Supply chain & ecosystem	HelloTractor is a digital platform that connects tractor owners with farmers requiring tractors. Tractors are fitted with low-cost IOT devices which collect data about the farm and the tractor. This data is analyzed using AI, to provide intelligent predictions on, for example, when tractor maintenance is required or likely crop yields.	>70% of farmer users report that increased quality of life, crop revenue and crop production[5]

AI and automation solutions can also generate significant cost efficiencies, expand access to critical economic infrastructure and build climate resilience for producers. Precision farming uses inputs more effectively, reducing costs and environmental wastage. Automation-enhanced asset sharing and aggregation means that farms can pay less to access critical inputs and hardware. Traceability solutions drive down the costs of certification (including “green” certification) and increase market access. Automated data collection and AI-enabled risk predictors can enable access to critical financial infrastructure like credit and insurance, which in turn help agricultural producers prepare for economic or climate shocks.

[3] GSMA, 2018. eFishery: Shaping the future of Indonesia’s aquaculture industry. Available here
[4] Apollo Agriculture, 2019. Increasing Food Security in Africa. Available here.
[5] MercyCorps AgriFin, 2020. Breaking New Ground. Available here.



Source: Genesis Analytics, 2023

However, a major risk is that these benefits will be distributed unevenly with consequences for competition, access to economic opportunity and ethics. While this study identified several examples of AI and automation solutions promoting inclusion (e.g. alternative credit scoring promoting access to finance among female SSPs), there are also negative economic, social and ethical consequences where solutions are not adopted widely. Where benefits are disproportionately accrued by groups that are already relatively advantaged, there will be consequences for food security, local employment and economic development in rural communities. For example, if larger tech-enabled producers enjoy rapid upticks in productivity that provide them with an unmatchable competitive advantage over SSPs, this may threaten rural livelihoods. Similarly, if men are disproportionate adopters of these technologies, this can further unbalance household power and income earning dynamics. Even where adoption is more equitable, there are valid concerns regarding data governance and the ethics of AI applications among SSPs.

To inclusively advance agri-food systems, AI and automation innovation must be steered towards more inclusive outcomes

AI and automation solutions are already transforming agri-food systems. Interventions are required in four areas to drive this transformation toward more inclusive outcomes. These interventions were identified through a process of joint solutioning where stakeholders from across the agri-food and technology ecosystem identified the key constraints and required solutions for AI and automation innovation to support more inclusive outcomes.

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.		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.		Governments, AgTechs
Support white label software infrastructure developers to align development with the demands of AgTech developers.		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.		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.		Donors, governments, AgTechs
Unlock government demand for climate-smart digital extension advisory through technical assistance.		Donors, governments, professional services
Capacitate farmer organizations to facilitate bottom-up development of farm data management solutions, and act as procuring entities for purchasing costly AgTech solutions.		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.		Donors, governments, social enterprise
Expand social support mechanisms and pathways to productive employment to support individuals affected by disruptions.		Donors, governments, social enterprise
Support regulators to examine the potential for harm in digital market conduct in agri-food systems.		Donors, governments
Socialize an environmental Extended Producer Responsibility approach amongst AgTechs to shift product end-of-life responsibility upstream.		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 agriculture.	Donors, AgTechs, NGOs, PE/VC investors
Pilot farmer-centric and participatory data governance models in agriculture.	Donors, governments, research/consulting services, NGOs
Equip farmer co-ops, NGOs and extension officers to support SSPs with recourse in the event of opaque or otherwise unethical AI decision-making.	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	Donors, governments, AgTechs, academia

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.[6] This anticipated population boom will require a 60-70% increase in global food production by 2050.[7] 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.[8]

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.[9] SSPs in LMICs are also among the poorest people in the world, with many living on less than $2 per day.[10] 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.

This report 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.

---

6 United Nations, 2021, *World population projected to reach 9.8 billion in 2050, and 11.2 billion in 2100,* available here
7 GSM Association, 2022, *Assessment of smart farming solutions for smallholder farmers in low and middle-income countries,* available here
8 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
9 Fanzo, 2017, *From big to small: the significance of smallholder farms in the global food system*, available here
10 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).[11] 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.

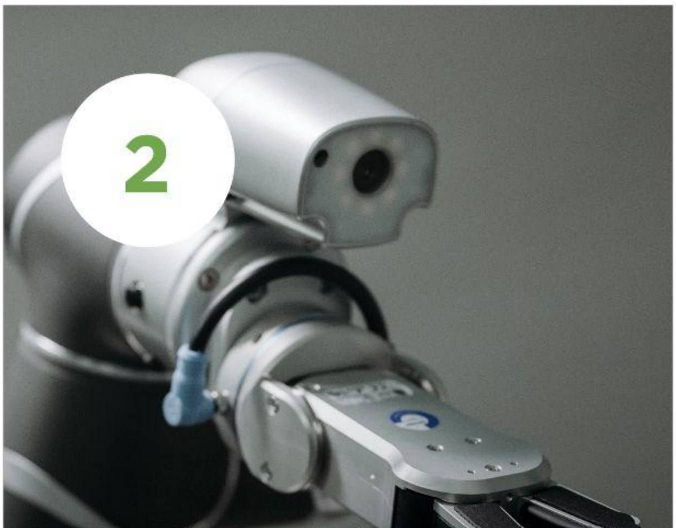
The cross cutting trade-offs and considerations for solutioning were then explored through several Joint Solutions workshops. The Joint Solutions methodology convenes small groups of diverse stakeholders, each of whom have a different perspective on a problem with diverse ideas on how to solve it. The 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.

[11] 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.

1

Why AI and automation matter for agri-food systems motivates why the functions of emerging AI and automation technologies match well with the evolving challenges of global agri-food systems, and the SSPs that participate in them.



2

AI and automation solutions provides a deep dive into the key AI and automation use cases relevant to SSPs, how they are being delivered and the data, infrastructure and intelligence requirements of the underlying technologies.

3

Impacts of AI and automation solutions maps out the potential impact channels from the identified use cases and identifies the trade-offs that will need to be managed by those working in agriculture development.

4

Considerations to Inclusively Advance AI and Automation in Agri-food Systems identifies specific interventions, investments and approaches that can help manage the trade-offs successfully.

WHY AI AND AUTOMATION MATTER FOR AGRI-FOOD SYSTEMS

Automation technologies have been transforming production, logistics and trade processes since the 18th century. Automation is defined as the application of technologies to complete routine tasks, usually carried out by humans, with minimal human intervention. We are already accustomed to basic automation technologies as a normal feature of life – automated teller machines in banking or automated luggage conveyor belts in airports. In the last 50 years, automation technologies have become much smarter and more cost effective. We are now accustomed to more sophisticated examples of digital automation, such as internet search engines replacing manual telephone directories, and GPS navigation apps replacing manual map reading.

This study focuses on the use and impacts of digitally-enabled automation, including AI, in agriculture. The study does not cover more foundational forms of automation, like mechanized or analogue automation. The two key criteria for determining what kinds of automation were considered in this study were: (i) decisions or tasks that form part of an automated process are based on the transmission and processing of significant amounts of electronic data, and (ii) these decisions or tasks are undertaken with minimal human intervention. The diagram below provides examples of AI-enabled and digitally enabled automation which meet these criteria, as well as examples that are not covered in the analysis.

Figure 1: Examples of AI and automation applications included and excluded from the study

	AI-ENABLED AUTOMATION	DIGITALLY-ENABLED AUTOMATION	ANALOGUE/MECHANICAL AUTOMATION & OTHER APPLICATIONS
Examples of applications	• Precision irrigation • Alternative credit scoring for small-scale producers • Pest detection for crops • Livestock tracking and bio-monitoring • Predictive yield mapping	• IoT-enabled irrigation • Smart contracts • Weather-based index insurance • IVR or automated SMS extension services • Automated temperature control	• Mechanised irrigation • Tractors • Online marketplaces • Extension services delivered through call centres • Digital payments
	Included		**Excluded**

AI is transforming what is possible through automation by not only automating more complex physical tasks, but also functions usually associated with human intelligence.[12] These 'intelligent' systems enable digital machines to perform tasks commonly associated with intelligent beings such as identifying objects, communicating naturally and responsively, and recognizing patterns in information. The term AI often conjures images of a science-fiction future in which machines have developed sentience but, in reality, the current capabilities of AI are far from general human intelligence. For example, an AI program can be trained to distinguish between pictures of dogs and cats, but AI doesn't have the capacity for appreciating art or music. Currently, AI applications can only perform the specific tasks they are trained to do rather than generalized or flexible functions. For example, an AI that is designed to play humans at the game of chess would not be able to tell the difference between an image of a cat and a dog (unless it had been explicitly trained to do that). However, the specific tasks that AI applications can be trained to execute often go beyond the limits of human capabilities. They can, for instance, process and analyze large volumes of data and recognize patterns in a fraction of the time it would take a person to do the task.

BOX 1: Defining AI and Automation

Artificial Intelligence refers to a family of algorithms and analytical processes that enable computers to solve problems and make decisions at or beyond human capability. An AI is designed to perform a task by translating inputs such as text, audio or numerical data into an output such as a decision. An AI charts its own pathway from inputs to an output, often learning to use more effective pathways to produce more accurate outputs.

12 For a more detailed taxonomy of AI, please see Box 1.

Automation is the application of technology to complete tasks with minimal human intervention. Automation applications execute tasks - typically routine ones - based on a predetermined set of triggers. Some automation processes are physical and rely on hardware, such as automated irrigation systems and autonomous harvesting. Others are digital and rely on software such as the disbursement of crop insurance claims to farmers due to a flood. Automation applications may, but do not necessarily, include the use of AI to trigger the completion of routine tasks. Where this occurs, this is referred to as AI-enabled automation.

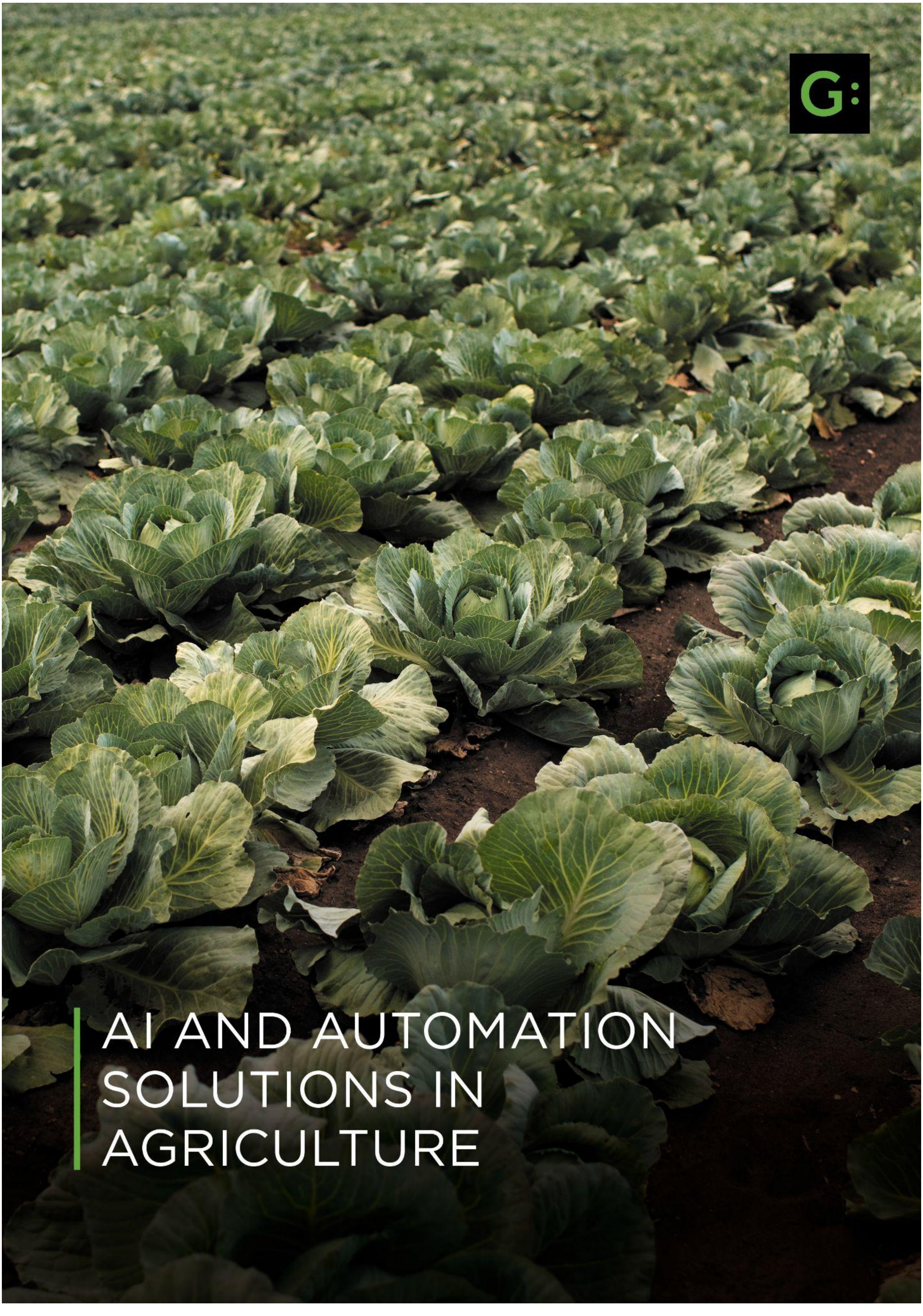
The very capabilities that give AI its transformative potential also introduce significant risk. For example, if an AI system is trained to complete a particular task using biased or incomplete training data, the system is likely to reproduce or exacerbate biases inherent in that data. Moreover, AI processes are often opaque and the criteria used to determine a particular output or decision cannot always be clearly identified or explained. For example, an AI system may predict that a particular rideshare driver is likely to become a dangerous driver and may remove them from a rideshare platform that is their primary source of income generation. The inability to explain decisions like these and/or the lack of robust dispute resolution systems can therefore strip individuals of their autonomy. Similarly, there is the long-understood risk of job displacement as AI systems become a more cost-effective and/or efficient way of fulfilling certain tasks. Responsible AI, or AI that embeds the capability to explain decisions as well as transparency, respect for privacy and a commitment to overcoming bias, is critical.

Advanced AI capabilities hold significant potential for addressing the global challenges currently confronting agri-food systems. This study identified five overarching trends in agri-food systems that are rewiring the entire ecosystem, creating significant opportunity alongside notable risk. The table below sets out these trends and the relevance that AI and automation solutions have in addressing them. The remainder of the report investigates the extent to which this potential is being realized, what the trade-offs are in terms of realizing this potential, and the policy and program levers best suited to managing these trade-offs.

Table 1: Trends in agri-food systems and the AI and automation solutions being used to address them

Agri-food system challenges	Relevance of AI and automation solutions
Population change: Rapidly increasing youth populations and longer life expectancy is creating a greater demand for food and rewiring the structure of traditional agri-food processes. Global growth in population size, especially among young populations in LMICs, is increasing pressure on agri-food systems to improve production efficiency and is creating new opportunities to meet surging demand through regional trade and new entrants. This demographic trend in most LMICs means that there will be more young work-seekers than ever before, many of whom will be looking to agriculture for a pathway to stable work.	AI and automation solutions can help farmers make better decisions about what to grow and about how to optimize inputs and farming methods, particularly by automating the delivery of personalized and location-specific advice or by reducing the costs of manual processes. Some of these applications may have a labor-shedding impact for on-farm production, particularly on commercial farms, as well as in the down-stream processing of agri-food products. Several other sources of work may, however, be created in the AgTech value chain.
Climate change: Extreme weather events and disrupted seasonal patterns harm agricultural producers who have limited resilience to climate change. Agricultural vulnerability to climate change is being felt worldwide and is negatively impacting on both global food security and livelihoods. Climate change is also harming nutritional food quality, reducing yields and introducing invasive species, among other impacts. The most impacted farms are those with limited climate resilience, which	AI and automation solutions can improve the performance of climate-related index insurance and related financial products, help farmers reduce their usage of water and other scarce resources, improve the time-to-market for climate-resilient crop and livestock varieties, and predict where climate-change impacts are likely to be most severely felt to actively prepare and apply mitigating strategies.

Agri-food system challenges	Relevance of AI and automation solutions
tend to be SSPs in LMICs.	
Technology and innovation: Technological innovation and adoption in agri-food systems is rapidly but unevenly advancing, which tends to favor larger-scale commercial producers. From genetic input enhancements to AI-enabled precision agriculture during the production phase, to digital marketplace usage during distribution, technology can significantly enhance efficiency. However, these applications are largely created and deployed by stakeholders in developed markets. By comparison, many SSPs in LMICs have not yet adopted basic farm mechanization technologies.	Advances in automated translation and conversational AI can assist in providing highly personalized and locally relevant digital extension advisory in local languages. Alternative data sources processed with AI algorithms can automate and improve the assessment of risk for SSPs to access the credit and other financial services needed to invest in new farming approaches and solutions.
Safety, nutrition and dietary changes: Global norms and standards around nutrition, diet and food safety are changing to reflect sustainability trends, which may disadvantage smaller producers that have a lower capability to respond. SSPs experience challenges in accessing lucrative markets due to shortfalls in meeting food safety requirements or by choosing products and processes that do not match novel demands, such as the demand for organically grown food. This can lead to the development of exclusive value chains in which the competitive advantage of larger incumbents hampers the participation of SSPs.	Automated data collection, scoring and verification of international standards and certifications can make the cost of certification significantly lower for SSPs, reducing the barriers to entry in export value chains. The use of real-time tracing and tracking applications in tight value chains can provide end users with information about where products have been sourced and about whether the farmers that produced them were afforded fair working conditions.
Transboundary issues: Increasingly regular occurrences of cross-border conflict, disease and contestation are disrupting agri-food supply chains, impacting on food security, employment and other sources of livelihood. Contestation over terms of regional trade, geo-political conflict, pandemic responses and climate change-catalyzed pests and diseases all impact on agricultural systems across national boundaries.	Automated regional surveillance applications have strong potential to identify pest and disease issues as well as implications from changes in temperature and rainfall across a particular region. AI applications that improve efficiencies in regional supply chains can generate more seamless linkages and drive regional economic development.



AI AND AUTOMATION SOLUTIONS IN AGRICULTURE

There is a broad range of AI and automation applications across the agri-food value chain, with innovators, researchers and funders all seeking to solve for a variety of challenges that SSPs face. This section presents an overview of prominent AgTech solutions that leverage AI and automation technologies in three parts: (i) the predominant use cases for SSPs and the value-chain stakeholders that work with them, (ii) the underlying technology requirements and considerations for these use cases, and (iii) the current distribution of the solutions and the factors that determine their uptake and adoption among SSPs.

USE CASES

AgTech solutions can be used to solve multiple problems in different markets and areas within agri-food value chains. Making sense of the impact of AgTech innovations requires a clear way to classify them. This study has designed a taxonomy of use cases and identified a set of priority use cases to focus the research.

TAXONOMY OF USE CASES

Use cases can be grouped based on the functions they perform and the domains in which they are applied. The research for this study explored AI and automation solutions across twenty-three BMGF and USAID priority countries[13] which were aggregated into fifteen distinct use cases. These were then sorted into six categories based on their function and the domain in which they are applied. Many AgTech solutions combine multiple use cases, but for illustrative purposes, each use case is discussed individually.

AI and automation solutions aim to generate more efficient agri-food systems through two distinct but often complementary functions: equipping stakeholders with better planning and monitoring tools, and automating manual actions.

- **Planning and monitoring solutions** provide policymakers, farmers and other stakeholders with tools that help to improve their decision-making, often by delivering more accurate data and advice. For example, on-farm health monitoring tools such as soil-sensing instruments provide SSPs with precise data that can inform later action. However, no immediate automated action is taken based on this information.
- **Automated action solutions** use information – often collected by planning and monitoring solutions – to trigger an action that would otherwise have been completed by a human. For example, robotic machinery that automatically sorts fruit into high, medium or low grades is an automated action solution. These solutions tend to replace existing tasks but there may be some instances of labor augmentation. To extend the example, automated sorting machinery may be complemented by a human quality control officer.

AI and automation solutions are applied in three domains: on-farm management, finance and risk management and supply chain and ecosystem management.

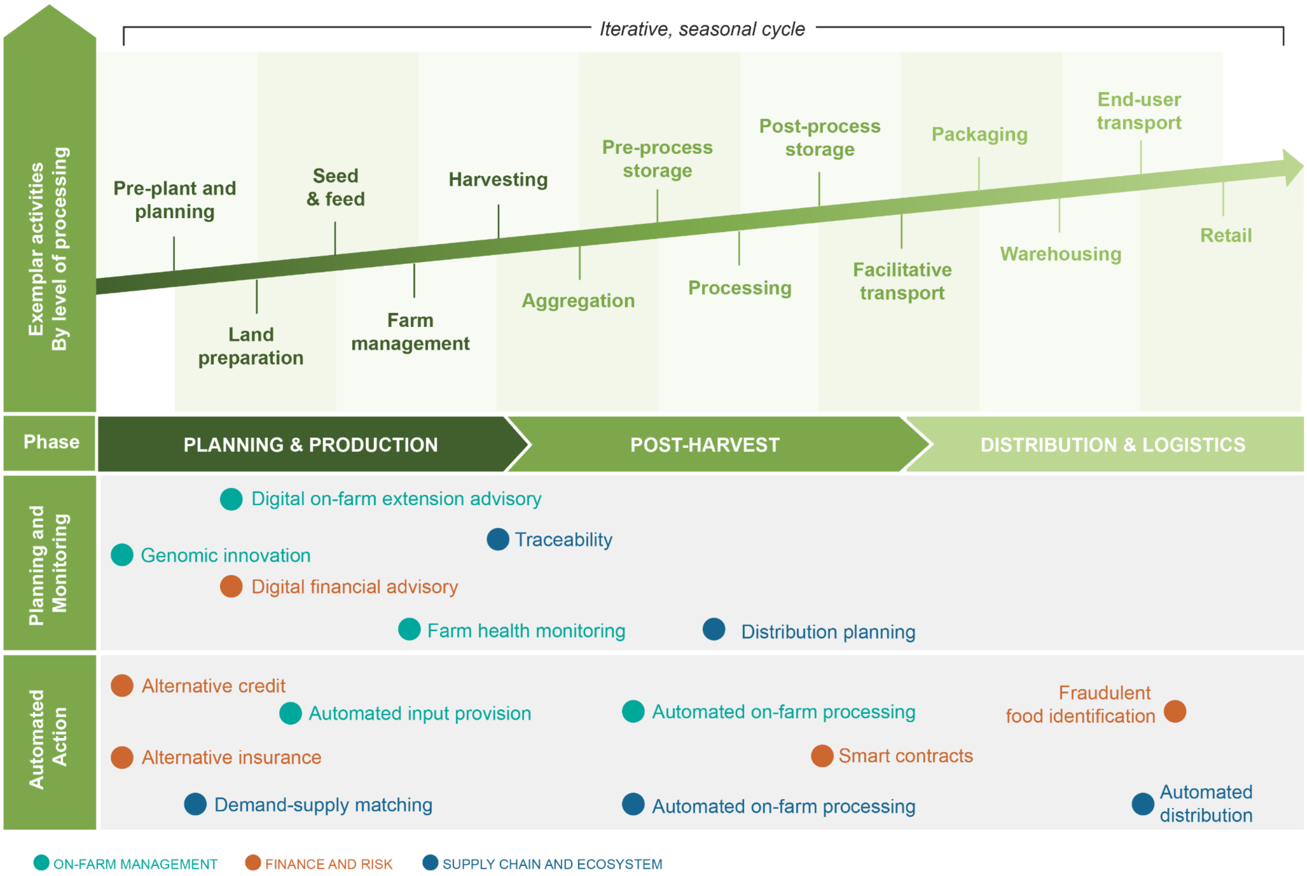
- **On-farm management solutions** use AI and automation technologies to facilitate better input planning related to such issues as what and when to plant; provide farmers with better quality inputs; mitigate against common on-farm risks such as pests, diseases and extreme weather; minimize production costs and improve farm yields. Solving these challenges is fundamental to ensuring that SSPs can regularly and reliably harvest quality outputs without incurring outsized costs. The largest set of AI and automation use cases are in this domain, and the majority of these relate to planning and monitoring.
- **Finance and risk management solutions** use AI and automation technologies to expand agri-food stakeholders' access to financial products and services, such as payments, credit and insurance. Access to these services continues to be particularly difficult for SSPs, who typically lack credit profiles and live far from banks and service centers. Technological solutions that overcome these challenges are designed to improve financial flows, reduce the cost of sizing and mitigating risk, and build resilience to external shocks. The most promising solutions in this category automate previously manual actions built into the design and delivery of these services.

[13] Bangladesh, Burkina Faso, Democratic Republic of Congo, Ethiopia, Ghana, Guatemala, Honduras, India, Kenya, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, Zambia

- **Supply chain and ecosystem management solutions** use AI and automation technologies to facilitate seamless linkages across the value chain. This helps to improve access to critical inputs and reduce friction costs at points of transaction, automatically matching market participants and improving access to markets. Linkages between SSPs and buyers are often informal and relationship-based. Farmers may not have reliable information about demand patterns such as what price to accept, what to sell and to whom to sell. This may also apply on the supply side, where farmers may not have good information about the price of agricultural inputs or machinery. Supply chain solutions aim to overcome these challenges by providing the farmer and other stakeholders with reliable, timeous information. Promising use cases here cover planning and monitoring as well as automated action.

The scoping highlights that there is significant AI and automation activity in the planning and production phase. The figure below presents a generalized agricultural value chain, with the fifteen use cases mapped indicatively to the value chain stages in which they are most commonly used. More detail on each use case is provided in Appendix 2.

Figure 2: Generalized agricultural value chain and use case framework



Source: Genesis Analytics, 2023

KEY USE CASES FOR SSPs

Eight use cases stand out due to their prevalence and potential. These cases were chosen for further analysis based on their prevalence in the LMIC landscape and their hypothetical potential to markedly increase yields and incomes for SSPs.[14] The majority of these solutions are used to assist farmers with on-farm management, with an even split across planning and monitoring, and automated action.

Farm health monitoring

Farm health monitoring solutions equip farmers with accurate, granular and real-time data relating to key aspects of small-scale farming, including crop health; soil, air and water quality; livestock location and vitals; and pest and disease management. This data helps them to respond precisely and rapidly to farm health challenges that would otherwise negatively impact yields. SSPs face challenges that are difficult to identify, diagnose or respond to precisely without granular data. For example, farmers may not know what pest species are afflicting their crops, how much or when to irrigate, or what the pH level of their soil is. Monitoring solutions provide them with more information to use when making production decisions, at a markedly lower level of manual effort.

Data that monitors crop health and soil, air and water quality is collected using a combination of frontier remote sensing technologies such as drones, IoT sensors and satellite imagery. This data is then processed and overlaid onto GIS maps on mobile or web interfaces, providing a rapid visualization of key insights. Drones traverse the farm collecting high-resolution imagery, which is then processed via machine learning algorithms. The resulting insights are typically overlaid onto digital maps, informing farmers on each of the relevant agricultural parameters, such as soil acidity, soil organic carbon, carbon dioxide levels, pH level and others. IoT sensors collect data on similar agricultural parameters and, in a similar way to drones, process and visualize data analogously. However, these sensors are typically small handheld devices that are built specifically to collect data on their particular parameter. Another distinction is that the devices are often stationary and are placed at strategic locations on the farm. Finally, satellite imagery may complement the more granular data collected by IoT sensors and drones.

Tracking livestock location and vitals requires the use of IoT wearables, devices that are often marketed as 'Fitbits for livestock'. As when using Fitbit devices, health insights are collected in real time and presented back to users on a mobile or web interface. The farmer attaches an IoT-enabled collar or anklet to the animal, most commonly a cow. The device then collects real-time insights such as steps taken, heart rate, number of chews and GPS location. This data is then linked to a mobile or web interface, which allows the farmer to quickly identify any animals that are, for example, lost, ill or pregnant. To extend the example, real-time tracking of cattle health is crucial for recommending action to the nearest veterinarian. More accurate and timely information enables a quicker response to challenges, increasing the likelihood of a successful yield of meat or animal by-products.

Identification of pests and diseases makes use of computer vision technology that analyzes images taken by smartphones or drones. Imagery is processed algorithmically and diagnoses and recommendations are presented to the farmer on a mobile or web interface. The farmer takes a photograph of the pest or damaged crop – either with a smartphone or a drone – and this is stored locally on the device or uploaded to a mobile or web platform. The platform then processes the image using an AI algorithm that is trained to identify the particular type of pest or diseases based on visual inputs such as color and shape. Once it has been identified with a reasonable level of confidence – a process that is nearly instant – the application notifies the farmer. The notification is often packaged with a recommendation on how to respond. This decision support tool enables SSPs to respond more accurately and efficiently to potential pest- and disease-related challenges.

[14] Assessment of use case prevalence is the Appendix

AI AND AUTOMATION IN PRACTICE

MOBILE APP FOR DIAGNOSING CROP PEST AND DISEASE

Plantix is a mobile application that can automatically identify and diagnose pest, disease or nutrient deficiency issues in crops, based on a photo taken on a smartphone. The application uses off-the-shelf neural networks to make the diagnosis. The app is available for free to farmers; only on Android. Plantix generates revenue by licensing their API to private firms to use their image recognition algorithm. The company also owns an ecommerce business, which distributes agricultural inputs from dealers and manufacturers within the Plantix ecosystem. Plantix has over 60 million crop images in their database, which informs them on where diseases occur and what product is needed where. Combined with their network of over 70,000 retailers, the Plantix app ensures that every Indian farmer not only knows which product to apply, but also where to get it. The Plantix app is available for download worldwide, with a focus on India where over 5.5 million of their 6.3 million unique users are based.

Digital on-farm extension advisory

Digital extension advisory provides farmers with simple, data-informed recommendations related to planning, production and post-harvest handling and processing. These may include recommendations such as what crop type and variety to plant, how to respond to predicted weather patterns, how to manage diseases or pests, when to harvest and at what price to sell. Traditional farmer responses to challenges such as these are informed by existing experience, familial advice and in-person advisory provided by extension officers. In rapidly changing agricultural contexts – due, for example, to climate change – informal advice and other expertise that was previously reliable may no longer be applicable or effective. Digital extension advisory provides farmers with data-informed recommendations that reflect existing and predicted conditions. This advice can improve yields and reduce unnecessary losses.

These solutions deliver extension advice through low- and medium-tech digital channels such as USSD,[15] SMS and IVR.[16] Digital delivery at scale aims to address low coverage of extension officers in rural geographies. Extension coverage can be extremely low in LMICs, with one extension officer to 1,000 farmers not being uncommon. Low-tech solutions that can be accessed with a feature phone may be particularly effective at expanding SSP access to digital advisory services. In addition, more advanced chat solutions are emerging, which use natural language processing to understand the farmers' requests or translate inputs. These solutions are nascent but promising.

The content of the extension advice is informed by agricultural data collected through hardware such as weather stations and satellites, and others. This data is analyzed to predict important agricultural parameters, such as when rainfall might be expected, where pests may move or what tomorrow's temperature might be. Data collection efforts need to be broad to be useful and cost effective. Effective digital extension advisory services require data that is less granular than on-farm health monitoring technologies. Moreover, the data collected to inform digital extension advisory may also be used for other purposes, such as weather-based index insurance, national-level agricultural investment planning or climate change response planning.

[15] Unstructured Supplementary Service Data (USSD) allows cell phones to communicate with service providers via on-screen messages, by using the number keypad to navigate through menus. It is usually accessed by dialing a specific USSD code, which is a number that starts with * and ends with #. USSD is commonly used to top-up airtime or mobile data, query bank balances or to receive one-time passwords.

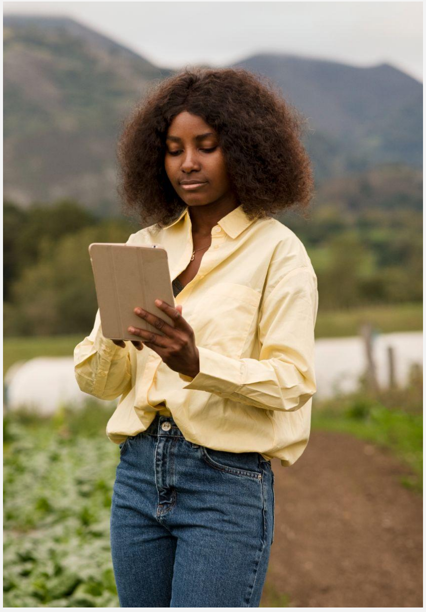
[16] Interactive Voice Response (IVR) is an automated system that allows users to access "call center-type" information without speaking to an agent. The user dials a phone number, and a menu is recited automatically over the phone. The caller uses the number keypad or speech recognition technology to navigate through the menu. IVR is commonly used when calling customer support lines for large organizations, such as banks or department stores.

Extension advisory may be delivered automatically based on particular triggers. A rainfall alert with recommendations may, for instance, be sent when heavy rains are predicted. However, services may also be more interactive, with farmers being able to request advice specific to their needs. Alerts that farmers cannot respond to, known as monodirectional extension services, are typically less personalized and more time-sensitive, and rely more strictly on generalized data collection. Messages that farmers can respond to, known as omnidirectional extension services, allow for more personalization and discussion, with the content being informed by a combination of data and the experience of the extension officer delivering the information. Next generation automated extension services may be developed using interactive large language models like those used in ChatGPT. These models provide automated, personalized responses to questions posed by users. While this technology is garnering widespread interest, we are yet to see it deliver locally relevant and accurate support for specific user groups such as SSPs. The delivery channel of digital extension advisory matters too; chat apps and phone calls are better enablers of omnidirectional extension services than USSD, SMS or radio.

AI AND AUTOMATION IN PRACTICE

IVR AND SMS HOTLINE FOR SCALING ACCESS TO EXTENSION SERVICES

8028 Farmer Hotline is a digital extension advisory initiative operated by the Ethiopian Agricultural Transformation Agency (EATA). Farmers use SMS and IVR to receive generalized best practice agronomic advice for a particular set of crops, provided in a variety of local languages. EATA added “Helpdesk” to the hotline, which connects farmers via phone call to a localized agricultural expert (typically an individual with a master’s degree in agriculture) that has experience working in a particular woreda, or district. Moreover, the hotline advisory an IVR/SMS survey system for collecting user feedback or data (e.g., what districts are reporting what pests), which is collated into a national agricultural information system, which in turn is combined with satellite data to generate an early warning message to inform monodirectional alerts that notify farmers of particular risks more importantly about the occurrence of crop disease and pest infestations. EATA and partners are experimenting with using AI to more rapidly and precisely analyze these data and provide localized and contextualized content to smallholder farmers. The service is free to farmers, and is funded by development donors and the Ethiopian government. The service has registered more than 6.2 million registered users who have processed 63 million calls since its inception in 2014.



Genomic innovation

Genomic innovation supports the creation of new varieties of crops, livestock and fish that are designed to overcome particular challenges, such as unpredictable droughts, persistent pests or insufficiently large harvestable portions. With genomically optimized varieties, farmers can improve the quality and quantity of output in response to challenging conditions without changing production processes or effort levels. For example, in response to increased drought severity induced by climate change, new varieties of millet have been developed that require less water to produce the same output as the ‘traditional’ seed.[17] These drought-tolerant strains can help SSPs reduce losses, maintain stable incomes and match demand, even under difficult weather conditions.

Genomic innovation may also make it possible to produce more effective agrochemical inputs such as pesticides and fertilizers. These inputs serve critical on-farm functions by keeping pests and diseases at bay and by stimulating crop growth. Genomically optimized agrochemical inputs aim to reduce the amount of input required

[17] See, for example, Srivastava et al., 2022. Breeding Drought-Tolerant Pearl Millet Using Conventional and Genomic Approaches: Achievements and Prospects. Available here.

while increasing the coverage and quality of the input. For example, a more efficient pesticide might more effectively repel locusts over a larger area and with less liquid application required. When achieved, this agrochemical efficiency can reduce operational costs and decrease the likelihood of catastrophic losses for SSPs.

Generating a new variety of crop, livestock or chemical input requires the identification of the combination of genomes that will achieve the desired outcome, such as the ability to grow a crop using less water. This identification process uses genetic data, often analyzed via machine learning techniques. Genetic data is generated via whole-genome sequencing, a complex, highly specialized process that determines the DNA instructions of each cell within the relevant organism. Moreover, certain areas are more intensive to sequence. For example, plants generally have more complex genome sequences than animals. Once sequenced, these datasets are analyzed by machine learning algorithms, which predict feasible gene combinations that are the most likely to generate an optimal new variety of agricultural produce or agrochemical input.[18] Once the appropriate genomic patterns have been identified, the seed or livestock is then created in a laboratory environment and provided to farmers. New strains or inputs may then be tested on-farm, which provides additional data points for the optimizing algorithm, ideally improving the efficiency and accuracy of the predictions.

AI AND AUTOMATION IN PRACTICE

PLATFORM COLLECTING AND SHARING GENOMIC MICROBIOME DATA

Eagle Genomics is a pioneering TechBio platform business applying network science across the OneHealth domain. The UK-headquartered business is accelerating life sciences research and development through its AI-augmented knowledge discovery platform, the e[datascientist]. Its platform is utilized by large agricultural, pharmaceutical and consumer goods companies (e.g., Unilever, GSK, Cargill) who make products that interact with various microbiomes, including microbiome-microbiome and microbiome-host interactions. This can involve animal feed for livestock, for example, as well as growth stimulants and agrochemical inputs. The e[datascientist] platform networks scientific data to support step-change innovation – e.g., understanding new key bio-active ingredients that could deliver health benefits or how the microbiome could be better modulated to support regenerative agriculture approaches. Eagle Genomics is bridging the 'translation gap,' so that scientific knowledge from a range of disparate sources and studies across industries can be applied to deliver robust, scientifically underpinned claims. Particular innovation journeys that enable differentiated products and product claims relevant to the AgoBio industry that are related to crops are yield increase, protection, fertility, productivity, climate adaptation/change mitigation - soil treatment, and smart agriculture.

Automated input provision

Automated input provision solutions complete manual on-farm tasks such as feeding, seeding, irrigating, applying fertilizer or spraying pesticide. These solutions can reduce the level of effort and scope for error associated with the manual completion of these tasks. SSPs typically spend several hours each day managing these key inputs during the planting season. In addition, errors such as the overapplication of pesticide may drive up costs through wastage and/or jeopardize yields or even expose SSPs to toxic chemicals. Automated input provision solutions assist farmers by automatically providing an optimal amount of the relevant input to the farm without requiring significant effort from the farmer. These solutions can free up time for SSPs to focus on other responsibilities, reduce wastage costs and, ultimately, improve farmer yield and income.

[18] With respect to agro-chemical inputs in particular, data on the genetic make-up of agro-chemical inputs are assessed in combination with data on the relevant microorganisms on which they are applied (e.g. tiny microorganisms living on the skin of a cow), to establish how the substance interacts with the organism, and identify areas where it could do so more seamlessly.

Automated input provision is carried out by hardware that forms part of the 'Internet of Things'. This can include complex bespoke robotics or simple mechanization such as an automatically opening flap on a smart feeder. This hardware is typically embedded with sensors and software that collect data on particular parameters and share this data with an external computing device. For more complex solutions, this data is analyzed via AI, which uses it to establish when and to what extent the automation should be triggered. Collected data is typically visualized on a corresponding mobile or web interface that provides alerts and analytics based on, for example, how much of the input remains. An automated fish-feeding solution may, for instance, automatically dispense a set amount of food into a pond based on a timer and the corresponding mobile application will notify the farmer when the feedstock is running low.

The extent to which these automations are autonomously triggered varies. Some automations are manually triggered via a switch or timer while others are linked to AI systems that trigger autonomous engagement. If a solution is more 'manual', the farmer sets a timer or flicks a switch to trigger the automated action. The trigger may be physical, like a light switch, but may also be a digital switch or timer housed on a mobile or web application. On the opposite end of the scale, more autonomous solutions have hardware that is linked to an AI system, which decides whether or not to trigger the action based on particular criteria. For example, some automated irrigation solutions may automatically drip when soil moisture is detected to be beneath a certain level and rainfall is not predicted. Data that informs the decision-making parameters may also be collected via separate items of monitoring hardware such as soil-monitoring remote sensors or drone-mounted crop health monitors. Solutions used by SSPs are typically less autonomous.

AI AND AUTOMATION IN PRACTICE

IOT-ENABLED FEEDING FOR AQUACULTURE

eFishery provides IoT-enabled smart feeding machinery aimed at improving the efficiency of input provision in aquaculture - particularly fish and shrimp farming.[19] The solution includes an accompanying mobile interface, which visualizes data on relevant parameters (e.g., feed consumed). This is collected by sensors mounted on the smart feeder, and stored on a secure cloud. The mobile application also allows farmers to remotely control the smart feeder. Farmers can buy or lease the smart feeder on a fixed monthly fee, and absorb any additional data costs. eFishery agents then install the device and onboard the farmer. The firm is also working with mobile network Telkomsel to roll out "NB-IoT" SIM cards, which are SIM cards that connect to a network specifically designed for IoT devices, in order to reduce data costs. The solution is utilized by over 6,000 fish and shrimp farmers in Indonesia.

Alternative credit

Access to reliable sources of finance is critical to SSPs, who may struggle to afford key inputs and machinery. However, these producers are typically excluded from traditional sources of credit, which require proof of collateral and/or formal repayment histories to establish creditworthiness. The seasonal nature of harvesting – and exposure to economic, social and environmental shocks – means that SSPs often struggle with cash flow. When financed, farmers can overcome affordability constraints to purchase key inputs and machinery. Better inputs and machinery can generate greater yields and incomes, increasing the likelihood of credit repayment. However, this may require an SSP to have access to an initial lump sum to invest.

Alternative credit solutions can enable financial inclusion by increasing the number of people who qualify for credit by using non-traditional data and predictive machine learning to build additional credit profiles. Non-traditional data may be sourced from a variety of sources, such as digital payment information, psychometric

[19] GSMA, 2018. eFishery: Shaping the future of Indonesia's aquaculture industry. Available here.

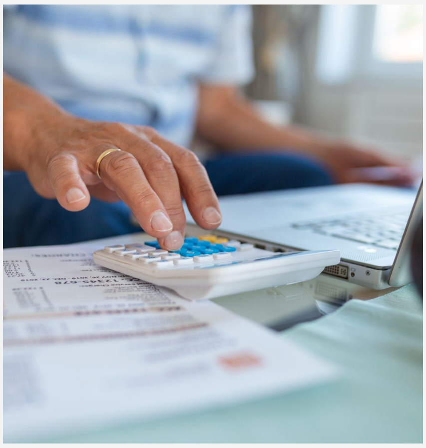
profiles, SMS data or social media activity. This data is then analyzed via machine learning techniques, which conduct near-instant risk assessments of whether an applicant is creditworthy. For example, a psychometric profile that indicates a more risk-averse personality may increase a calculated credit score. These credit scores and profiles allow financial service providers to more confidently assess the risk of extending credit to SSPs and improve services of the previously underserved. In turn, increased access to credit for SSPs can overcome affordability constraints for the purchase of key inputs.[20]

The data collection and sharing process typically involves a web of stakeholders including donors, credit scoring start-ups, underwriters, big banks, credit agencies and farmer cooperatives. Robust private and public data governance regulations are critical to ensure that the framework for the requisite data sharing is balanced by robust privacy measures. Strong regulatory frameworks to avoid predatory lending are also essential. With respect to privacy, receiving informed consent from credit applicants is particularly important, as decisions are made based on information that is not typically associated with financial service provision. Informed consent requires SSPs to understand why and how their data is used, shared and stored, what the process is for opting out, what the impacts of opting out may be, and what recourse measures are available if the provider does not adhere to the stated policies.

AI AND AUTOMATION IN PRACTICE

FINTECH PLATFORM ENABLING REAL-TIME CREDIT SCORING AND eKYC

Dana is a Bangladeshi FinTech platform that provides digital, real-time credit scoring API to digital platforms like e-commerce, Agri platforms, digital wallets (including agricommerce platforms like iFarmer) and digital lending infra to banks, FIs or microfinance institutions to enable them to launch digital lending services. Dana also offers an Agri scorecard for farmers via an assisted model. This aims to enable banks and other financial institutions to provide credit and buy-now-pay-later (BNPL) services to people who are otherwise credit invisible. Credit scores are based on a number of different traditional and non-traditional data sources, including psychometric questionnaires, partner data and financial transaction data. Dana has 28,000 users and 12 network partners. Dana is also connected with 180,000 SMEs of different digital platforms via API connectivity.



Alternative insurance

SSPs are dependent on successful yields and an unforeseen shock that disrupts a harvest can have a catastrophic impact. Insurance aims to build resilience to shocks like these. By providing financial compensation for unexpected shocks, insurance allows farmers to replace, repair or reinvest in whatever was lost or damaged in the course of the unexpected event. Moreover, access to insurance may also increase access to credit, as greater resilience to shocks typically results in greater creditworthiness. Unfortunately, traditional insurance is not typically accessible to SSPs as it requires manual risk assessment, claim verification and compensation disbursement. These are expensive and time-consuming processes, particularly when the insured person is located in a rural or remote area.

Alternative insurance aims to provide an accessible insurance option for SSPs by using automated data collection and analysis to drive down risk assessment, claim verification and compensation disbursement

20 It is important to note that alternative credit typically only assists in overcoming barriers to credit origination, not necessarily the other steps of the credit value chain (e.g., disbursement, utilization, monitoring and repayment). In short, there is a distinction between those who qualify for finance initially, and those who maintain long-term access to finance. If alternative credit solutions are not effective at providing and incentivizing long-run access to finance, the solution will likely be far less impactful.

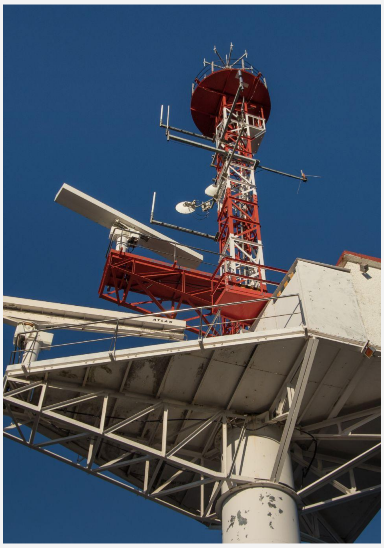
costs. Data may be collected from satellites, weather stations and/or local cameras. For example, satellite imagery can be used to identify if the farm is in a flood zone and, using the data that has been gathered, AI can predict the likelihood of loss by flooding. The data can also be used to determine whether a flood has occurred as well as the severity of the incident if a claim is made. By driving down risk assessment and verification costs, alternative insurance aims to increase access to insurance and, in turn, increase resilience to socio-economic shocks.

For some solutions, insurers make an automatic payout to policyholders when a particular weather parameter deviates significantly from historical patterns, a practice that is known as *parametric* or *index* insurance. Weather-based index insurance typically relies on data from meteorological stations, which can sometimes be more than 20km away from a given farm. This means that an insurable event could happen at the farm but that the nearest weather station does not record it. This is known as basis risk. In this case, the farmer will not receive a payout, will not be able to absorb the shock, will have little recourse with the insurer and may lose trust in the insurance system as a whole. To overcome this challenge, insurers are installing multiple, smaller and less expensive weather stations with smaller ranges and/or leveraging machine learning models that can accurately fill data gaps.

AI AND AUTOMATION IN PRACTICE

PROVIDING INSURANCE SERVICES TO FARMERS BASED ON WEATHER DATA

ACRE Africa links insurance services to smallholder farmers across Africa. The firm's parametric insurance offering is informed by a combination of publicly available and paid historical weather data, as well as real-time data collected by ACRE-owned "small" weather stations. These weather stations aim to reduce basis risk by increasing the resolution at which data is collected. If the weather parameters deviate significantly from historical patterns, then farms receive a payout via mobile money. The product is marketed via "champion" farmers, who are hired and incentivized to generate new sign-ups, which are often completed via USSD. ACRE is experimenting with the use of computer vision AI to automate bespoke end-of-season claim verification procedures, which are currently carried out manually by expert agronomists. ACRE is also innovating though a novel picture-based monitoring tool to reduce bias and blockchain technology to expedite contract monitoring, claim payments and ensure transparency. In Kenya, the firm also offers extension advisory as a free add-on, where the advisory content is curated by KALRO. ACRE has connected over 2 million farmers to insurance since 2009.



Traceability

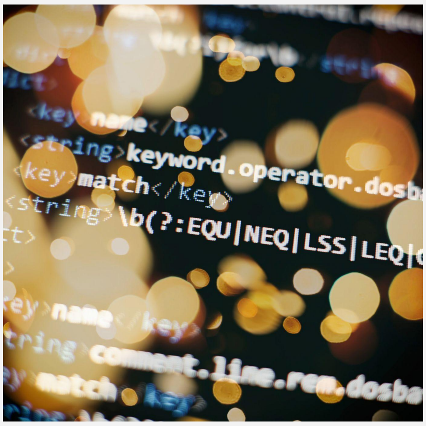
Traceability systems provide verified information about the journey of a product across the supply chain. For SSPs, this can enable access to new markets and drive more transparent pricing. For example, wholesale buyers and end consumers may demand supply chain standards with respect to labor protections, carbon emissions or organic growing techniques. These demands are particularly prevalent in the high-value export market. If there is no system for SSPs to verify adherence to these standards, they may not be able to access high-value supply chains, limiting their ability to earn an income that is sufficient to live on. More transparent information also incentivizes socially responsible behavior as stakeholders understand that any deviation from acceptable standards will be recorded.

Automatically generated unique codes - stored on a distributed ledger[21] or a centralized database - provide information about the relevant standards that the traceability solution tracks. For example, if a solution is designed to trace the point of origin of an agricultural good, a system-generated code that uniquely identifies the small-scale farm on which it was produced is manually or automatically entered into a blockchain or centralized database when a crop, livestock or aquaculture harvest occurs. This unique code remains attached to that good throughout the supply chain so that the end buyer (e.g. Nestlé) is able to quickly and reliably identify its point of origin. As distributed ledgers are tamper-evident, this technology is the preferred storage solution if there are no trusted and well-resourced third-party verification partners in the supply chain. If there are, a centralized database may be sufficient.

AI AND AUTOMATION IN PRACTICE

OPEN-SOURCE REGISTRY IMPROVING MARKET INSIGHTS AND LINKAGES

BlueNumber® is a public benefit organization that provides "blue numbers" to farmers, which enable that farmer to self-declare information such as name, gender, location, products & services, contact information and sustainability information. Farmers own their own data and decide the extent of the information to share, and with whom. Buyers must pay farmers for the data they want to prove traceability or regulatory compliance. This data is referenced on a global, open-source online registry for agricultural buyers to identify potential farmers to buy from, for governments to evaluate farmer compliance with key regulations, and for farmers to sell data to support their income. Interactions between BlueNumbers are also recorded to enable traceability of goods and services as they make their way down the supply chain. Bluenumbers were launched at the UN SDG Summit in 2015 and free to all.



Demand-supply matching

Matching platforms make it easier for SSPs to find buyers and sellers for particular goods and services at transparent prices. Platforms like these aim to provide better information and reduce transaction costs for SSPs. Many farmers may not be able to predict what produce will be in demand in the future, such as more than one season away, and may make the mistake of investing in the production of produce for which there is a low demand. Moreover, due to a lack of transparent information, farmers may also be missing out on more lucrative clients or may be artificially price-squeezed by wholesale buyers who absorb a larger margin when selling downstream. Matching platforms are intended to enable farmers to allocate resources in alignment with market demand, reduce unfair pricing and lower advertising, transportation and other friction costs.

Matching occurs on two-sided web and/or mobile platforms akin to mass marketplaces like Amazon or booking platforms like Uber. SSPs can be active on either side of a matching platform, as they not only need to purchase inputs and mechanized services but to sell produce too. On the selling side, farmers list goods and services at specific prices, often tagged in categories to make identification easier. These platforms may also allow several nearby farmers to aggregate produce and list as one entity in order to improve negotiating power. On the buying side, SSPs can search for where to purchase required inputs and can compare price and product offerings.

Platforms often include recommendation algorithms, which help buyers to connect to the most suitable products, and demand-clustering algorithms, which help the platform allocate resources across both sides of the market efficiently. Recommendation algorithms learn based on previous transaction, search and click data,

---

21 *A distributed ledger is a shared, accessible database that is synchronized across participating people or institutions, and stored across a set of computers. All changes to the database must be consensually approved by participants. A useful analogy is to think about a distributed ledger as a shared Excel document that is stored across various computers, that can only be edited once there is consensus amongst the relevant participants about content of the edit. The details of all the edits (e.g., time of edit, "before-and-after" content), once approved, are tracked and attributed to the editor.*

so that users receive better recommendations with more use. Demand-clustering algorithms aim to ensure that there is neither an oversupply nor undersupply of the goods that are in demand at any point. In addition, some solutions are also experimenting with linking buyer-supplier matching platforms to extension advisory recommendations and alternative credit providers. In this combination, a particular input or machinery is recommended to the farmer, who is directed to a buyer-supplier matching platform.

AI AND AUTOMATION IN PRACTICE

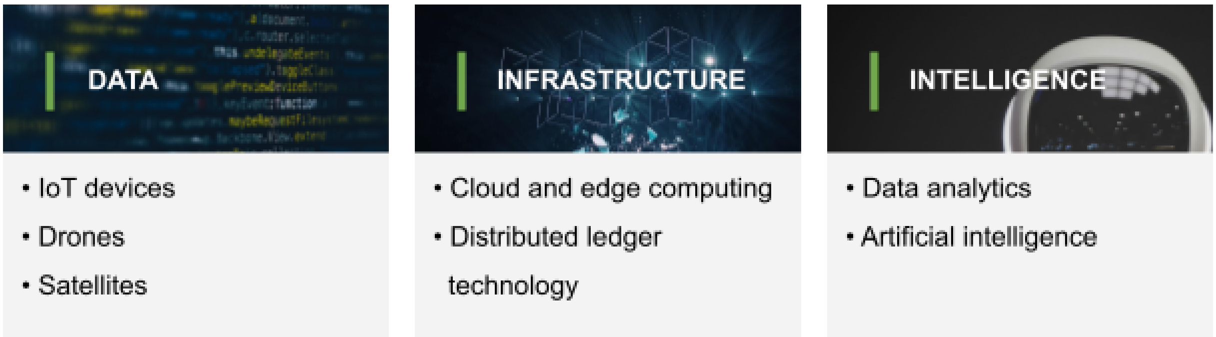
PAY-FOR-USE PLATFORM ENABLING ACCESS TO MACHINERY

HelloTractor is a two-sided software as a service platform (SaaS) that links tractor owners to farmers who require tractors. To ensure that the appropriate equipment is supplied by the appropriate tractor owner, the firm uses clustering algorithms to efficiently match tractor demand to supply, which considers the available supply, logistics of delivering a tractor to the particular area, and the area's terrain. Tractors are fitted with IoT devices that track the length, intensity and type of use, which informs how much the farmer pays. Tractor owners pay the platform an annual fee to list their machinery, and farmers pay the tractor owners based on a "pay-as-you-use" model, with HelloTractor receiving a percentage. HelloTractor also employs booking agents to market the product and organize bookings. These agents earn 5% commission on each booking, and have the opportunity to buy and list on the platform a tractor, once they have booked 1,200 acres worth of tractor use. The platform is operational in 14 countries across Africa and Asia, and hosts over 3,000 tractor owners.

TECHNOLOGY REQUIREMENTS

The technologies underlying AI and automation AgTech solutions comprise at least one of three layers: a data layer, an infrastructure layer, and an intelligence layer. This section of the report explores the technologies within these layers that are involved in the eight priority use cases. For each layer, this section explores how the technologies work, what their utility for SSPs is, and their biggest constraints to impact.

Figure 3: Technology layers underpinning AI and automation AgTech solutions



The data layer refers to three kinds of hardware: IoT devices, including mobile phones, which collect data through embedded sensors and transmit it via the internet; satellites that use a variety of instruments to collect earth observation and imagery data over large areas; and drones that gather high resolution aerial data for a particular location.

The infrastructure layer considers distributed ledgers that store data; smart contracts that can automatically trigger activities and transactions on a distributed ledger; and cloud and edge computing that enables on- or off-premise storage and processing of data.

The intelligence layer translates data into insights and supports decision-making. AI enables machines to perform tasks commonly associated with intelligent beings, such as identifying objects, communicating in a natural language and recognizing patterns in information. AI learns to perform these tasks from data. Data analytics generates insights by identifying blockages, by forecasting and by developing projections. Data analytics can provide similar insights to AI by using more foundational methodologies that don't necessarily rely on 'learning'.

The data, infrastructure and intelligence layers work together to trigger automated actions or recommend actions. The foundation of most AgTech solutions is the data collection layer, which captures specific information on SSP behavior and activities as well as general information on agri-food systems. The devices used in data collection, such as automated timers on IoT devices used for feeding, can trigger automated actions when thresholds are detected. This data is stored and processed in the infrastructure layer, which ensures that it is in a usable format for AgTech solutions and can be reused or made available for research. This layer can also instruct other devices to trigger an automated action. Insights are then extracted by the intelligence layer after data has been collected, stored and processed. Users often interact with the outputs of the intelligence layer. For example, algorithms may provide translated content to SSPs, an analysis of cassava genomes to researchers, and a map of ongoing pest outbreaks in a region to program officers. Intelligence solutions can trigger automated actions in robotics by delivering instructions for drones, automated feeders and other devices, or system responses such as an instruction for the disbursement of credit to an SSP.

There are six enablers that influence the scalability and impact of these technologies. Each of these enablers are critical to the successful functioning of these underlying technologies and are defined in the table below.

Table 2: Underlying technology enablers and their descriptions.

ENABLER	DESCRIPTION
Data Inputs	The availability of large, high-quality and variable quantitative and qualitative data is critical for technologies that monitor the agricultural sector, perform analysis and derive insights. Agricultural data in LMICs can be scarce, incomplete or of a low quality.
Connectivity	Connectivity through, for example, mobile networks, allows for communication between technologies and for data to flow between the layers. High-quality networks can enhance the speed and performance of underlying technologies. SSPs often operate in areas with poor network coverage, which may limit their ability to effectively use digitally delivered agricultural solutions.
Access	Underlying technologies are typically imported into LMICs. This can result in regulatory, IP and other technical barriers to using the technologies. These barriers may, in turn, impede the ability of digital solution providers to access and use the technologies.
Cost	The cost of underlying technologies can impact adoption by AgTech solution providers and SSPs, and influence how they are used. This includes the cost of developing, operating and managing these technologies.
Expertise	Underlying technologies often require specialized expertise for their operation and maintenance. Specialized expertise in LMICs may be scarce. This challenge can be more pronounced in remote areas, where maintenance of hardware is required.
Capability	Capability refers to the ability of a technology to meet its desired objective. This is considered in relation to the challenges faced by SSPs and the ability of the technology to address them. For example, satellites may be unable to provide the resolution needed to deliver precision advisory services for SSPs.

The appendix includes tables that outline the prospective applications of the technologies in the agricultural sector as well as their descriptions. This can be accessed here. The appendix also includes a summary of the results of the analysis that was conducted for each technology. This can be accessed here.

DATA LAYER

IoT devices – also known as physical sensors – provide periodic information on the location and status of an object and/or an environment. These include devices such as soil sensors, which are used to monitor soil moisture and Ph levels. This data is transferred to the cloud through the IoT network, which can be used to provide SSPs with recommendations about, for example, when to water and which fertilizer to use. Technologies such as these are leveraged across the agricultural value chain to collect specific and timely data.[22]

Drones are remote-controlled, aerial robots that gather high-resolution data over a particular area. This technology is particularly useful for agricultural producers that struggle with medium to large land holdings and densely populated crops. Providers of AgTech solutions may also use drones for aerial imaging data, which is used as an input into services like insurance assessments and credit products.

Satellites are communication systems which orbit Earth from space and receive and transmit signals using transponders. Satellite technology is used to collect *satellite imagery data* across various spectral, spatial and temporal ranges.[23] Satellites have a wide range of applications across multiple sectors. Popular applications include GPS navigation using geo-spatial positioning, weather analysis and forecasting using spectral data, and field health detection using spectral data and temporal data. There are four types of satellites, which differ in how far they are from the earth. Over 70% of satellites are Low Earth Orbit satellites, which orbit at high speed and are able to get close to the earth. This enables them to transfer data faster than satellites that are in orbit further away from the earth.

KEY TAKEAWAYS: Data Layer

Smart farming applications, which consist of a full network of IoT devices that are connected via the internet, will most likely be limited to larger and commercially oriented farming in the foreseeable future. The cost and functionalities of IoT devices make it unlikely that SSPs and AgTech solution providers will be able to leverage full-scale, smart farming sensor data collection at any time soon. It seems more likely that a few SSPs will use low-cost IoT devices for the purposes of automated irrigation, livestock tracing, feeding and soil quality management. These are likely to be hand-held IoT scanners developed by organizations such as AgroCares[24], which are used to monitor plant nutrients.

Drone technology is increasingly being used by AgTech solution providers. Data collection using drone services is more often undertaken by SSP cooperatives than by individual farmers because SSPs often have small landholdings, which they can personally inspect without the need for costly aerial intelligence. Drones therefore appear better suited to providing timely and higher-quality insights on the performance and behaviors of groups of SSPs.

Satellite data has the largest reach of all data collection technologies and can be used to develop insights and support the monitoring of agri-food systems. This data can therefore have an impact on numerous SSPs. To date, AgTech solution providers have had to rely on open-source satellite data or purchase satellite data. CubeSats are an important new technology that may change the playing field. These 'nano-satellites' are more cost-effective than traditional satellites and are being launched by governments and companies in a number of LMICs. Innovations in the instruments that these satellites carry may provide governments and innovators in LMICs with high-quality earth observation data.

The appropriate mix of data collection technologies for a market is influenced by the affordability of the technologies and the maturity of the digital agricultural sector. For example, satellite data has the broadest reach of all collection types and is appropriate for all markets, whereas drones and IoT devices are more appropriate for SSPs in higher income and more developed markets.

Data collection technologies that provide specific information on SSP activities are yet to scale in LMICs. IoT devices can collect specific, on-farm data that helps SSPs monitor their crops and livestock and optimize their farming practices. Their use is concentrated in traceability solutions and irrigation systems. Drones can also provide

22 The Digital Supply Chain. 2022. *The Internet of Things - An emerging paradigm to support the digitalization of future supply chains*

23 Spatial resolution is the size of the smallest item displayed in a satellite image. For example, some images will have a resolution of 100 m^2 and others of 10 m^2. Spectral resolution is the wavelength of electromagnetic spectrum that a satellite sensor can capture which reveals data on the geographic makeup of an atmosphere. Temporal resolution data consists of the timestamps of the images taken by the satellite. Data with higher temporal resolution are more frequent.

24 AgroCares has developed three IoT devices which are leveraged to gain precision insights that are delivered through a mobile phone App. Scoutbox scans insect traps for harmful insects, Nutrient scanner monitors on the spot soil nutrients and Lab-in-the-box which gives users the ability to test soil conditions on site.

accurate insights on crop health, pests and weed growth on a farmer's plot. These 'personalized' insights are yet to scale in LMICs as these technologies are expensive for individual farmers, who can use more cost-effective alternatives as they are often small landholders who can easily observe their plots and the status of their crops or livestock. The utility of agricultural imaging therefore increases with the landholding of the farm. Drones must also be flown frequently to allow farmers to react to weeds, pests and crop health issues in time. This poses a challenge in LMICs where farmer communities tend to be remotely located. SSPs with densely populated crops like wheat[25] may be an exception as they stand to gain from aerial imaging.

Technologies that collect information on groups of farmers and the agricultural market are more prevalent and have a wider range of impact. A network of IoT devices that gather data on environmental conditions across a region can improve sector intelligence and this could impact a large number of SSPs. Drone services can rather be used to capture data on the number of plots in an area and their agricultural performance, with the costs of these services being carried by the public sector or spread across a cooperative of farmers. Satellite technology is ideal for data collection in isolated and dispersed LMIC localities as a single satellite can provide data for large or small geographic areas. Digital solution providers do not have to launch their own satellites to access satellite data. Instead, they can purchase data from existing satellites or use data from institutions like Copernicus Open Access Hub, Sentinel Hub and USGS Satellite Imagery for free. Combining satellite imagery with data collected on the ground enables scientists and innovators to develop algorithms that can better estimate environmental conditions, even in localities where IoT, drone and ground-level data has not been collected.

The cost of data collection technologies is the core constraint for this layer and most pronounced in IoT sensors and drones. IoT devices in LMICs are often imported and incur tariff and registration costs. Solution providers must recover these costs from customers, although some have adapted to use more cost-effective devices that are already available in the local market rather than importing. Solution providers and SSPs incur significant maintenance costs for their IoT devices as the skills required to maintain them are often scarce in LMICs. The need for maintenance services may also deter uptake for SSPs due to the risk of long periods of downtime in which the farmer sees little value in the device. Drones suffer from similar cost challenges as drone piloting courses and license registration is costly for prospective pilots.[26] Costs associated with satellites are driven by data quality requirements. High-resolution satellite data is ideal for early warning and locality-specific insights but often has to be purchased. The costs of designing, building and deploying satellites has been prohibitive for LMICs but more cost-effective alternatives like CubeSats are now being launched in many African countries. The spatial, spectral and temporal resolution of CubeSats is currently lower than larger satellites, which can carry more scientific instruments. In addition, CubeSats have shorter lifespans, often not longer than a year. The miniaturization of satellite instruments is nevertheless allowing these satellites to deliver data that has historically been provided by larger satellites.[27]

The capabilities of some of the data technologies constrain their use by SSPs. IoT devices are often designed outside of LMICs and in controlled environments. This can reduce their resilience to unfamiliar or harsh climatic conditions, leading to more frequent replacements. Scaling the impact of drone technology in LMICs is primarily constrained by the technology's ability to address challenges that are specific to SSPs. Outside of cooperatives, SSP landholding is small and likely not tedious to manage, which can trivialize the impact of agricultural imaging data for SSPs. Until recently, the resolution and frequency of satellite imagery data limited the useability of the data in LMICs. For example, enabling precision agriculture for SSPs would require spatial resolutions less than 5m in multispectral bands.[28,29] Innovations in satellite instrumentation do, however, continue to improve the resolution and range of data captured. This includes 'synthetic aperture radar' (SAR) satellites, which use microwaves to gather data regardless of poor visibility caused by rain, storms and clouds.

---

25 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA). 2021. Wheat Plant Counting Using UAV Images Based on Semi-supervised Semantic Segmentation. Available here.

26 UNICEF is alleviating this barrier through its drone training academy in Malawi whose curriculum consists of a drone basics module where students are provided with key skills on drone piloting and drone mechanics (UNICEF. 2020. *The African Drone and Data Academy.* Available here.)

27 Freeman, Malphrus & Staehle. 2020. *CubeSat Science Instruments* in 'Cubesat Mission Handbook: From Mission Design to Operations'. Available here.

28 Frontiers of Agricultural Science and Engineering. 2018. *High resolution satellite imaging sensors for precision agriculture*. Available here.

29 This highlights the importance of research into developing algorithms that can translate low resolution data into higher resolution data. These processes of *interpolation* can be strengthened by complementary, on-ground data.

INFRASTRUCTURE LAYER

Cloud Computing provides innovators with access to remote, third-party-managed applications and flexible data storage and processing services that are connected to via the internet. This infrastructure is the backbone of many AgTech solutions and there are three categories of cloud computing highlighted below. Each category provides the AgTech provider with a wide range of services.[30]

Table 3: Cloud computing categories and their applications

CATEGORY	APPLICATION
Infrastructure as a service (IaaS)	This provides foundational computing resources like storage and networks. IaaS includes services from providers such Microsoft Azure and Amazon Web Services (AWS) with EC2. IaaS is typically managed by a businesses' IT administrators.
Platform as a Service (PaaS)	This provides the technology environments needed to develop and deploy applications. PaaS services are typically bundled with IaaS services and introduce access to operating systems, and other middleware services needed to run applications. IaaS are typically managed by software developers.
Software as a Service (SaaS)	This provides a suite of software services needed for an AgTech solution. SaaS services can be bundled with PaaS services and introduce access to existing applications or data. End users typically use this solution. CropIn is an example of an SaaS provider in agriculture. CropIn provides AgTech providers with a complete suite of services that they can 'plug' into: CropInApps allows users to import their own data from sources like IoT devices or use data available on the platform from sources like satellites in order to gather data; CropIn Data Hub cleans and processes data to make it usable; CropIn Intelligence allows users to develop or use existing AI models to extract intelligence for decision-making.

Edge Computing relies on locally hosted and operated mobile devices and networks for data processing instead of having this done in the cloud. This method provides computing services in areas where sparse internet connectivity limits the ability of digital solution providers to leverage cloud computing. An example of this type of computing can be found in solar fields, where the devices are used to gather and process data to enable remote sensing for weather, to calculate battery usage reports and to adjust positioning. Other examples are applications on smartphones that can be used to detect whether an image of a leaf is suffering from a pest without having to upload this image to the internet.[31]

Distributed ledger technology, like blockchain and others, stores data in a distributed ledger. Distributed ledgers are shared databases that prevent data manipulation and improve data auditability by tracing the lineage of data and its transformations, only allowing changes when they are verified as authentic by the distributed ledger's protocols. The use of distributed ledgers is motivated by how they can immutably record the ownership of an asset (such as an SSP's yield of coffee) and record the transfer of ownership of the asset (such as the sale of a coffee yield to an intermediary) in a way that is auditable. This facilitates traceability and can be done without a centralized authority managing this data. Transactions such as a transfer of ownership can be independently and automatically executed through a *smart contract.*[32] Significant research has been undertaken to improve the ability of distributed

[30] The Digital Supply Chain. 2022. *The cloud, platforms, and digital twins - Enablers of the digital supply chain.*
[31] COMPASS '18: Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies. 2018. *GreenApps: A Platform For Cellular Edge Applications.* Available here.
[32] Smart contracts automate actions on the distributed ledger in response to events on the distributed ledgers such as a transaction, or external events such as a flood.

ledgers to facilitate high frequency and large volumes of transactions for use cases such as digital currencies. The performance of distributed ledger technology appears sufficient for SSP use cases.[33] [34]

KEY TAKEAWAYS: Infrastructure Layer

Cloud computing has reduced the need for digital solutions providers to operate their own infrastructure. Cloud solutions designed for the agricultural sector, which provide increasingly complete foundations for AgTech solutions, will allow providers to focus their attention on design thinking and product innovation and less on technology infrastructure. This infrastructure may also facilitate more rapid scalability of AgTech solutions by allowing established providers in dominant markets like South Africa and Nigeria to easily replicate their solutions in other markets. It may also enable competitors in emerging markets to scale quickly and compete. The growth of these platforms should be monitored as dominant platforms may incur new technical and market risks.

Edge computing using devices such as smartphones may reduce the need for high-quality network connectivity for AgTech solutions. Cost effective edge computing solutions may enable solution providers to innovate and create new solutions that serve SSPs in remote communities without incurring network costs.

Distributed ledgers can often be substituted for more standard data storage and automation technologies. The distributed ledger's greatest utility may be in strengthening SSP rights to the data they produce through their interactions with technology. Scaling this use case may require policymaker awareness of the need for individual data sovereignty, both inside and outside of agriculture.

AgTech solutions that rely on connections to the internet may be difficult to scale in markets with low or costly network coverage. While mobile network coverage in LMICs continues to improve, rural communities are costly for mobile network operators to service. Innovations in technologies that can provide connectivity in hard-to-reach locations, such as StarLink, and LEO satellites, may help to deliver AgTech solutions that require connections to SSPs in the most hard-to-reach communities.

SaaS is the infrastructure that is most widely leveraged by AgTech providers in LMICs, while the utility of distributed ledger technology is acknowledged but not prevalent. Cloud computing supports AgTech solutions by cost effectively enabling real-time data access, accelerating computer task completion and enabling communication systems. AgTech solution developers in LMICs have seen efficiency gains leveraging SaaS and can access the latest in processing infrastructure, which allows them to focus on product innovation and ensure that their solutions are localized effectively. It also allows solution providers to easily replicate their solutions in new markets. There are a small number of AgTech platforms in LMICs that provide multiple SaaS solutions. The emergence of dominant AgTech platforms should be monitored as it may introduce new technical and market risks seen in other markets. For example, a dominant platform that services many farmers and other platforms may create a concentration or single-point-of-failure risk. A dominant platform may also seek to establish 'walled gardens' as has been seen with platforms such as M-PESA in the financial services sector.[35] The distributed ledger has had less prominent uptake and is typically used in traceability solutions.

Poor network connectivity that prevents the effective connection of on-farm devices with cloud-hosted solutions is the primary barrier for digital infrastructure. SSPs in LMICs are often located in remote rural areas that have been a lower priority for the rollout of connectivity infrastructure. Advancements in connectivity may, however, increase the market for AgTech solutions and spur innovation in the space. Scaling mobile networks is expensive but good progress has been made in LMICs. New innovations to reach remote areas, such as TV WhiteSpace, or constellations of satellites such as StarLink, may be key to achieving universal connectivity.

---

33 The Digital Supply Chain. 2022. *Blockchain technologies in the digital supply chain.*

34 Pacific Asia Conference on Information Systems (PACIS)At: Dubai, UAE. 2021. *Quantum Computing - The Impending End for the Blockchain?.* Available here.

35 Platforms often attempt to absorb customers, data, and value and lock these within its ecosystem. This can create silos. For example, regulators in Kenya had to intervene in the mobile money market to instruct M-PESA - the dominant mobile money player - to introduce interoperable payments with other payment systems. Preceding that, value that entered into the ecosystem would often remain in the ecosystem. Preventing the flow of data or information from one ecosystem to the other is a common approach to trying to entrench customers in a platform. Platforms that gather significant volumes of data may also be incentivised to sell this data, creating further ethical considerations for customers.

The availability of alternatives to distributed ledger technology and the cost of distributed ledger expertise results in it being used only in a narrow set of use cases. The benefits gained by AgTech developers using distributed ledger technology may not warrant the associated costs. In many cases, existing alternatives to distributed ledgers may be sufficient to address the challenges faced by SSPs in LMICs. An exception may be solutions that operate across borders and without a single infrastructure operator. Another exception may be in solutions that aim to guarantee the rights of data subjects, such as BlueNumber or Fairfood but these applications transcend the agricultural sector and are embedded in a complex system of laws and regulations. The expertise required to leverage distributed ledger technology is scarce in LMICs and can also be expensive for AgTech developers to obtain. Expertise constraints could be offset by the use of existing distributed ledger infrastructure, such as nChain, although this creates a dependency on third-party technology.

INTELLIGENCE LAYER

Artificial Intelligence enables a machine to perform tasks commonly associated with intelligent beings such as identifying objects, communicating in a natural language and recognizing patterns in information. AI operates across domains such as language, vision and robotics, and performs a variety of functions. These are briefly described in the following box. Readers who would like deeper insight into the trajectory of AI innovation and its potential impact on the agricultural sector after reading this section can find that in the Appendix.

BOX 2: AI DOMAINS AND APPROACHES

There are a wide variety of AI taxonomies which all seek to communicate the different ways that AI operates and the different functions it can perform. The wide variety of AI taxonomies highlight the complexity in defining the technology. The following highlights that there are 5 different domains where AI operates. These domains differ based on the real-world issues that are being solved.

Analytical AI is the application of AI that discovers new insights, patterns, and relationships in large datasets. Analytical AI can inform decision making along the agricultural value chain. For example this may include the calculation of the optimal interest rate for SSPs borrowing credit or the calculation of the optimal time for an SSP to plant their crops based on a variety of data such as the crop type, historical and forecast rainfall, and more.

Functional AI is the application of AI to machinery that interacts with the physical world by executing automated actions. Robotics is a form of functional AI which, for example, helps to train autonomous vehicles to navigate and drive safely. Robotics is typically leveraged in the mining, transport and manufacturing sectors to perform dangerous, repetitive and physically onerous tasks. This could be used to automate the routing of farm tractors.

Interactive AI is the application of AI that enables automated communication with people. This form of AI can interpret and respond to human commands in a personalized way. Common applications include chat-bots which may be used for personalized advisory services for SSPs. Interactive AI often leverages Textual AI, which is discussed below.

Textual AI is the application of AI to text or speech data, typically through natural language processing (NLP). NLP is used in tasks such as translation,answering questions and the generation of new content. NLP has an important role to play for SSPs in such areas as interpreting questions and providing advice or automatically translating responses into local dialects.

Visual AI is the application of AI to images and visual data which allows machines to classify or segment the contents of an image.[36] Visual AI is applied in the field of 'computer vision', which could involve the classification of a crop pest from a mobile phone photo or the identification of which segments of a satellite image contain a certain crop. This information can be used in a number of ways, including to advise on farmer responses or to predict national crop yields.

[36] Iqbal H. Sarker. 2022. *AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems.* Available here.

These AI domains will use a variety of methods. AI includes machine learning (ML) which is a family of algorithms that use data to 'teach' machines to recognize patterns, make decisions or predictions and reason. ML can be used within each of the domains discussed above. Deep learning is a subset of ML, which trains neural networks with multiple layers to learn more complex features of the data. This can also be used within each of the domains discussed above. Another notable approach is reinforcement learning which trains AI systems to solve complex problems by rewarding desirable and punishing undesirable behavior.

Data Analytics is an approach to deriving important insights from data that can support decision-making. There are three notable fields that are relevant to AgTech: *GIS,* which draws insights from satellite and other spatially referenced datasets and allows for spatial intelligence on land, weather, human settlement, and other metrics such as identifying the location and size of farms; *crop modeling*, which involves mathematical algorithms that simulate and predict crop growth using quantitative data about the crop and its environment, such as weather and soil conditions, and crop management issues such as fertilization and planting density, and; *data science* which draws insights from big and complex data using computer science, statistics, AI and information science.[37] [38]

KEY TAKEAWAYS: Intelligence Layer

AI innovation is accelerating rapidly and reducing the amount of data innovators needed to train algorithms. Next-generation algorithms may be able to perform a wider variety of tasks that leverage 'knowledge' of agriculture, although it is difficult to predict which use cases this may unlock. Frontier AI innovation such as Large Language Models is the territory of big tech providers, which have the resources and data needed to develop and test these algorithms. A deeper commitment to AI ethics and its intersection with agriculture will be key in securing an inclusive and responsible AI innovation agenda.

AI solutions require access to large volumes of high- quality and variable data. Unlocking the potential of AI requires scaling data collection, improving how this data is collated, and ensuring wider access to important datasets that can be reused. This will require investments in widely relevant open-source datasets with a focus on data relevant to LMICs, and languages with scarce machine- readable data. It also requires strengthening countries' agricultural information systems, where important and relevant data is stored, and supporting research into agricultural data knowledge graphs.

Openly accessible and easily downloadable algorithms perform well enough for AgTech solutions involving narrow tasks. This has transformed the activities that require the most effort when developing new AI systems as, in many cases, the challenge of developing algorithms lies primarily in the collection of training data. The democratization of AI is being accelerated by AIaaS, which provide innovators with easy access to a suite of AI solutions. AgTech innovators are therefore in a better position to focus efforts on product innovation and less on algorithmic innovation.

The explosion in interest in AI and the growing interest in the democratization of AI has scaled the availability of skills needed to develop and maintain AI algorithms. However, there are three areas in which it may be useful to influence the availability of skills. Firstly, analytics is a male-dominated field that would benefit from greater female representation; secondly, there is an opportunity to improve interdisciplinary skills by improving knowledge transfer between the agriculture and AI domains; and thirdly, it is important to avoid a deterioration in the understanding of AI mechanics, risks and impacts, which could occur if falling expertise requirements to develop AI solutions leads to less expert developers.

Intelligence technologies have far-reaching impacts as they are embedded in almost all AgTech solutions. These technologies require large volumes of data and translate this data into insight. This process includes foundational analysis, such as an estimation of the amount of arable land in a country, to sophisticated systems that

---

37 Springer Handbook of Geographic Information. 2012. GIS in Agriculture
38 Digital Agri Hub. 2022. *Assessment of smart farming solutions for smallholders in low and middle-income countries*

can interpret and respond to SSP queries. These technologies sometimes impact SSPs directly, such as when they provide a farmer with advice or, more indirectly, when they inform national planning. These technologies offer the greatest value in circumstances in which there is a significant amount of complex information that must be understood as, for example, in calculating the impact of climate change, or in which there is a need for high levels of accuracy that is difficult to achieve manually. These technologies also help to scale service delivery as they can automate calculations and the delivery of insights.

AI innovations are changing the scale and kind of data required to develop algorithms. Transfer learning is allowing innovators to make significant progress in training their algorithms using open datasets supplemented by smaller amounts of specific training data. AI algorithms are also increasingly able to digest and use different kinds of data at the same time. Combining multiple data sources and types to deliver more personalized insights is valuable to the agricultural sector. For example, it may be possible to train an AI to translate recommendations for an illiterate SSP into an easily understood picture or diagram.

Access to data is a core barrier to scaling the impact of intelligence technologies for SSPs in LMICs. Inaccurate or scarce data restricts the range of tasks that AI systems can be trained to perform as well as how accurately they can perform these tasks. Although AI models are moving towards greater data efficiency[39],they will continue to require a baseline of training data to ensure they work correctly in local contexts. Data collected for AI training and operations by private sector providers is considered a business asset and is rarely made publicly available. Consequently, prospective digital solution providers often have to collect their own training data, which can carry significant expenses. Improving innovator access to a variety of data sources can therefore increase the range of AI innovation and reduce the cost of developing them. Data scarcity is of particular concern for NLP as it can prevent the development of models for lower-resourced languages that have less machine-readable content available for training.

LMICs are characterized by data quality and availability challenges which can be resolved by scaling data collection and improving access to data. There are three important ways that data sharing and accessibility is being improved:

- Strengthening domestic **agricultural information systems (AGRIS)**, which are useful stores of a range of relevant data and are nascent in most LMICs. This is being done through investments in foundational infrastructure and government capacity. Creating additional datasets for AGRIS is strengthening a ‘whole of agri-food system’ view. This includes transforming manual records into machine readable format, and developing comprehensive farmer registries.

- Developing **open datasets** with data relevant to agriculture in LMICs, which can support innovation and reduce development time and costs. Development partners such as GIZ and IDRC are active in this space, funding institutions such as Lacuna Fund to develop reusable and open data that is relevant to LMICs.

- Supporting the emergence of **agriculture knowledge graphs** which are powerful data structures that can effectively store and classify data from a variety of sources, and store the relationships that exist between these datasets. These graphs help to break down data silos and improve research by allowing the collation of data regardless of source and type. The development of agriculture knowledge graphs is being explored by institutions such as Google, CropIn and Microsoft.

Access to intelligence solutions is improving, but there are concerns that frontier AI innovation remains concentrated outside LMICs. Improved access to open-source AI-algorithms and access to AIaaS which provides out-of-the-box, ‘plug-and-play’ AI solutions is lowering barriers to entry. There are multiple openly available AI-algorithms that can be freely downloaded and trained using new data.[40] With sufficient data, common algorithms appear to be capable of performing as accurately as needed by innovators and service providers in the digital agriculture space. This again means that innovation efforts can focus on understanding how technologies are packaged and re-used to solve local requirements. However, it also means that AgTech providers in LMICs need to strengthen their understanding of the specific impacts on and performance of AI algorithms in the local markets in which they are applied. Despite this, it is concerning that the most cutting-edge AI models such as the GPT family

[39] When delivered through foundation models this is at the expense of model size which may create new access barriers as discussed in the appendix.
[40] OpenAI, TensorFlow, Azure and PyTorch

described in the box below are often developed by big tech firms outside LMICs and are either too large for regular businesses to replicate or are not yet openly available to the public. This concentrates frontier AI innovation and the AI research agenda in big tech. Improving AI access for SSPs will require AgTech providers to contextualize the impacts of AI algorithms to LMICs.

BOX 3: LARGE LANGUAGE MODELS

Large language models (LLMs) are rapidly pushing the frontier of AI forward and have ushered in 'the Age of AI'.[41] LLMs are interactive, textual models trained on enormous amounts of text data. LLMs are revolutionary in their ability to accurately perform a wide variety of tasks such as translation, text summarization, responding to queries, image annotation and others. These models are more capable than ever at interpreting human requests, and delivering human-like responses.

LLMs are being experimented with extensively by big-tech players such as OpenAI through GPT-4 and Meta through LLaMA. OpenAI built ChatGPT using AI models called GPT-3.5 and more recently GPT-4. ChatGPT was specifically designed for chatbot applications[42], with the ability to robustly interpret and act on information. These advances are made possible by a novel AI architecture called the transformer which can learn the context of data, and consume enormous volumes of data.

LLMs have garnered the attention of the world, partly due to their potential to transform multiple sectors - including agriculture. LLMs could be used to extend personalized advisory services to SSPs in LMICs with much less effort than would have previously been required. Innovators are rapidly developing prototypes of conversational AI for SSPs. Continued innovations in LLMs and transformers extend these possibilities. For example, ChatGPT built on GPT-3.5 exclusively accepts text prompts whereas the updated ChatGPT using GPT-4 accepts both text and image prompts which may offer new ways to extend advisory services to illiterate SSPs. Research and data collection efforts are needed to explore whether LLMs trained on LMIC specific agricultural and language data can provide high quality, personalized advisory services.

There are limitations in the application of LLMs in agriculture in LMICs. Users of AgTech solutions built on LLMs may experience the technology negatively due to inaccurate outputs. As all models are trained on data, the models may amplify and perpetuate biases within the underlying training data. These models may also produce nonsensical outputs - especially if delivering this content in under-resourced languages which are largely in remote SSP communities. AgTech solution developers in LMICs may also be unable to leverage the most cutting-edge LLMs due to the prohibitive cost of training and using the models in their applications.

Deep technical expertise is required to build, test and scale intelligent solutions, but agricultural expertise is essential to ensuring that the solutions are safe and beneficial to LMICs. Specialized technical skills are required to effectively and safely use AI and ML. The availability of these skills has grown rapidly in recent years, driven by the proliferation of data, the scaling of AI educational content and innovation hubs, and the 'hype' around AI data science. Increased AIaaS uptake may require continued focus on **understanding AI evaluations** due to the risk that the underlying mechanics and risks of AI will be less understood and harder to evaluate over time. Understanding AI evaluations will also require an understanding of the ethics and implications for local markets. This poses a challenge in LMICs, where **senior talent** is often scarce and expertise tends to be **male-dominated**, which may generate biases in the design thinking behind the solutions provided. The growth in the availability of skills has not occurred evenly across LMICs. To ensure that innovation is well suited to local environments, AgTech solutions will require a combination of technical, agronomic, design thinking and market expertise. Strengthening **multi-disciplinary training and collaboration** between AI, agricultural and market experts could improve the adoption of frontier approaches to analysis by agriculturalists, and strengthen data science and AI practitioner understanding of the agricultural sector.

[41] Gates Notes. 2023. *The Age of AI has begun*. Available here.
[42] Medium. 2023. *GPT-4 vs. ChatGPT: An Exploration of Training, Performance, Capabilities, and Limitations*. Available here.

BOX 4: QUANTUM COMPUTING COULD ENABLE ANOTHER WARP JUMP IN AI CAPABILITIES

Quantum computing uses the laws of quantum mechanics to solve operations that are too complex for classical computers.[43] Unlike classical computers, which use binary digits (bits) to represent data as either 0 or 1, quantum computers use quantum bits (qubits) that can represent multiple values simultaneously. Quantum computing has accelerated rapidly, with key labs at Google, IBM and other institutions locked in a race to build processors with the most qubits. However, more recently, focus has shifted away from maximizing the processing power of a single chip toward building modular computers that leverage multiple connected quantum processors. This shift is expected to accelerate the realization of general-purpose quantum computers, which would be magnitudes more powerful than today's quantum computers and almost unimaginably more powerful than classical computers.[44]

Next generation quantum computing would revolutionize AI and ML models by effectively removing computing power (in today's terms) as a barrier. It would mean that complex algorithms could be trained magnitudes faster, using far more data, and generate far more accurate output. This would have a wide range of applications across sectors, including agriculture. For example, this could enable extremely precise precision agriculture solutions that predict - at a deeply granular level, cognizant of geographic, climate and crop context, and with extremely high accuracy - what input application will generate optimal yield.

[43] IBM, 2023. What is Quantum Computing? Available here.
[44] Brooks, 2023. What's next for quantum computing? Available here.

DELIVERY MODELS

The use cases explored in the previous section paint a visionary picture of the future of smart farming. However, this picture is far from being mainstream. Although AI and automation use cases are being tested – and even scaled – in pockets, the distribution of these applications is highly uneven. This section explores these distribution patterns and identifies the promising delivery model innovations that can drive more equitable adoption among SSPs in LMICs.

KEY TAKEAWAYS: Delivery Models

AI and automation solutions are highly concentrated in LMICs like India, Kenya and Nigeria, where the size and maturity of the digital agriculture ecosystem is more enabling. While there are many examples of AgTech providers in these countries exporting their solutions to other LMICs, there is generally a disparity between the coverage and maturity of AI and automation solutions in these hubs compared to other LMICs.

Even in LMICs with a high prevalence of AI and automation solutions, SSPs in a low connectivity environment with low trust in technology and low ability to pay are far less likely to adopt AgTech solutions compared to larger-scale commercial producers. The main drivers of this adoption pattern relate to issues of trust, accessibility of technology, the knowledge and ability to use these solutions, and the ability to pay among SSPs.

These barriers are being overcome by delivery model innovations that leverage a combination of low-tech delivery channels, in-person intermediary networks and partnerships with value chain stakeholders willing to subsidize the cost of AgTech solutions. These innovations are critical for the inclusion of SSPs but create significant scale constraints due to the high-touch approaches required. AI technologies have the potential to play a key role in addressing this scalability constraint in an inclusive way by emulating the role of a trusted in-person community advisor to SSPs, and in addressing the complexities of local language and low levels of literacy among SSPs.

AI and automation agriculture solutions in LMICs are highly concentrated in a few markets with a combination of enabling conditions. India, Kenya, Nigeria and South Africa are pioneers in the adoption of agritech innovation among LMICs and have diverse digital agriculture ecosystems, including more robust mobile money ecosystems. India has a thriving agricultural ecosystem with a fast emerging AgTech sector, making the country the leader in South Asia. Kenya, Nigeria, and South Africa have the highest prevalence of digital agricultural solutions in Africa, with Kenya as the leading AgTech hub.[45] While there are many examples of AgTech solutions being developed in other LMICs, on balance, SSPs in these countries have far less access to a range of AI- and automation-enabled AgTech solutions.

In each of the leading countries, AgTech solutions have gained momentum from maturing digital ecosystems and well-developed mobile money infrastructure. Increasing penetration and use of mobile phones stimulates demand for digital services, strengthens digital skills and increases rural youth and female engagement, creating an enabling environment for AgTech solutions. These advances have been supported by policies that aim to provide secure, reliable, affordable and high-quality telecommunication services focused on broadband connectivity and mobile penetration in rural areas. These countries also have stronger AgTech innovation environments, which include research and development (R&D) activities and better availability of local talent.[46] Three of the four countries have a large number of SSPs, the exception being South Africa, which has a higher concentration of commercial farms. Table 4 illustrates the differences between these frontier countries and other LMICs with regard to the underlying factors contributing to successful solutions.

---

45 World Bank. 2020. *Scaling Up Disruptive Agricultural Technologies in Africa.* Available here

46 FAO and ITU. 2022. *Status of digital agriculture in 47 sub-Saharan African countries.* Rome. Available here

Table 4: Metrics contributing to AgTech solution distribution

	Number of AgTech solutions[47]	Number of SSPs (in millions)	Mobile broadband connections[48] (% penetration)[49]	Mobile ownership[50] (1-100)	AI readiness indicator[51]	Capacity for innovation (ranking 1–7)[52]
India	200	140[53]	61	59.7	56.11	4.5
Kenya	136	7.5[54]	75	58.9	45.54	4.7
Nigeria	87	38[55]	69	56.3	35.15	3.9
South Africa	73	2[56]	151	75.5	48.24	4.9
Malawi	42	2[57]	37	38.2	24.85	3.3
Ethiopia	42	12[58]	50	37.2	27.95	3.5
Bangladesh	39	15[59]	60	61.1	36.10	3.8

India, Kenya, Nigeria and South Africa are becoming gateways to their regions and beyond, exporting AgTech solutions to LMICs with similar challenges. Several illustrative examples are given in Table 5. Compared to other LMICs, these countries have enhanced business environments, which attract investors to fund the expansion of AgTech solutions into other markets. AgTech companies require scale in order to be commercially viable. Given that uptake of AgTech solutions among SSPs, where the bulk of potential demand exists, is difficult, expanding into multiple geographies is one way of achieving scale. By way of example, Box 5 below illustrates the expansion journey of Hello Tractor, an AgTech company operating in several African and Asian markets. From an ownership perspective, it is likely that the bulk of IP for AgTech solutions in LMICs will reside in these regional hubs.

Table 5: AgTech solutions, countries of origination and expansion

AGTECH COMPANY	COUNTRY OF ORIGINATION	EXPANSION INTO OTHER COUNTRIES
Zenvus	Nigeria	Ghana, Liberia, Niger and South Africa
Aerobotics	South Africa	Malawi, Niger, Nigeria and Rwanda
ACRE Africa	Kenya	Nigeria, Rwanda and Tanzania
HelloTractor	Nigeria	Kenya, Ghana, Angola, Ivory Coast, Uganda, Tanzania, Sengal, Mozambique and Malawi, as well as across South-East Asian countries such as Thailand, India, Bangladesh and Pakistan
CropIn	India	Argentina, Bangladesh, Belarus, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, China, Colombia, Costa Rica, Cuba, Ecuador, Egypt, Ethiopia, Georgia, Ghana, Guatemala, Honduras, Indonesia, Iran, Jordan, Kenya, Mexico, Montenegro,

47 Digital AgriHub. *Dashboard.* Available here
48 GSMA. 2021. *GSMA Mobile Connectivity Index.* Available here
49 Total number of 3G and 4G sim cards divided by population, as a proxy for smartphone ownership
50 GSMA. 2021. *GSMA Mobile Connectivity Index.* Available here
51 Oxford Insights. 2021. *Government AI Readiness Index 2021.* Available here
52 World Economic Forum. 2018. *The Global Competitiveness Report 2017–2018.* Available here
53 Department of Agriculture, Cooperation & Farmers' Welfare. *Annual report 2020 - 2021.* Available here
54 IFAD. 2019. *From low to high: Increasing productivity and purchasing power in Kenya*. Available here
55 Baban Gona. *Uncommon facts about smallholder farmers in Nigeria.* Available here
56 WWF. Climate smart smallholder farming. Available here
57 FAO. 2021. *Small family farmers produce a third of the world's food.* Available here; and Stakeholder interviews. 2022
58 FAO and ITU. 2022. *Status of digital agriculture in 47 sub-Saharan African countries.* Rome. Available here
59 The Financial Express. 2019. Smallholders need intensive care. Available here

AGTECH COMPANY	COUNTRY OF ORIGINATION	EXPANSION INTO OTHER COUNTRIES
		Morocco, Mozambique, Myanmar, Nicaragua, Nigeria, Papua New Guinea, Peru, Philippines, Russia, Rwanda, Serbia, South Africa, Tajikistan, Tanzania, Thailand, Togo, Turkey, Uganda, Ukraine, Vietnam and Zambia

BOX 5: HELLOTRACTOR'S GLOBAL EXPANSION THROUGH CLOUD-BASED TECHNOLOGY

HelloTractor and its automated tractor-booking platform is introduced in the use case landscaping section here. HelloTractor was conceived by American founder, Jehiel Oliver, who came up with the idea while working on a project aimed at improving access to mechanization in the rice value chain in the Philippines.

Nigeria was selected as the initial target market due to its large size and the high number of SSPs and tractor owners in the country as well as its potential to be a first mover. Jehiel learnt from the use of IoT tracking of high-value assets in Africa to quickly bootstrap the IoT stack and build a mobile app on top of the IoT data. Over time, HelloTractor developed its own engineering and data science team to support its expansion across 14 African and Asian markets, with approximately 3,000 tractors across the platform providing mechanization services to over 650,000 smallholder farmers.

HelloTractor's geographic expansion has been largely opportunistic. The company only has physical offices and teams in Nigeria and Kenya, countries it has selected carefully as geographies in which it could be a market maker. Its operations in other geographies are opportunistic and consist of offering its SaaS solution to large clients looking for a technology solution to manage their tractor fleets. The ability to turn on a cloud-based solution in a new geography without needing a physical presence, and the lengthy process of recruiting country teams, has enabled this rapid geographic expansion.

Even in leading countries with the most AgTech solutions, there are uneven adoption patterns in favor of larger and more commercially-oriented farmers. AgTech solutions face significant barriers to scale, and adoption is informed by the characteristics of the end user. SSPs in a low-connectivity environment with low trust in technology and low ability to pay are far less likely to adopt AgTech solutions compared to commercial producers with better connectivity, greater familiarity with technology and a greater willingness to pay. SSPs generally operate in rural areas with lower rates of digital inclusion. In varying levels across gender, age and income in LMICs, rural populations tend to be less trusting of digital tools and may not have adequate levels of digital literacy to enable them to engage and benefit from all the offerings available. This is often compounded by a reluctance to change that is generally associated with aging farming populations.

While AgTech solutions are being leveraged by both SSPs and larger or more commercially-oriented farmers in LMICs, the main barriers to greater adoption among SSPs are trust, the accessibility of technology and the ability to pay. These barriers – and the delivery model innovations showing promise in overcoming them – are discussed in the following subsections.

Overcoming trust barriers through intermediaries

AgTech solutions typically rely on digital channels to deliver information and services to their intended users in order to keep costs low and support scalability. However, these channels often do not match with the established preferences of SSPs who prefer receiving advice and knowledge from family members, local community members or extension workers. These channels underscore the importance of in-person, local and trusted stakeholders for delivering advice to SSPs that are both trusted and onboarded.

AgTech providers are pivoting their delivery models to leverage existing trusted intermediary networks among SSPs to drive uptake and adoption. In addition to direct delivery, these solutions are being designed to support the intermediaries to be more effective in providing SSPs with support. There are three main intermediary networks supporting this process. Digital advisory solutions can provide **extension workers**, who are more familiar with digital applications, with the information and resources they need to accurately advise SSPs without constant training. In addition to extension workers, who are usually employed by the government, **agent networks** linked to AgTech solutions are becoming commonplace, largely because it is difficult to deploy these solutions to farmers without an in-person engagement. In some cases, these agent networks are being recruited and deployed as a stand-alone business, providing a distribution channel for multiple input, financial service and AgTech providers. **Lead farmers** are successful and trusted farmers in their communities, who can act as pioneers in adopting AgTech solutions and helping other farmers benefit from digital advisory solutions. AgTech providers like Plantix are also using agriculture influencers, popular locals publishing videos on the best agricultural practices through social media, to market their solutions.

BOX 6: AGRA'S VILLAGE-BASED ADVISORS INTERMEDIATE AGTECH SOLUTIONS FOR SSPs

To address the critical shortage of government-operated extension workers in Kenya, AGRA implemented a village-based advisor (VBA) model to train lead farmers, who are well trusted by their communities, to provide extension advice to their peers. The VBAs are also linked to input companies to promote seeds of improved crop varieties and fertilizers together with good agricultural practices. They often become agro-dealers of inputs at the village level, providing a link for last-mile delivery of inputs and AgTech solutions.[60]

Currently, AGRA's VBA network comprises 39,000 VBAs in 10 African countries, and has been a critical component in the delivery of AGRA's digital solutions for farmers. For example, AGRA and Microsoft launched the AgriBot in 2019 to provide automated extension and advisory information at scale to SSPs through SMS, USSD, and WhatsApp channels. After registering, farmers input their personal details and location in order to receive personalized information on weather forecasts, optimal seed varieties, pest warnings and good agronomic practices. Within its first year of piloting in Kenya, the AgriBot recorded over 48,000 farmer registrations.[61]

A significant driver of this uptake was incorporating the role of VBAs into the design and implementation/distribution of the AgriBot. While farmers can register for and use the bot directly, the tool also supports VBAs to register farmers and provides them with the content required to deliver impactful extension advice. The use of VBAs resulted in many farmers being registered as they trusted them compared to anonymous/unsolicited messages they received. The bot also supports engagement between the VBAs and their farmers- VBAs and farmers can message one another through the bot at no cost. The move now is to get service providers onto the bot to provide more services such as crop insurance, markets (off taking) and financial services.

There is a limit to the scalability of intermediary networks, making AI critical in supporting the transition from intermediary engagement to direct engagement with the farmer. The current ratio of extension workers to SSPs averages 1:1,000 in Africa, and 1:750 in India.[62] Working only through in-person intermediaries will always have a scale constraint to the coverage of AgTech solutions due to the cost of recruiting and training these networks. Hopefully, SSPs will slowly become accustomed to engaging directly with AgTech solutions after witnessing their benefits through intermediaries. It will be critical to have digital advisory solutions that can substitute for in-person engagement by emulating the experience of engaging with a trusted local community member. AI solutions hold great potential to deliver this experience by providing personalized and localized recommendations and on-demand information in the same way that human intermediaries currently can. In the healthcare sector, for example, conversational AI applications are showing promise in emulating the role that community healthcare workers play in providing primary health care advice.[63]

Overcoming technology accessibility barriers through low-tech and low-literacy channels

Beyond issues of trust, digital delivery of AgTech solutions can be exclusionary due to poor accessibility of digital technologies among SSPs. AI and automation solutions generally require high digital connectivity and high tech devices as enablers for data processing. However, significant numbers of SSPs operate in low connectivity

[60] AGRA. 2021. *The Role of VBAs is Crucial to Vision for Inclusive Agricultural Transformation, says AGRA President*. Available here
[61] Harper, nd, *The Digital Acceleration of Africa's Green Revolution*, available here
[62] ResearchGate. 2019. *Agriculture Extension System in India: A Meta-analysis.* Available here Stakeholder interviews. 2022
[63] Car et al., 2020, *Conversational agents in healthcare: scoping review and conceptual analysis*, available here

environments without smartphones, do not have access to smart devices, and do not have the literacy to make use of information delivered in writing, especially when delivered in a non-local language.

AI and automation solutions can be delivered through low-tech channels such as USSD, SMS and IVR, with smart technologies being applied on the back-end. The role of AI and automation technologies in AgTech solutions designed for SSPs is often underestimated as these low-tech delivery channels are assumed to be the entire range of technologies used in the solution. AI and automation solutions frequently use frontier technologies, like machine learning, to generate the personalized insights and content that is delivered through channels popular with SSPs such as SMS and IVR. Leveraging popular and accessible channels is critical to ensuring the reach of a solution. Solutions delivered through smartphone and web applications may become increasingly feasible in maturing markets, assuming the information reflects user literacy levels and data costs are not prohibitive.

To accommodate for ranges of literacy and digital literacy, content and interfaces are currently being designed in a way that makes AgTech solutions more accessible. SSPs across the globe differ in their preferences for the format of information they are provided with and in the way they interact with digital tools. They may. For instance, have a preference for IVR-delivered content in one locality and video in another, which may reflect the digital maturity of the market. Voice is a lowest common denominator and is accessible to less literate users through feature phones that do not require an internet connection. AI solutions that can compress and transform insights into formats that are digestible for SSPs by, for example, responding to a complex SSP query using an SMS or graphic user interface, will become extremely valuable. The ability to collect and distribute information to and from SSPs in the language of their preference will also be crucial. Here, AI applications that can automate translation of content into local languages – and understand written or verbal inputs from SSPs in local languages – will be particularly important.

Overcoming commercial viability barriers through bundling and B2B2C delivery models

As some of the poorest people in LMICs, SSPs often cannot afford to pay for AI and automation products and services. Solution providers must therefore develop creative commercial and business models to ensure they are commercially sustainable. This includes changes to the way in which products are charged for, who pays for these products, and in the funding types AgTech solutions seek. This often requires relationships with agricultural input providers, government agencies, development donors or local agricultural organizations.

Commercially sustainable AI and automation solutions are difficult to achieve, resulting in many solution providers relying on donor funding. This may be contributing to an inefficient allocation of capital. A failure rate of around 90% of AgTech startups[64] can be partly attributed to the complexity of developing sustainable commercial models. Recovering the costs of these solutions by charging SSPs is often not feasible.[65] AgTech providers can also struggle to scale without an existing customer base or distribution network. Resolving these challenges can be particularly difficult for AgTech solutions that are founded and led by technologists as, in contrast, sustainable AgTech solutions are often spearheaded by commercially minded leaders. Equity and venture capital are unwilling to onboard investments with providers that have weak business cases. Philanthropic and grant funding often fills this gap, motivated by development agendas and permitted by looser investment requirements relative to the private sector. This can lead to wasted capital that is invested in solutions with the potential for social impact, but unproven or weaker potential for commercial sustainability. Donor funding is furthermore often only provided for two to five years while entrepreneurs often have a longer funding requirement in order to reach scale. For example, EKutir, DeHaat and WayCool have taken approximately eight years to offer full-stack or multiple services.

Some of the most successful solutions have leveraged extensive partnerships and bundling to derive revenue from sources besides SSPs themselves. Established players in the agricultural sector, such as input and financial service providers, have ready access to large customer bases. AgTech solutions with low margins can generate revenues by partnering with established players and charging them to bundle their AgTech solutions into existing services and products. The AgTech solutions are then provided to SSPs at no cost. The bundle of services can create more value for established players' customers, provide new sources of insight for their businesses, and strengthen service offerings through opportunities for innovation. Box 6 illustrates how Pula leverages agricultural

---

[64] AgFunder News. 2022. *Farmers have been burned by agtech too often. Here's how to win back their trust.* Available here
[65] Many SSPs are unwilling to pay for a service that they think could be substituted for free (e.g. extension services), are often unable to carry lump-sum costs (e.g. purchasing an IoT sensor), or are less likely to invest in solutions that may offer a benefit (e.g. seeding guidance based on weather).

input companies to offer insurance at no cost to the SSP. These B2B2C models are powerful and are enabled by forums such as ThinkAg, which connects AgTech solutions providers, established players and financiers.[66] In addition, AgTech solutions with high upfront asset purchase costs are overcoming affordability constraints by offering asset repayment plans on a pay-as-you-go basis for solutions such as solar-powered irrigation pumps that use IoT to monitor usage. Finally, some AgTech solutions may be able to derive new sources of revenue from the insights they collect from their users. For example, AgTech solutions with insights from SSP advisory services could use this information to manage and oversee input supply chains, thereby integrating backwards into the value chain.

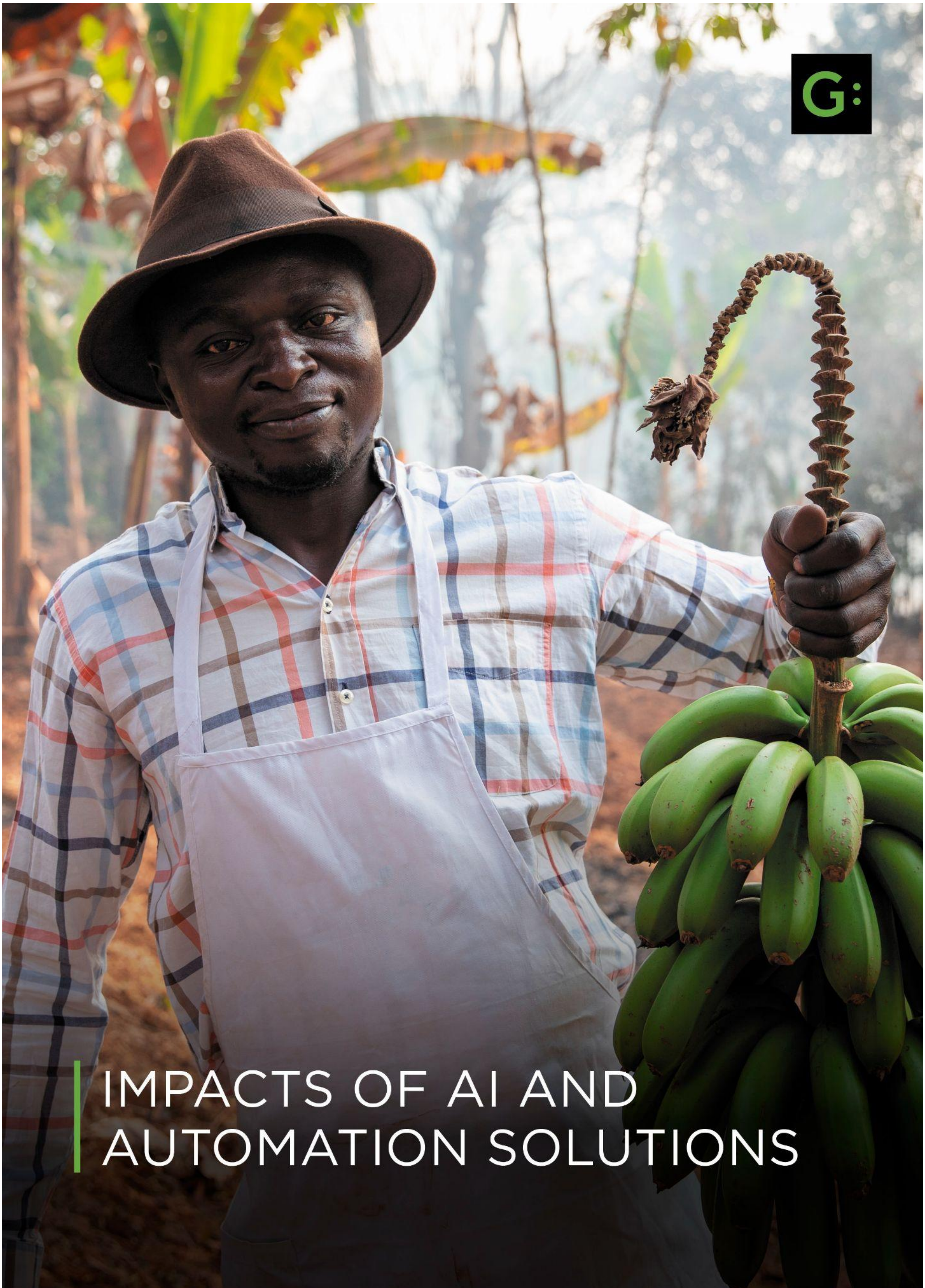
BOX 7: PULA USES PARTNERSHIPS TO SUPPORT COMMERCIAL VIABILITY

Pula is an automation-enabled agricultural InsureTech company that uses a combination of tech innovation and partnerships to significantly reduce the cost of providing agricultural insurance to SSPs, without the farmers needing to pay for the insurance themselves.

Pula is not itself an insurance company, but rather works with local insurance companies and global reinsurance firms to cost-effectively enter the SSP insurance market by drastically reducing the cost of product design, risk assessment, customer onboarding, claims processing and payouts using technology. Pula has developed several agricultural insurance indices, such as an area yield index for crops that estimates yields for a specific agronomic area, and a normalized difference vegetation index for livestock, which measures the health of grazing land in an area, using earth observation and meteorological data processed through data analytics techniques. This data informs automated decision-making for compensation in the event of loss, which drastically reduces the cost of developing and operating agricultural insurance products designed for SSPs.

However, it is Pula's approach to creating partnerships that ultimately solves for commercial viability. By bundling agricultural insurance with products that SSPs already purchase, like seeds and fertilizer, the high cost of onboarding customers is negated. Bundling also helps to solve the 'who pays' problem as SSPs do not need to cover the cost of the insurance. This is covered by agri-input companies with an incentive to help SSPs become more productive and recover for yield losses, or by governments and donors. These players are willing to subsidize the insurance premium payments for SSPs to differentiate their products from competitors and to benefit from the data and insights that Pula compiles.

66 ThinkAg. 2022. *The Platform*. Available here.


IMPACTS OF AI AND
AUTOMATION SOLUTIONS

Determining the impact of AI and automation technologies on agricultural value chains is complex and contested. There are several factors that prevent a clear understanding of the direct and indirect impacts of AI and automation solutions on the agricultural sector. These include:

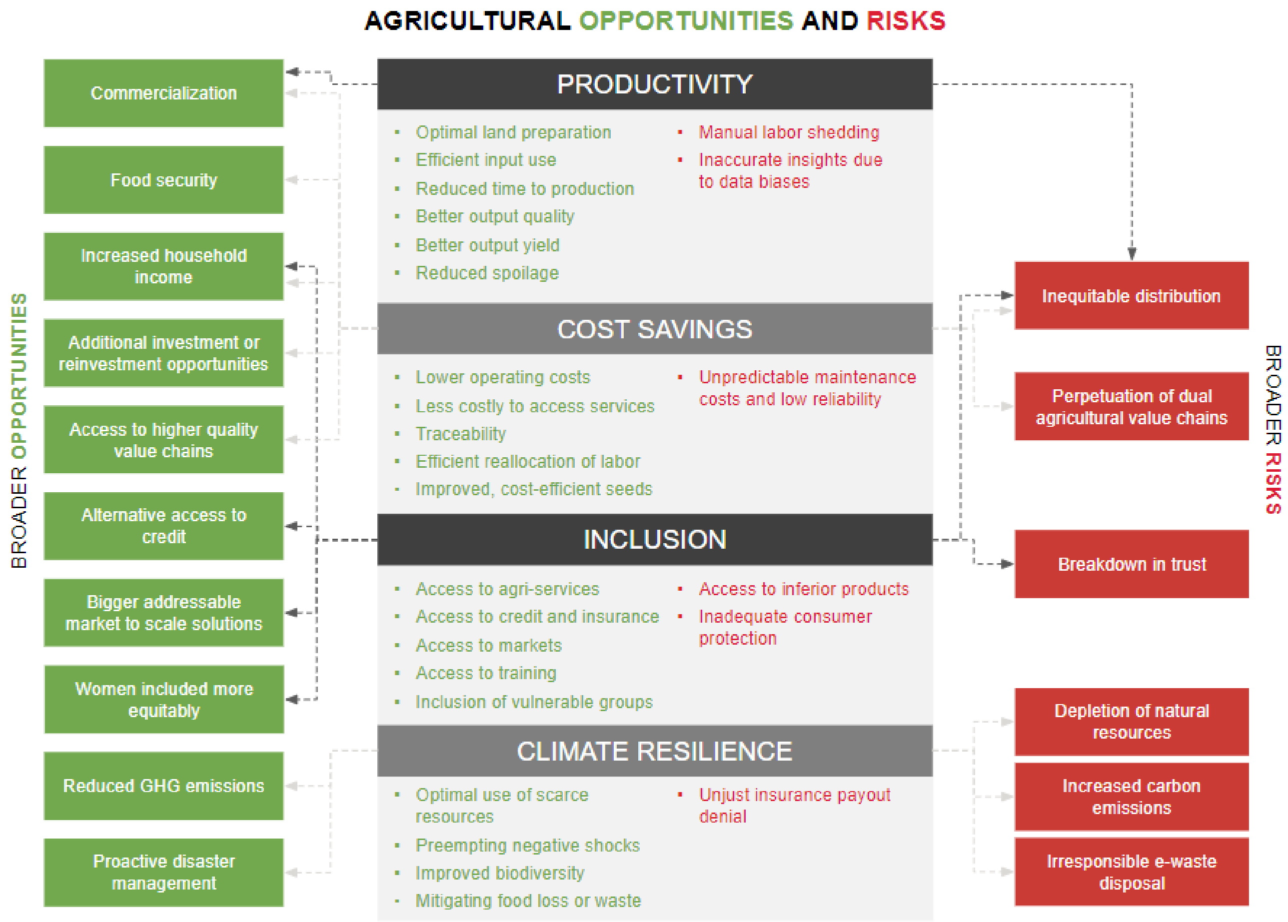
- ***A lack of empirical data:*** The introduction of AI and automation solutions in agriculture is a relatively new concept, often deployed in emerging countries and particularly in rural areas, where there is a shortage of systematic data collection. Impact data is often only available in isolated cases and is provided by the companies implementing the solutions.

- ***Bundling of solutions:*** AgTech solutions are often bundled together with other products and services, such as inputs, and delivered through a channel offering multiple services, such as an agent network. For example, a digital climate advisory service may also offer SSPs access to microcredit, insurance and rental equipment in addition to advice on climate smart agricultural practices. This makes it difficult to isolate and determine the net impact of any one of these technology solutions or the impact of the technology from the impact of the non-tech products it is bundled with.

- ***Independent implementation of solutions:*** There is a tendency for AgTech solutions to be implemented in silos and without an understanding of the long-term ramifications for SSPs. Poor design can jeopardize adoption rates and the sustainability of these solutions, and can lead to negative outcomes that could have been avoided had they been implemented with a more holistic approach.

To address this complexity, this study identifies the general impact pathways of AgTech solutions. There are four critical pathways through which AI and automation will have the biggest impact: i) improved productivity, ii) cost efficiencies, iii) inclusion and iv) climate resilience. There are two ways that the impact across these pathways can be considered. *Firstly,* impacts can be considered as either opportunities or risks. *Secondly*, these impacts can either be directly attributable to the agricultural value chain as agricultural opportunities and risks or indirectly attributable to broader socioeconomic, environmental or development issues, such as household income, environmental landscape and food security, which may be defined as broader opportunities and risks.

Figure 4: Overview of impact channels and associated agricultural and broader opportunities and risks



Source: Genesis Analytics, 2023

The range of impacts highlights that there may be important impact trade-offs across AgTech solutions. The way that these risks and opportunities emerge varies by channel and is dependent on the context of the AgTech solution and the way in which it was implemented. However, the number of potential opportunities outweighs the number of possible risks. The preceding figure provides an overview of the impact pathways, direct opportunities and broader impacts that are further described below.

Necessary preconditions

To realize the positive impact that AI and automation solutions offer to the agricultural sector, several enablers need to be in place. Failure to create an enabling environment for these technologies could result in the identified opportunities not being fully realized, or potential risks not being effectively mitigated. There are several cross-cutting factors that need to be in place, which include:

1. ***Digital inclusion:*** This involves several critical ICT infrastructure requirements that are essential to guaranteeing individuals' participation in digital services. *Firstly,* reliable, fast and ubiquitous **mobile and internet networks** are needed. *Secondly,* many remote AI or automation solutions require smallholder farmers to own a **smartphone device** to manage or engage with the solution. *Thirdly,* access to **electricity** is vital for individuals to access digital solutions. This is a particular concern for individuals located in remote or rural areas, where the majority of smallholder farmers reside, and where expansion of national electricity grids remains a significant challenge. *Fourthly,* capacity building to enhance the **digital and technical literacy** of SSPs (particularly those with limited formal education or older generations). *Fifthly,* the **affordability** of these solutions is critical to inclusion.[67] SSPs with limited financial resources may struggle to leverage solutions if they cannot afford devices or data, are unable to obtain credit or are unable to afford upfront capital investments. *Finally,* there are social and cultural norms that can influence gender

[67] Affordability here also considers whether low-cost domestic assembly of innovative solutions is viable.

dynamics as regards mobile phone ownership within a household. This creates uneven access to AI and automation solutions among men and women.

2. ***Effective public-private collaboration:*** Regulation typically lags behind technological developments which can inhibit the establishment of a secure and trusted environment for digital products and services. Flexible regulatory approaches need to be adopted by governments and policymakers to provide a framework that is fit for purpose in an evolving digital environment. An effective framework provides guidelines for regulating technological developments to ensure effective consumer protection, build trust in digital systems, and prevent data misuse. It does this without stifling innovation. The implementation of effective regulatory frameworks necessitate effective development cooperation amongst public and private stakeholders because, without adequate participation, effective regulation may not have the intended effect of supporting an all-inclusive digital ecosystem.

3. ***Human-centered design:*** A human-centered design approach is critical to the success of AI and automation solutions targeting SSPs. This places the SSP at the heart of the solution development process which ensures that the solution resonates with the SSP's circumstances and is tailored to meet their needs. The approach helps to ensure that appropriate digital channels are used, that relevant services and information are provided, and that the solution is coupled with a sustainable revenue model that supports adoptions by SSPs.

4. ***Holistic and complementary strategies:*** There are many stakeholders developing and offering innovative AgTech solutions. However, these solutions or programmes are often implemented in isolation. This has led to a fragmented market and disjointed progress across countries and markets. Strategies geared toward improving SSP productivity and livelihood requires effective harmonization amongst various stakeholders to be effective.[68] This is separate to the point of stifling competition and innovation, but rather focuses on various policy agendas and programmes being porous and creating an 'open-door' policy amongst program officers and policymakers alike.

[68] The Delivery Models section highlights how inefficient capital may contribute to the fragmentation and congestion of the AgTech solutions market.

IMPACT PATHWAY 1: **PRODUCTIVITY**

Innovations in AI and automation have the potential to advance agricultural productivity and contribute to the maintenance of global food security - an urgent necessity given the predicted rise in global population.[69] Traditional farming methods alone will not be able to support the rising demand for food. However, the introduction of innovative AI and automation methods can help increase food production, allowing for improved efficiency and a better quality of agricultural produce. The priority use cases that are mostly likely to result in positive productivity impacts include farm health monitoring, digital advisory services and automated input provision.

Agricultural Productivity Opportunities

AI and automation solutions can improve SSP knowledge and decision-making across all stages of the agricultural production cycle. This presents several agricultural opportunities for SSPs:

1. ***Optimal preparation:*** Data collected from sensors, satellites, or drones can help SSPs identify optimal areas for new crops and livestock. These data-generated insights can also help SSPs use their arable land more strategically by identifying which crops and livestock are best suited for farming based factors such as soil and grazing quality.

2. ***Efficient input use:*** Automated irrigation systems can ensure that inputs are evenly distributed and efficiently used. AI-enabled weather forecasting helps SSPs plan what type of crop to grow and when seeds should be sown. Automated advisory services in the form of chatbots built into AgTech solutions, and services like ChatGPT could extend knowledge to users who would not have access to it otherwise.

3. ***Reduced time to production:*** Sensor data provides precise readings from soil, water, crops and livestock, which can reduce time to production as inputs can be administered on time and in line with the underlying environmental requirements. Technologies such as drones can identify when certain areas or crops are ready for harvesting while owner-renter platforms, such as TroTro Tractor provide access to mechanization services that can reduce harvesting time, and demand-supply matching platforms can assist SSPs to find appropriate input and output markets.

4. ***Better output quality:*** Precision farming and predictive analytics provide farmers with accurate guidance on irrigation management, crop rotation, timely harvesting and nutrition management for agricultural and/or grazing land. This allows the SSP to cultivate a better quality of produce.

5. ***Better output yield:*** Digital advisory services provide SSPs with real time advice on weather conditions, farming practices, and preferred input suppliers based on the quality of products available. This, combined with predictability in yield forecasting using cropping lifetime, enables SSPs to cultivate better quality output while also using inputs more efficiently. This results in higher yield quantities after harvest periods.

6. ***Reduced spoilage:*** IoT sensors, drones and satellites allow farmers to monitor the incidence of crop diseases and pests on the ground at a micro level as well as from the air at a macro perspective. Aerial or spatial imaging solutions provide farmers with detailed information on current crop health, allowing them to take timely action and mitigating against them losing large amounts of produce as a consequence of pests and bacteria. Radio-frequency identification (RFID) tags or physical bio-sensors also allow SSPs to monitor livestock health. Further, sensor-enabled storage facilities and logistics can help reduce spoilage in the post-harvest and distribution phase of the production cycle.

Broader Productivity Opportunities

Enhancing the productivity of SSPs can also lead to new commercialization opportunities and contribute to local, regional and global food security. Automated on-farm practices, coupled with precision cultivation techniques and digitally accessible advisory services, improves yield quality and results in more output being generated with fewer inputs. This can secure a critical contribution to local, regional and global food security given the expected increase in demand for food and the growing importance of SSPs in meeting this demand. Stronger

69 United Nations. 2022. *Global Issues: Population*. Available here.

local production can also improve domestic resilience to global food supply shocks. This surplus yield can further improve SSP commercialization opportunities, generating additional revenue. This, in turn, can generate more income for the household, which can be used to meet other needs. The importance of increases to household income are discussed further under Inclusion.

Agricultural Productivity Risks

Productivity-enhancing applications may have negative impacts on SSP employment, or unintended consequences that weaken SSP productivity. Developing policies and programs that mitigate these two risks will be critical to the wellbeing of SSPs.

1. ***Manual labor shedding:*** automated input provision systems are designed to use water, labor, fertilizer and power requirements efficiently. Consequently, less on-farm labor is required. While labor shedding is a concern, there are several nuances that describe the shifts in labor and the factors that determine how risk-bearing they are. These are discussed in the box below.

BOX 8: CONSIDERING THE LABOR EFFECTS OF AI AND AUTOMATION

On-farm laborers often perform menial tasks, with employment being influenced by seasonal fluctuations. Additional ad hoc labor is required during particular periods such as planting or harvesting. However, automated on-farm processes minimize the demand for this ad hoc labor. As such, these individuals will have fewer seasonal employment opportunities in a sector that is typically a significant and reliable employer of low-skilled labor.

The overall labor shedding impact attributable to the introduction of AI and automation is dependent on underlying country and local circumstances. In South East Asian countries, where population rates are decreasing, the introduction of a blended workforce, combining digital solutions with traditional farmers and tools, is proving to be effective as there are fewer people entering the farming profession due to the physicality required by the profession, which is becoming unmanageable for aging populations. This, coupled with high job rate turnover and seasonal externalities, which makes small-scale producers dependent on highly mobile migrant labor, makes the profession unattractive or unsustainable. AI addresses these labor challenges by augmenting or removing certain on-farm jobs and reducing the need for unreliable, ad hoc labor. However, in African countries, where the majority of populations are youthful and population growth rates are increasing, on-farm automation likely presents a greater risk to overall unemployment rates.

Although labor shedding in agriculture will occur in some instances, like most disruptions, the introduction of automation technology will lead to new sources of employment. Research on the impact of automotive technologies such as robotics, and AI on job security can portray misleading insights if the methodologies used do not factor in important dynamics.[70] The adoption of new automation technologies in the agricultural sector can bring additional commercial viability as it will require additional investment, infrastructure development and service provision, all of which will require new skills and jobs. Further, previous predictions of the impact of technology on agricultural employment failed to take into consideration that as economies evolve; jobs that become redundant are replaced by new jobs that are created as a result of progress. Finally, when analyzing whether automation negates job creation, it is important to consider whether automation technologies can realistically be fully automated or whether they require other manual inputs overseen by humans.

Many of the new jobs being created in the deployment of AgTech solutions are relatively low-skilled jobs with minor barriers to entry. For example, the need to deliver AgTech solutions through in-person intermediaries is creating demand for booking, sales and engagement agents in rural areas. At least 35% of AGRA's village-based advisors (VBAs), described in more detail in the Delivery Model section, have commercialized their roles by becoming agents for agri-input dealers. Booking agents on platforms like HelloTractor can access financing options to purchase their own tractors and become tractor owners themselves once they have enough tractor services booked. An in-depth study conducted by the Bureau of Labor Statistics

[70] Economists Carl Benedikt Frey and Michael Osborein published a 2013 working paper on impact of automation technologies on existing jobs. The methodology used to estimate this impact has since been proven inaccurate and over inflated the predicted impact.

(BLS) found that, despite farmworkers and agricultural equipment operators being high-risk occupations that are subject to redundancies as a consequence of automation, between the period of 2019 and 2029 job opportunities will grow by 1.0% and provide 9,100 new jobs.[71] Actual figures are likely to be even greater given that, between the period 2008 and 2018, employment in this sector was projected to decline by 2.4% but actually grew by 9%.[72]

2. ***Inaccurate insight due to data biases:*** AI-enabled solutions that produce biased or inaccurate insights could result in SSPs making incorrect on-farm, harvest and post harvest decisions. Inaccurate data inputs used in these solutions, poor localization of these solutions, and inadequate quality assurance for these solutions may result in AI hallucinations, where solutions incorrectly address SSP challenges and impede productivity by producing nonsensical outputs. Further, the need for contextually relevant datasets hinders progress in building AI applications that are scalable and robust for populations across the globe. SSPs that suffer from actioning poor insights may not have trust in and choose not to use AgTech solutions again.

Broader Productivity Risks

Differences in SSP adoption rates of AgTech solutions may result in a widening productivity divide between groups of SSPs. If innovative technologies are not adopted evenly amongst SSPs, there is a risk of an inequitable distribution of benefits. This may occur if SSPs that are more commercialized, or have higher incomes, are able to take advantage of AgTech solutions to improve their productivity, competitiveness and earning potential. This would widen the productivity divide between these SSPs and the remote or lower-income SSPs that may not have access to these solutions or be able to afford them. A perpetuating cycle may continue to increase the divide between SSPs who can access these solutions and the SSPs that are the most vulnerable and require the most support. While this dynamic will be true for farmers within a particular country, it can also be true when considering inequitable distribution between countries. The phenomenon of AgTech hubs in certain LMICs, such as India, Kenya and Nigeria, has the potential to significantly improve the productivity and competitiveness of agricultural exports from these markets relative to the LMICs in which SSPs have not adopted these solutions.

---

71 United States Bureau of Labor Statistics. 2022. *Monthly Labour Review: Growth trends for selected occupations considered at risk from automation.* Available here.

72 Ibid.

IMPACT PATHWAY 2: **COST EFFICIENCIES**

Cost efficiencies are one of the foremost opportunities presented by AgTech solutions. Spending on AI technologies and solutions within the agriculture sector is estimated to reach USD 4 billion by 2026 - a compound annual growth rate of 25.5% between 2020 and 2026.[73] This significant investment in AI and automation technologies present ample opportunities for smallholder farmers to harness opportunities for cost efficiencies. Digital advisory services allow SSPs to use inputs more efficiently. Smart tractors, agribots and robotics present a viable solution for agricultural operations that struggle to find sufficient labor. Smart farming practices also allow SSPs to reduce waste by applying the appropriate mix and amount of pesticides to affected areas only, or through precise irrigation and fertigation with targeted crop protection application. All of these solutions lower operating costs incurred by small scale producers.

Agricultural cost saving opportunities

1. ***Lower operating costs:*** There are several ways that SSP operating costs can be lowered by AgTech solutions. Digitized booking platforms and online equipment rent models result in reduced land preparation costs being incurred by small-scale farmers as they no longer need to own expensive machinery or incur the costs involved in trying to source this equipment. Precision farming methods also allow farmers to use inputs more efficiently, which reduces how often they have to be replenished. Precise soil readings translate into more targeted applications of fertilizers; automated on-farm processes such as irrigation reduce the amount of laborers required; and, solar-powered solutions like water pumps can help smallholders save energy costs

2. ***Less costly access to services:*** The digitization of essential agricultural services such as community advisory, tractor renting and the purchasing of inputs incurs fewer costs for SSPs as they no longer have to travel to the nearest village or city to access these services.

3. ***Traceability:*** SSPs and the value-chain stakeholders they work with sometimes have to prove they are compliant with specific input quality and ethical pay standards before being able to access certain markets. This has traditionally incurred costly certification processes. The introduction of blockchain technology and other automated tracking technologies, such as QR codes, enables more cost-effective traceability of information across the food supply chain, reducing the cost and effort of certification for SSPs.

4. ***Efficient reallocation of labor:*** Automated on-farm practices and access to additional equipment via digital platforms allow for the more physically demanding farm practices to be augmented. This allows farm workers who previously would have endured these activities to direct their efforts elsewhere, potentially allowing for lower turnover rates and reduced injury rates which farm owners could be held liable for.

5. ***Improved, cost-efficient seeds:*** Genomic technology can accelerate the rate of genetic improvement for seeds, which typically takes between 10-15 years using traditional plant breeding methods.[74] Specifically, sequencing of plant genes allows for the identification of genetic lines with “deleterious mutations” in the genomes that can subsequently be deleted.[75] Essentially, this method of identification allows for the detection of seeds that have genetic alterations that increase their susceptibility to diseases. The elimination of these seed types provides SSPs with more climate-resilient seeds, minimizing the costs of crop loss.

Broader cost saving opportunities

Impact pathways through which cost saving impacts can be realized can provide SSPs with three additional areas of opportunity. Reduced operating costs bolsters household income for SSPs. This income can then be redirected to other services that enhance livelihoods such as education, healthcare and housing maintenance or repairs, or even to savings, which increase financial resilience. Increased household income presents opportunities for SSPs to reinvest this income in order to make their farms more robust and, subsequently, even more profitable.

---

[73] Forbes. 2021. *10 Ways AI has the Potential to Improve Agriculture in 2021*. Available here.
[74] Bohra, Abhishek et al. 2020. *Genomic interventions for sustainable agriculture*. Plant biotechnology journal vol. 18,12 (2020): 2388-2405. Available here.
[75] Varshney, Rajeev K et al. 2018. *Can genomics deliver climate-change ready crops?* Current opinion in plant biology vol. 45,Pt B (2018): 205-211. Available here.

Finally, cost saving technologies can allow farmers to access higher quality value chains as higher household income allows for improved access to finance, payment solutions and the social capital required to organize producers and communities across a value chain. Traceability solutions can also allow SSPs to participate in higher-value, export-oriented value chains.

Agricultural cost saving risks

Costs associated with the implementation of AgTech solutions may create risks for technical providers and SSPs. This is detailed below:

1. ***Unpredictable maintenance costs and low reliability:*** The equipment required to implement IoT sensor networks or automated systems often entails high upfront costs. This can crowd out lower-income rural farmers, especially women and young people, who do not have sufficient income or who typically struggle to access credit from accessing these technologies. Farmers who are able to purchase these technologies may also incur significant and unpredictable maintenance costs if they inherit the responsibility for maintaining a device once it has been paid for or funding has reached its tenure. This subsequently places the long-term viability of the AgTech solution in jeopardy, as the farmer may not be able to afford the upkeep of the technology. AgTech providers that offer shared services using drones must also carry these high upfront costs and are at risk of not recovering them if there is insufficient uptake of these services.

2. ***Losses owing to genomic seed variation:*** Governments that fully subsidize the introduction of a certain genomic seed variety for farmers with bundled yield-based and weather-based index insurance are vulnerable to financial losses if these crops are attacked by pests that result in complete crop failure. Despite the farmers being insured against unforeseeable weather and yield events, the government will make a complete financial loss. An unintended consequence of this extent would be significant for LMICs, in which agriculture is a significant contributor to GDP[76], and could create ripple effects in which the adoption of such new and improved seed varieties are curtailed.

Broader cost saving risks

AgTech solutions can run the risk of perpetuating the 'dual agricultural value chain' characterization of LMICs that is created by differences in affordability between groups of SSPs. The agricultural sectors of developing countries are often characterized by dual value chains operating in parallel for the same product: one informal or traditional and the other formal or modern. Many AgTech solutions aim to help SSPs save costs and improve their productivity, enabling them to access more formalized or commercial markets. However, these digital solutions are often offered to SSPs as a 'smart farming-as-a-service' model, which has an automated service disruption function if the farmer fails to pay their monthly subscription fee. This poses a challenge for lower-income SSPs, who do not have consistent and reliable monthly incomes, which is not uncommon given the cyclical nature of the sector. This may compound the challenge of adoption disparities amongst SSPs where inequitable distribution of AI and automation solutions only allow some SSPs access to modern value chains, as discussed above. Alternatively, there is a risk that, in an adequately regulated digital ecosystem, AgTech solution providers will be guided to adopt a 'leave no one behind' approach and create incentive pricing methods tailored to the demands of SSPs. Business model solutions such as pay-as-you-go (PAYG) are an example of such approaches. However, such solutions present a greater risk with cost savings on the technical provider side.

[76] Typically, agricultural production contributes between 18% and 40% of GDP in LMICs.

IMPACT PATHWAY 3: **INCLUSION**

Advances in AgTech solutions are critical for broadening access to opportunities and promoting inclusion in the agricultural sector. The combination of technology and traditional farming methods has the potential to drastically improve inclusion by providing more equitable access to agricultural opportunities for all genders, abilities and ages. More than 500 million households depend on smallholder farming for their livelihoods, despite the fact that they have access to only 25% of arable land globally.[77] The majority of these SSPs, who produce more than a third of the world's food, experience financial or market exclusion, leaving them susceptible to diminished incomes and lower productivity. Alternative credit scoring and buyer-seller matching via digital platforms present opportunities for SSPs to be more included in formal services that enable the agricultural sector. This can allow for alternative income streams for SSPs by establishing incentives on premiums earned due to responsible, sustainable farming.

Agricultural inclusion opportunities

A deliberate effort to design AI and automation agricultural solutions to enhance inclusion has the potential to open up several access points. These include:

1. ***Access to agri-services:*** AgTech solutions can provide rural and remote SSPs with access to fundamental agricultural services digitally. For example automated digital climate advisory services provide SSPs with access to precise, timely information triggered to adapt to real-time weather events, preferred inputs and farming techniques via feature phone channels like USSD or SMS, regardless of their location.

2. ***Access to credit and insurance:*** AgTech solutions create new sources of data to understand and model SSP behavior. This includes data on digital payments, WhatsApp community forum engagement and more. These alternative data points can be used to develop creditworthiness models that support the extension of credit to excluded SSPs. The estimated annual demand for credit from SSPs in LMICs is USD 160 billion but just over a third of this demand is being met (USD 54 billion).[78] [79] In addition, AgTech solutions are making the provision of agricultural insurance products more widely available through bundling. Covering more SSPs with insurance is critical to protecting livelihoods when SSPs face devastating shocks to their livelihoods caused by weather or pest events.

3. ***Access to markets:*** Digital platforms and the rise of e-commerce present more efficient mechanisms of matching buyers and sellers, especially when underlying infrastructure, such as roads and network coverage, already exists. This creates opportunities for more SSPs to sell produce to more formal or modern markets at a fair price. Appropriate consumer protection and fair market competition regulation will become increasingly important as more and more SSPs engage with e-commerce platforms. This is to ensure that the slashing of prices to beat competition, or alternatively, price gouging does not occur for SSPs and consumers respectively.

4. ***Access to training:*** Online training content and customized training services can provide SSPs with the opportunity to improve their practices. Agent networks and intermediaries that leverage AgTech solutions can also serve as digital ambassadors and help less digitally savvy farmers upskill themselves.

5. ***Inclusion of vulnerable groups:*** The rise of AgTech solutions presents an opportunity for marginalized groups, such as women, young people and disabled people, to be included. For example, automated on-farm processes make farming practices less physically demanding, a critical requirement for inclusion of disabled people. In addition, many AgTech solutions, such as Sooretul or CreditAccess Grameen, are specifically geared towards the needs of rurally based women. Additionally, the rise in female entrepreneurs focusing on the development of AgTech products and services provides young women in rural communities using these solutions with influential role models and leaders.

---

[77] GSMA. 2021. *Emerging business models to support the financial inclusion of smallholder farmers.* Available here.
[78] GSMA. 2021. *Emerging business models to support the financial inclusion of smallholder farmers.* Available here.
[79] ISF Advisors. 2022. *State of the Sector: Agri-SME Finance.* Available here.

Broader inclusion opportunities

Inclusive digital agriculture empowers vulnerable groups and breaks down barriers to entry. This can result in several follow-on benefits. Firstly, if more households are able to participate in the agricultural sector as a result of digital technologies, there will be an overall improvement in household income levels in rural areas. Secondly, by leveraging alternative data for credit scoring purposes, SSPs will have additional options for accessing the capital or debt financing required for purposes other than farming such as tertiary education or the purchasing of a home or vehicle, which means they would no longer have to self-fund or rely on predatory lenders. Thirdly, greater participation in the agricultural sector creates a bigger addressable market, which can help AgTech solutions scale on the back of greater demand for these solutions. Finally, women can be included more equitably in the agricultural sector as a result of access to digital financial services, online training, online advisory services and improved market opportunities. Women are the backbone of the agricultural sector and play critical roles across many parts of agricultural and off-farm value chains. However, in many LMICs, their contributions are either underestimated or limited by prevailing societal norms or gender-specific barriers. By facilitating greater access for women, there is also the opportunity to narrow the gender wage gap as automated on-farm technologies mitigate against women being excluded from on-farm labor as jobs that require extreme physicality can now be automated.

Agricultural inclusion risks

Several risks directly related to the agricultural value chain can arise if adequate due diligence practices or human-centered design (HCD) approaches for AgTech solutions are not adopted. These include:

1. ***Inferior products:*** Digital platforms that provide SSPs with easier access to inputs from a variety of suppliers may expose them to an increased risk of purchasing inferior or counterfeit products. Poor platform security, policies and protocols may result in weak oversight and inadequate verification of sellers and their products. This is likely to be an effect of inadequate funding or investments in the agriculture sector,[80] coupled with the significant upfront investment required to develop e-commerce platforms within the limitations of tight margins, which can compound the issue of counterfeiting, adulteration and substandard product development. This could result in dire consequences for an SSP. For example, if a farmer is sold diluted fertilizer, this could result in an accelerated rate of crop deterioration. Further, out-of-date or old pesticides can become too dangerous to use. However, if there is poor product oversight, these products can still be made available to SSPs in LMICs where e-commerce controls are more nascent.

2. ***Inadequate consumer protection:*** Effective regulation is critical to ensuring the responsible development of digital solutions, particularly those that relate to digital finance. Out-of-date policies and regulations that do not cater for the dynamics of new technologies may not protect consumers from new risks. For example, if data protection policies are inadequate or consent is not obtained by smallholder farmers, data monetization business models can result in the third parties accessing farmer information through AgTech service providers. The ethical paradigms of implementing AI and automation technologies across the agricultural value chain Is discussed further in the below information box.

BOX 9: AI ETHICS AND DATA GOVERNANCE

The implementation of AI and other innovative solutions across the agricultural value chain can lead to several key ethical considerations that have the potential to strip farmers of their autonomy and lead to breakdowns in trust. In addition to the data accuracy issues discussed above, these include.[81]

1. ***Data ownership:*** There are concerns regarding the collection and dissemination of farmer data to third parties. This raises the contentious issue of whether farmers should relinquish control of farm data to

[80] Currently the annual shortfall in agri-financing is estimated to be USD 160 billion.
ISF Advisors. 2022. *State of the Sector: Agri-SME Finance.* Available here.

[81] Ryan, M. 2019. *Ethics of Using AI and Big Data in Agriculture: The Case of a Large Agriculture Multinational.* ORBIT Journal, 2(2). Available here.

BOX 9: AI ETHICS AND DATA GOVERNANCE

these parties, who could subsequently use it to influence other farmers. Further, data retrieved from farms is often inaccessible to farmers themselves. This causes tension between the agribusinesses' intellectual property rights and the protection of the farmer's data ownership.

2. ***Economic issues:*** The use of smart information systems is relatively expensive, which may create a digital divide across slightly more commercialized farms that are focused on monoculture compared to more varied, subsistence farms.

3. ***Privacy and security:*** Agricultural Big Data is susceptible to privacy and security risks because it could be used nefariously by corrupt governments, competitors, or market traders. This is particularly the case in LMICs, where there is less data protection regulation. Alternatively, Big Data can be used in legitimate ways that still ultimately disadvantage SSPs. For example, accurate soil productivity maps that are accessible by more commercial, financially secure farmers can be used for legal targeting and acquisition of land by these larger corporations or governments at an undervalued price owing to information asymmetries.

4. ***Accuracy and Accessibility of Outputs:*** Automated advisory services are prominent in agri-food systems and in bundled AgTech solutions. The impact of automated advisory services by SSPs is influenced by the accuracy of the services and their availability in languages the SSPs can understand. SSPs who receive inaccurate and incoherent outputs from AI enabled AgTech services may experience adverse consequences. This may be due to AgTech solution developers leveraging models that are trained using insufficient data, leveraging inappropriate models, or inadequately evaluating the accuracy of model outputs. Automated advisory may be exclusionary for SSPs in LMICs that speak under-resourced languages as there is insufficient data to effectively train models to operate in these languages..

5. ***Environmental protection:*** IoT sensors, robots and devices may cause harm, distress, and damage to animal welfare and the environment if they are not disposed of responsibly. This aspect is discussed in more detail under Climate Resilience.

It is of paramount importance that SSPs understand the value of the data they are providing or generating before engaging with AgTech solutions. As such, it is important that efforts are made to build SSP knowledge of the value of and rights to their data so that SSPs understand how their data will be used by AgTech solution providers before consenting to its use.

Broader inclusion risks

Improper use of data and failure to engage with the most vulnerable of SSPs can negate the positive opportunities for inclusion in the agricultural sector. The potential risk of disintermediating digital platforms providing SSPs with inferior products or the incorrect advice can lead to a breakdown of trust in digital products and services generally and the long-term participation of SSPs in the digital economy could be jeopardized. Similarly, there could be ongoing exclusion barriers amongst those SSPs that are the most vulnerable and thus the hardest to include due to affordability barriers. A further consequence could be an ever greater income divide between individuals who are able to afford these enabling factors and those who cannot such as aging farmers, farmers with less digital or technical literacy or female farmers who cannot access credit.

IMPACT PATHWAY 4: **CLIMATE RESILIENCE**

Agricultural value chains and agri-food systems have an important relationship with climate, and can be both affected by and a contributor to climate change. The implications of climate change are already affecting food security through rising temperatures, unpredictable changes in precipitation patterns and higher frequency of extreme weather events such as droughts or flash flooding. On the other hand, over 29% of total greenhouse gas (GHG) emissions are attributable to the food system.[82] Technological innovation can play an important role in safeguarding agri-food systems against adverse climate changes, whilst also making agricultural practices less demanding on the environment. Of the priority use cases analyzed, genomic innovation and alternative insurance access present the most significant opportunities for enhancing SSP resilience to climate change.

Agricultural climate resilience opportunities

AI and automation technologies have the potential to enhance SSP resilience to climate change and natural disasters by opening up access to assets and mechanization, improving decision-making, and extending access to insurance. These technologies could allow for several agricultural opportunities to be realized. These include:

1. ***Optimal use of scarce resources:*** Automated irrigation systems and fertilizer administration allow for more uniform and precise administration of inputs. This can lead to more sustainable land management as the use of natural resources, including water and soil, can be optimized. For example, less water would be wasted, allowing for sustainable water systems and better nutritional content in the soil, improving the longevity of cropland and the quality of harvests. Smart farming techniques have demonstrated a positive impact on feed conversion ratios (FCRs) for aquaculture farming practices, which results in improved water quality for the surrounding area by reducing instances of overfeeding.[83] Overfeeding can lead to water contamination, pollution and fish mortality.

2. ***Preempting negative shocks:*** Together with on-the-ground data, satellite information can make SSPs more proactive to climate events and enable them to pre-plan responses rather than reacting to these events after the fact. Satellites provide an immediate first impression of weather events without requiring lengthy assessment first. This allows for environmental data to be distilled into actionable information; reaching SSPs via automated messaging platforms. In addition, automatic dispatch of emergency services can be linked to certain 'tipping points' that can be identified by satellites using machine learning. This can make SSPs more resilient to climate events such as droughts, pests or diseases. Further, these innovations assist SSPs in adapting to longer-term stresses such as erratic weather patterns or the shortening of certain seasons.

3. ***Improved biodiversity:*** Biodiversity helps to sustain vital ecosystem structures and processes, such as soil protection and health, water cycle and quality, and air quality. It also provides the genetic resources for the breeding of new, locally adapted crop varieties. Biodiversity is therefore essential for agricultural production and food security. AI and automation technologies can improve invasive mechanical agitation of soil during the land preparation phase and allow for more environmentally sustainable preparation of arable land. This, coupled with integrated crop and weed management, will ensure that agricultural land is better conserved. In addition, innovations such as microscopic radio transmitters and radar-reflecting tags can be used to track invasive insects to their nests and destroy their colonies.[84]

4. ***Mitigating food loss or waste:*** More than a third of global food production is lost or wasted.[85] This results in unnecessary GHG emissions, the wastage of natural resources and unnecessary soil erosion. Precision agriculture mechanisms and automated fertilizer systems can help reduce harvest loss to pests and diseases. Automated, energy-efficient cold storage and blast cooling technology can also be used to help maintain post-harvest quality and reduce spoilage, while buyer-seller matching is critical to preventing unnecessary food loss and waste.

---

[82] The Intergovernmental Panel on Climate Change. 2022. *Food Security: Special Report on Climate Change and Land.* Available here.
[83] GSMA. 2022. *Assessment of smart farming solutions for smallholders in low and middle-income countries.* Available here.
[84] For more information on these technologies, see *Wildlife Conservation Society,* available here; or *Challenges and Prospects in the Telemetry of Insects*, available here.
[85] The World Bank. 2022. *Climate-smart Agriculture.* Available here.

5. ***Climate resilience and alternative income:*** The concept of a carbon sink resulting from the sequestration of carbon in the soil or from averted emissions will have a net positive influence on GHG emissions and/or CO2 levels. This is relevant to SSPs in their efforts to generate alternative revenue by using carbon sequestration data as business intelligence to monetize with purchasers, which would bring in premiums, or with carbon traders/off-setters, which would bring in cash as an alternative source of income.

Broader climate resilience opportunities

Climate smart agriculture leveraging AI and automation technologies can improve agricultural management and reduce the negative aftermaths following climatic shocks. According to the Intergovernmental Panel on Climate Change, it is critical to augment supply-side agricultural practices to address future GHG emission concerns. Climate smart agricultural practices such as increased soil organic matter and erosion control, improved cropland, livestock, grazing land management, genetic seed improvements for tolerance to heat and drought, and diversification of biomes can all result in **lower greenhouse gas emissions**. Less biodiversity loss and weather prediction models present an opportunity for *ex ante*, **proactive disaster management measures** to be taken; minimizing the devastation of climatic events. For example, climate smart agricultural technology prevents nutrient-rich topsoil from being washed away. Healthy topsoil with high organic content and vegetation can effectively regulate against sand or dust storms, acting as a windbreak. Further, soils and their associated ecosystems can counteract the devastating impacts of flooding by reducing or delaying runoff, thereby lowering flood volumes and reducing damage.

Agricultural climate resilience risks

Although innovations in climate-risk insurance that leverages digital technologies provide meaningful examples of positive impact for some, there are many remaining obstacles that prevent insurance coverage from becoming the default situation in LMICs. Comprehensive risk management is essential to better protect SSPs in developing countries, who will be more adversely impacted by climate change than SSPs in developed countries. However, access to insurance across LMICs remains unequal and fragmented. Further, insurance offerings often lack access to rich, localized datasets, which assist in creating tailored products to address the risks faced by SSPs. It is estimated that weather-related disasters have claimed the lives of over 1 million individuals and amounted to over USD 4.21 trillion in financial damages over the past 20 years.[86] This is anticipated to worsen in years to come as climate events become more frequent and devastating, which is of greatest concern for low-income households who do not have sufficient financial means to cope with climate shocks.

1. ***Unjust denial of insurance payouts:*** Satellite data presents a new opportunity for developing bespoke alternative insurance models for the climate risks endured by SSPs. However, if these insurance models do not factor in geographic and climatic nuances, there is a risk that SSPs will be unfairly denied their policy payouts. These nuances are discussed in further detail in the information box below.

BOX 10: WEATHER-BASED INSURANCE

Satellite data and remote sensing technology can significantly improve the financial resilience of SSPs by providing proactive early-response measures. However, there are certain factors that distort the concept of 'blanket' climate-based risk insurance for SSPs. Satellite data allows for the remote monitoring of indices such as soil moisture content, precipitation, vegetation health and others. It can also be used to forecast extreme weather events such as storms. Collected over a long enough time period, this data allows for forecasting on crop yields and underlying environment conditions.

Building disaster resilience in LMICs is essential to minimize the volatility in crop yield and income that SSPs will face when confronting worsening weather patterns. This requires that several obstacles be overcome in order to establish sustainable demand for and trust in climate-based insurance policies by SSPs. These include:

86 Development and Cooperation. 2022. *Managing climate risk with private insurance*. Available here.

1. ***Investment and infrastructure challenges:*** Growth in private-sector-led investment in climate-based risk insurance programs is hindered by substantial initial investment costs and continued high operating costs owing to infrastructure issues. Considerable market research is required to understand the financial needs of SSPs ahead of product development, which requires substantial upfront investment. Further, the underlying circumstances of SSPs require insurance companies to offer climate-based insurance policies to them at very low premiums. Distribution and climate-account management are also difficult due to power supply and internet access barriers in rural and remote areas. Not only do these factors adversely impact on the long-term sustainability of these product offerings, they also deter many private insurance companies from entering this space, resulting in a limited choice and low reliability of climate-based insurance options for SSPs.

2. ***Nascent product knowledge:*** SSPs typically have limited knowledge of how insurance products work, a factor that could be taken for granted when they sign insurance contracts. Further, governments' understanding of effective insurance cover can be outdated or limited as it relates to a particular sector such as climate risk in agriculture. Consequently, misalignment about the level of investment required to create effective insurance products can occur in government and the private sector.

3. ***Crop variation discrepancies:*** AI solutions that implement field boundaries and crop-type identification for insurance purposes are highly effective in monoculture environments but, in instances of intercropping, they are not as effective. Consequently, geospatial services that are used for advisory and insurance have the tendency to be optimized for monoculture farming, which is often not the case for subsistence or small-scale farming, where intercropping is necessary. Further, a movement toward monoculture practices in itself has environmental implications. For example, it is more difficult for several species of bees to pollinate in areas that lack crop variation.

4. ***Data discrepancies do not account for micro-climates:*** Insurance companies require reliable statistics regarding both weather conditions and the damage incurred by weather-related events, and data collection is a bigger challenge in rural and remote areas. This, coupled with the influence of microclimates, negatively impacts the accuracy of the statistics used to inform insurance policy payouts. For example, inaccuracies in critical threshold readings that determine whether or not a policy is paid out may emerge due to:

    a. Challenges in measuring rain distribution such as rapid rainfall over a short period compared to more evenly distributed rain over a longer period.
    b. Rainfall on windward and leeward sides of hills, mountains or ridges as some of these areas receive more rain than others.
    c. Follow-on events subsequent to certain weather patterns. For example, rainfall after a significant drought period can lead to the hatching of locust eggs and result in significant and immediate crop depletion.

It is critical that innovations in climate-based insurance take into consideration these challenges to ensure SSPs are sufficiently protected against risks associated with climate change and extreme weather conditions.

Broader climate resilience risks

The positive gains made in the resilience of SSPs to climate change due to AgTech solutions could be jeopardized by adverse knock-on effects. More than 3.5 billion people and 70% of crop production are vulnerable to climate change.[87] [88] If AI and automation technologies are not appropriately monitored and regulated, there is a risk that these figures will become even more significant. Smart farming technologies are intended to make agricultural processes more efficient and, by doing that, to increase the productivity of SSPs. However, there is a risk that the productivity of intensive farming practices in, for example, aquaculture and the production of soybeans, meat and dairy, is improved to such an extent that the associated depletion of natural resources becomes

[87] Development and Cooperation. 2022. *Managing climate risk with private insurance.* Available here.
[88] Bill & Melinda Gates Foundation. 2021. *Smallholder farming is a proven path out of poverty, but climate change is changing the rules.* Available here.

irreversible. For example, agrochemical fertilizers and pesticides can accelerate soil degradation and erosion as they sidestep the process whereby nutrients are naturally returned to the topsoil layer of croplands from the biodegradation of leftover vegetation from the previous season's harvest. This critical microbial process ensures that nutrients are able to be transferred from the soil to the plant subsequent to the land preparation phase of farming. Further, intensive fish farming can result in eutrophication, where the waste produced from farming practices distributes excess nutrients into neighboring water supplies, disrupting the balance of water ecosystems.

Although climate-smart agriculture has the potential to lower GHG emissions due to agriculture, there is a risk that the increased usage of data-transmitting devices will create new dependencies on data centers, which contribute to emissions. Data centers currently account for over 2% of all global carbon emissions, which is equivalent to the total contribution of the airline industry.[89] The increased computing power required to run smart tech applications in the cloud will result in more data centers being required and in usage of these centers increasing, which has the potential to exacerbate the carbon emissions they produce.

In addition, if the use of smart farming technologies such as IoT sensors becomes more widespread in the future, this can result in irresponsible e-waste disposal, which has irreparable consequences for the environment. For example, informal disposal of electronic equipment through shredding or melting material releases dust particles and toxins into the air, aggravating air pollution and damaging respiratory health of nearby communities. While the negative effects on air from informal e-waste recycling are most dangerous for those who handle this waste, issues with pollution can be widespread geographically. The burning of e-waste releases fine particles into the air, which can travel thousands of miles, creating numerous health risks including chronic respiratory diseases and cancer. Improper disposal of e-waste in regular landfills or in illegal dumpsites releases heavy metals and flame retardants into the soil, causing contamination of the underlying groundwater, which can adversely impact croplands and biodiversity in the area. The introduction of heavy metals such as mercury, lithium, lead and barium causes chemical reactions including acidification and toxification, which is unsafe for animals, plants and people and which ultimately depletes the availability of clean drinking water. Finally, there are adverse environmental costs associated with rare earth mining as rare earth minerals are a critical input in the manufacturing of many smart farming technologies and devices. Mining practices can create pollutive consequences and irreversible environmental land damage.

[89] NowVertical. 2022. *The Impact of Data Centers on Global Carbon Emissions & How Removing ROT Data Can Help Reduce It.* Available here.

IMPACT TRADE OFFS

The impact assessment has identified how disruption from tech innovation will inevitably create both winners and losers. Overall, the identified impact pathways are largely positive in significantly increasing the capabilities of the SSPs who can access these solutions, with some significant risks across the value chain. This section concludes with eight trade-offs for consideration.

1. ***In the quest to grow income-generating work opportunities in agriculture, it is important to consider which groups are likely to be the winners and the losers.*** The millions of SSPs that rely on farming activities to earn an income or support their families are the greatest potential stakeholders, where they are able to leverage AgTech solutions to secure more sustainable livelihoods. Many additional jobs will be created through the provision of AgTech solutions, including for the lead farmers and agents that can earn an income from distributing AgTech solutions, and the agri-preneurs who can become tractor owners, input dealers or data collectors. The likely losers in this case are low-skilled laborers providing seasonal and manual labor on farms and in the processing parts of the value chain. The key to managing this trade-off is to determine how best to support those pushed out of work opportunities by transitioning them into new opportunities, especially given that a farm laborer will not automatically be able to take up new opportunities in the AgTech value chain.

2. ***Leveraging technology to include underserved groups has massive potential, but comes with its own set of risks to manage*****.** Significantly improving access to agronomic advice and the financial services required to implement modern farming practices will help to 'level the playing field' among SSPs given the current gaps in agricultural advisory, credit and insurance. However, this will necessarily involve exposing SSPs to digitally delivered services they are not familiar with, creating new consumer protection, ethics and environmental risks. LMIC regulators will have to consider approaches that balance the need for innovation with protecting vulnerable consumers, including the requirement that AgTech providers build the understanding and capacity of their new customers and extended producer requirement responsibilities for environmental protection.

3. ***Supporting SSPs to commercialize and 'upgrade' production for higher value, export-oriented value chains can pose a threat to local food security.*** AgTech solutions will support SSPs to achieve the quality, volume and certifications required to commercialize and access export value chains with better market prices. This shift in production choices may lead to reductions in the supply of food and in the nutritional diversity of food in local communities if SSPs move away from producing local staple food items that have lower market prices. This trade-off is not necessarily created by AI and automation. Debates about commercialization and its impact on the social structure of rural societies are not new but will be intensified by the potential these technologies have to support rapid commercialization.

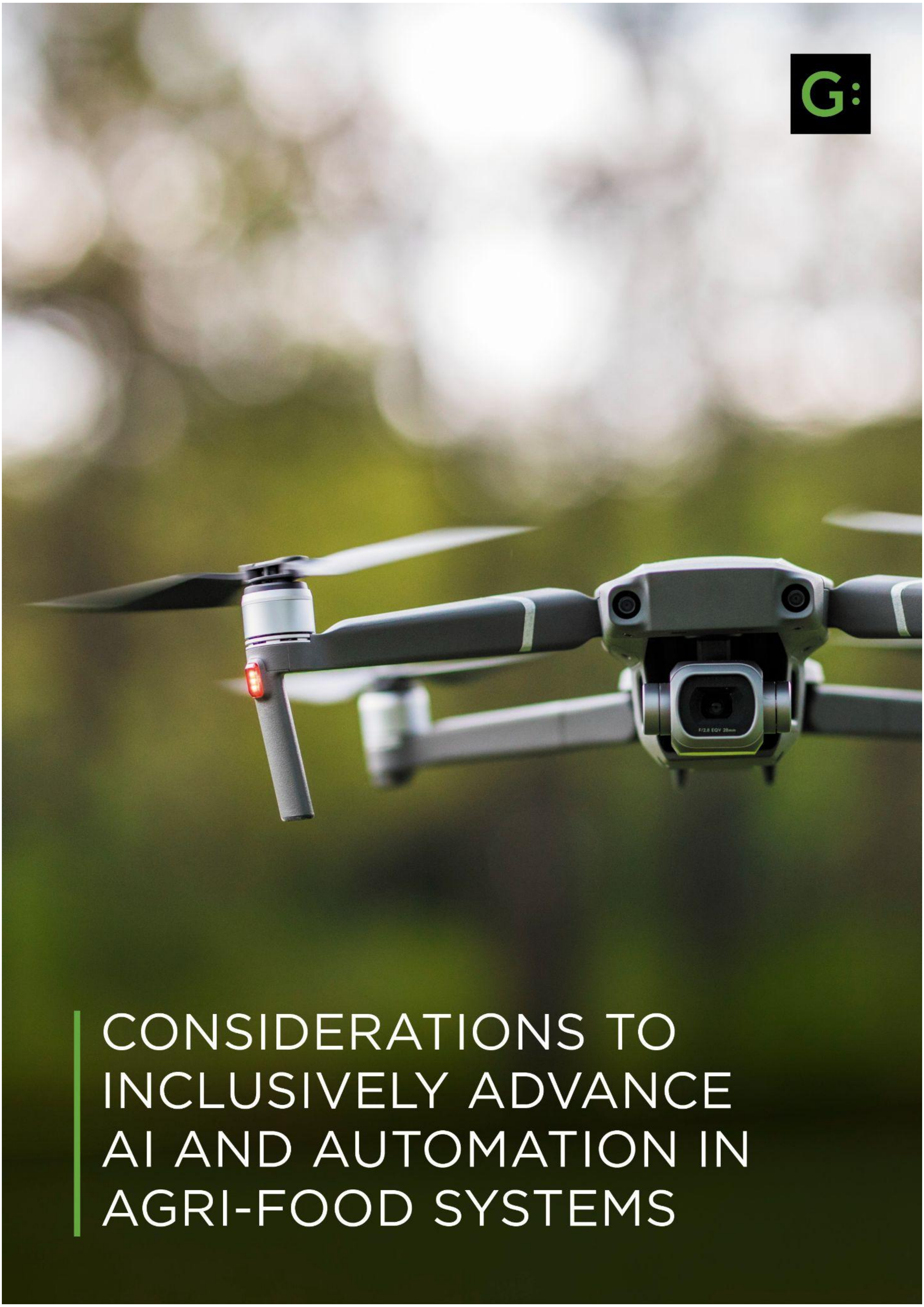
4. ***The high-touch intermediated delivery models required to include SSPs in AgTech solutions also restrict the scalability benefits of automation.*** Delivering AgTech solutions to SSPs through trusted intermediary networks is critical for inclusion and uptake. However, this approach has inherent scale limitations due to the cost of building intermediary networks and the current limitations on delivering truly personalized automated services. Managing this trade-off may require developing commercially-viable intermediary networks, such as shared agent networks that can be used by multiple providers, and investing in AI technologies that can safely and effectively emulate the experience of engaging with a trusted human intermediary. Natural-language-processing AI applications will be particularly impactful here.

5. ***Commercial incentives among AgTech providers do not always align with public good outcomes.*** Private AgTech providers guided by commercial objectives are better suited to delivering sustainable impact using efficient business models and pursuing revenue sources that offer pathways to scalability. These interests are sometimes misaligned with the broader need to create replicable and inclusive solutions, create competition amongst AgTech providers, and protect SSPs from exploitation. Philanthropic and donor funding targeted at AgTech providers with less commercial models that are, however, willing to share IP or data, may nevertheless be an inefficient allocation of capital if there is not a sustainable business case. Determining conditions for donor or public sector funding that maintains the virtues of commercial incentives but also contributes to public good objectives will be key.

6. ***A vibrant market of many AgTech providers can stimulate innovation and competition, but often leads to fragmentation and barriers to sustainability.*** A market with numerous AgTech providers offering similar solutions that require and compete for large sources of demand may be inefficient and unsustainable. However, the competition that this creates can stimulate innovation. This consideration is relevant in local and international contexts - scaled AgTech solutions from markets such as India, Kenya and Nigeria might be easier to replicate in smaller, foreign markets at the expense of locally developed solutions. The trade-off between market innovation and sustainability could be navigated by understanding the benefits and risks of 'picking winners', avoiding negatively influencing competitive forces and facilitating partnerships between stakeholders such as AgTech companies and research institutions, AgTech providers and distribution platforms and start-ups and commercial investors. It could also include developing market infrastructure that removes the distribution and customer management layer of providing services.

7. ***'Narrow' datasets enable the development of specific solutions and intelligence whereas 'broad' datasets may facilitate the development of widely relevant solutions and intelligence.*** Narrow datasets can, for example, refer to data collected on a specific farmer, community or value chain. This might include IoT devices for a farm or drone footage of a specific crop type in a specific area. 'Broad' data is more reusable. This might include the collection of machine-readable text for languages, satellite data with ground truth, or sparse networks of IoT devices across a region collecting rainfall data. Investment in data collection technologies and the development of open datasets is costly and need to be prioritized. This will require identifying the areas of data collection that offer the highest returns.

8. ***Openly-accessible digital infrastructure will reduce barriers to innovation, but may not offer the same quality and functionality as privately managed alternatives.*** Data and technology infrastructure, such as country AGRIS for country data or FarmStack by Digital Green for infrastructure, can be made openly accessible. Solutions such as these provide wider access to the inputs needed for research and innovation, and reduce the costs innovators must carry to test and then develop new solutions. Infrastructure can also be provided by private players such as CropIn, which may offer pay-per-use access to dependable infrastructure or access to datasets that the company has invested in gathering and cleaning. Figuring out which elements of various AgTech solutions are valuable and sustainable to provide on an open-source or white-label basis will be critical in supporting the development of an optimal mix of open and private infrastructure.



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

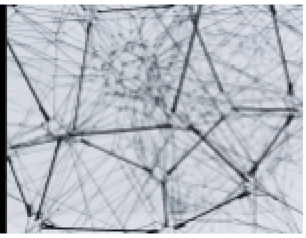
Through extensive stakeholder consultations and solution workshopping, this study has identified four key objectives for the inclusive advancement of AI and automation in agri-food systems. Under each objective, we outline key actions that will make significant progress toward achieving the set objective. 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.		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.		Governments, AgTechs
Support white label software infrastructure developers to align development with the demands of AgTech developers.		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.		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.		Donors, governments, AgTechs
Unlock government demand for climate-smart digital extension advisory through technical assistance.		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.		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		Donors, governments, social enterprise
Expand social support mechanisms and pathways to productive employment to support individuals affected by disruption.		Donors, governments, social enterprise
Support regulators to examine the potential for digitally enabled harmful market conduct impacting agri-food systems.		Donors, governments
Socialize an environmental Extended Producer Responsibility approach amongst AgTechs to shift product end-of-life responsibility upstream.		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.		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.		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.		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		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[90] 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).

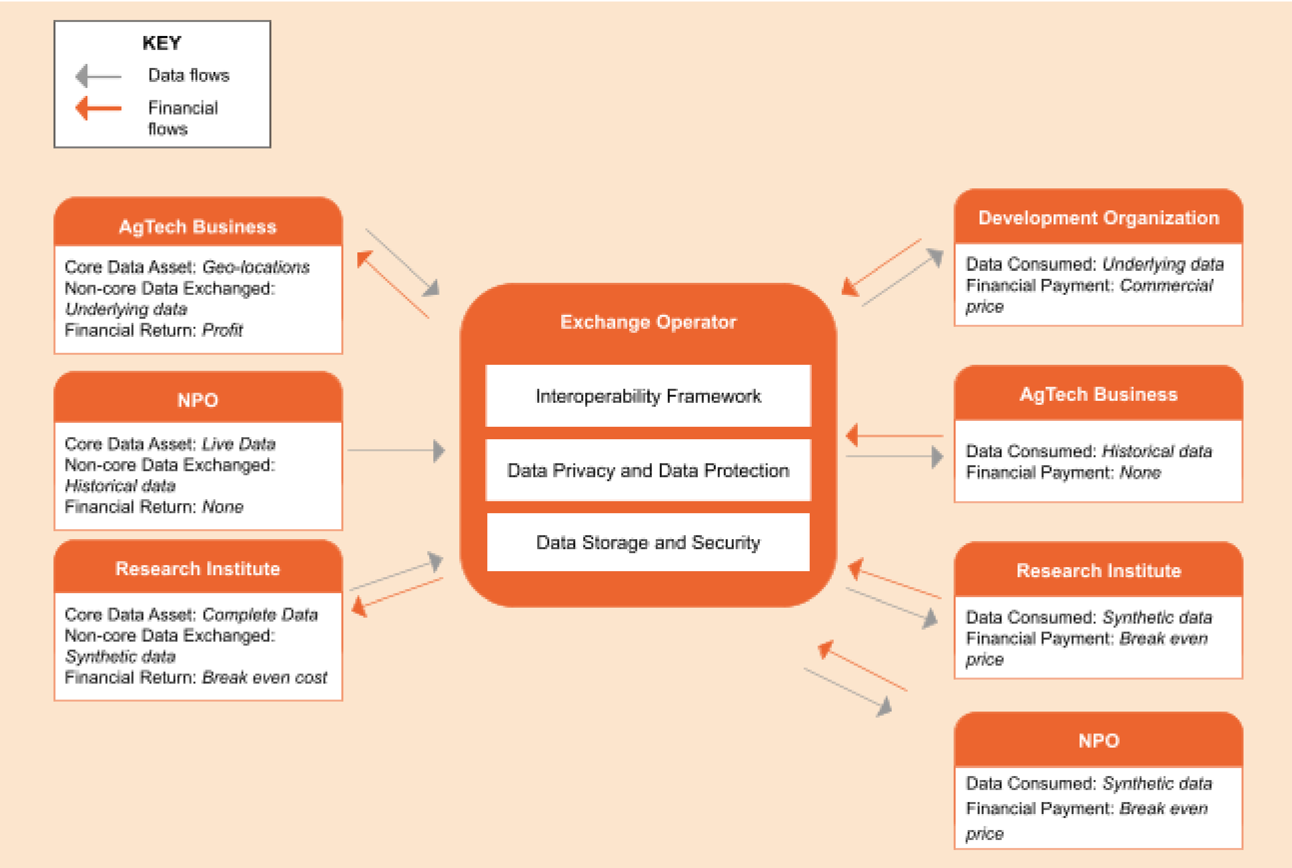
A successful data exchange is as much about technology as it is about providing incentives and creating a sustainable business model. To participate in a data exchange, commercial data asset holders will be prescriptive about who can use their data assets and what they expect in exchange. Understanding 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.

[90] 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.[91] 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.[92] 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".[93] 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.

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

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

[93] 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 — coordinated by farmer organizations — 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.

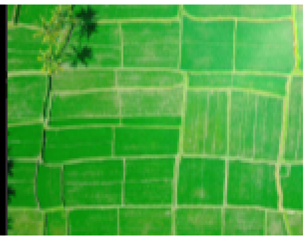
BOX 17: AMEA'S BLENDED LEARNING APPROACH

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.[94] 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.

[94] 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.[95] 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

[95] 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.[96]

[96] 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,[97] membership for AgTech producers to EPR or PRO schemes[98] 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.

[97] International Comparative Legal Guides. 2023. *Environmental, Social and Governance Law.* Available online.
[98] 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.[99] 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.

[99] 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.[100] 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.[101] 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[102] to the potential of introducing a legal framework for small autonomous agricultural robots.[103] 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.[104]

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

[100] Development Gateway. 2023. Farmer-centric data governance models. Available here.
[101] ODI. 2019. *Illegal wildlife trade pilot: What happened when we applied a data trust.* Available here
[102] OECD. 2020. *Examples of National AI Policies.* Available online.
[103] 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.
[104] 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).[105] 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[106] and the Mayo Clinic[107] 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

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

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

[107] 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.

APPENDIX

APPENDIX 1: **STAKEHOLDERS ENGAGED**

Stakeholder	Organization
Abdelaziz Lawani	Global Partners, Africa Goes Digital, Tennessee State University
Akbar Sher Khan	Impagro Farming Solutions
Andrew Merluzzi	USAID
Aminul Hoque Chowdhury	USAID
Amira Cheniour	Seabex
Andrew Merluzzi	USAID
Andrew Ward	Croplife International
Beatrice Gakuba	AWAN Afrika
Benson Njuguna	ACRE Africa
Beta Mahatvaraj	Farms.io
Brian Chiputwa	World Agroforestry Centre (ICRAF)
Brian King	Consultative Group for International Agricultural Research (CGIAR)
Byomkesh Talukder	Dahdaleh Institute for Global Health Research, York University
Canford Chiroro	Khanyisa Research and Consulting
Carlos Boelsterli	MicroRisk
Chaerin Lim	Data Driven Digital Agriculture, World Bank
Christopher Light	E-Livestock Global
Danny Smith	Katapult
Diana Popa	MicroRisk
Ernest Mwebaze	Sunbird AI
Gazi Yar Mohammed	Dana Money
Heike Baumüller	Center for Development Research, University of Bonn
Hemendra Mathur	Bharat Innovation Fund, ThinkAg, Federation of Indian Chambers of Commerce & Industry (FICCI)
Humphrey B.G. Mutaasa	The National Farmers Federation
Ivana Feldfeber Kisilevsky	DataGénero
Jade Abbott	Lelapa AI
Jan Priebe	GSMA Agritech
Jean-Michel Voisard	Chemonics
Jehiel Oliver	Hello Tractor, Inc.
Joel Nwakaire	African Technology and Policy Studies Network
Josh Woodard	USAID
Joshua Templeton	USAID
Joyce Nakatumba-Nabende	Makerere University
Ken Lohento	FAO Regional Office for Africa
Krishna Mishra	EKUTIR
Krishna Srinivasan	Farms.io

Lavanya Thomas	ALLIN TECH LTD.
Lilian Waithaka	ACRE Africa
Mark Irura Gachara	FAIR Forward, GIZ
Matthew Smith	International Development Research Centre (IDRC)
Meetu Kapur	Mason Fellow, JFK Fellow, Harvard Kennedy School
Morup Namgail	IFFCO Kisan
Nicole Kreling	GIZ
Nixon Gecheo	AGRA
Parmesh Shah	Data Driven Digital Agriculture, World Bank
Parmesh Shah	Data Driven Digital Agriculture, World Bank
Philipp Olbrich	FAIR Forward, GIZ
Puvan Selvanathan	BlueNumber
Ranveer Chandra	Microsoft Corporation
Rassarin Chinnachodteeranun	ListenField
Riyaz Pishori	Principal Program Manager for Microsoft Research for Industry, and the PM for FarmVibes.AI, Microsoft
Ruth Schmidt	FAIR Forward, GIZ
Sajedul Hoq	Feed The Future Bangladesh Digital Agriculture Activity
Shachee Doshi	USAID
Simone Strey	Plantix
Siobhan Green	Digital and data governance, DTC global
Soma Dhavala	Wadhwani AI
Sophie Walker	Chief of Party of Laos Microenterprise
Sriram Bharatam	Kuza One
Stewart Collis	Bill and Melinda Gates Foundation
Sujit Janardanan	CropIn
Sumer Singh Johal	AgStack @ The Linux Foundation
Surajit Sinha	Farms.io
Suvankar Mishra	EKUTIR
Temesgen Gebeyehu	AI for good
Venkat Maroju	SourceTrace
Venkatesh Sivaraman	Farms.io
Vineet Singh	Digital Green
Vukosi Marivate	University of Pretoria, Lelapa AI, Deep Learning Indaba, Masakhane NLP, Lacuna Fund
Zia Hassan Siddique	Dana Money

APPENDIX 2: **USE CASE EXAMPLES AND PRIORITIZATION**

On-farm management

Function	Use case	Indicative examples	Prevalence
Planning and monitoring	**Farm health monitoring** Smart farming technologies that monitor key aspects of a farm, such as soil moisture, air quality, livestock vitals, pest location and crop health.	AgriEdge, Bharat Agri, AquaEasy, Cowdy, Cowlar, Heifer International,MooOn, MyFugo, Seabex, Synnefa, Zenvus	
	Digital on-farm extension advisory Regional- and crop-specific agricultural advice that helps farmers reduce losses and increase yields, provided through digital channels.	AgriEdge, Apollo Agriculture, Bharat Agri, eFishery, Seekewa, Synnefa, TechShelta	
	Genomic innovation Creation of new crop, livestock or input varieties that are genetically edited to meet a particular requirement, such as drought resistant.	Cattle Edge, Eagle Genomics	
Automated action	**Automated input provision** Automatic, mechanized completion of on-farm tasks such as feeding, seeding, irrigating, applying fertilizer or spraying pesticide.	AutoGrow, BoniRob, Deepfield Robotic, Eruvaka, eFishery, GramworkX, Nano Ganesh, SunCulture, Synnefa	
	Automated on-farm processing Technologies that automate post-harvest processing tasks, such as grading, sorting and packaging. House on the farm.	Adroit Technologies, Agrograde, Kewpie, Releaf, Smart Information Flow Technologies, TOMRA	

Finance and risk

Function	Use case	Indicative examples	Prevalence
Planning and monitoring	**Digital financial literacy advisory** Generalized education, training and advice on financial concepts, aiming to overcome core, digital and financial literacy barriers.	AgroMall, Apollo Agriculture, Seekewa	
Automated action	**Alternative credit** Creation of credit profiles for small-scale farmers using non-traditional sources of data, to enable expanded access to finance.	FarmDrive, Harvesting Initiatives, Releaf, Sathapana Bank, Slide, Traive Finance, Yoma Bank, zCrowdfund	
	Alternative insurance Automated risk assessments, claim verifications and disbursements that enable expanded access to insurance services.	Apollo Agriculture, Pula Advisors, Worldcovr	
	Smart contracts Contracts stored on a blockchain that automatically execute the agreement when a set of conditions are met.	AgriChain, Agroplexi, Worldcovr, Whrrl	
	Fraudulent food identification Use of AI-enabled computer vision technologies to verify whether a particular food matches the claims on the label.	Wageningen Data Competence Center, IBM Hypertaste	

Supply chain and ecosystem

Function	Use case	Indicative examples	Prevalence
Planning and monitoring	**Traceability** Verified information on parameters of a product's supply chain journey, such as carbon emissions, point of origin or labor standards.	BlueNumber, Greenway, TraceX, SourceTrace, QualiCheck	
	Distribution planning Interfaces that allow farmers and supply chain stakeholders to track and plan distribution and logistics activities, such as fleet or cold chain management.	AgriChain, Agricxlab, ConTrak, Inspira farms, Inficold, Skymetweather	
Automated action	**Buyer-supplier matching** Digital marketplaces and matching platforms that enable SSPs to find buyers and sellers for particular goods and services.	Apollo Agriculture, eFishery, TechShelta	
	Automated off-farm processing Technologies that automate post-harvest processing tasks, such as grading, sorting and packaging. Housed off the farm.	Intello Labs, Marsh Harrier	
	Automated distribution Machinery that automatically completes distribution and logistics tasks, such as automatic shipping through self-driving vehicles.	AgriChain	

APPENDIX 3: **TECHNOLOGY CONSTRAINTS**

This table is a summary of the interaction of the enablers to the underlying technologies. The cells are coloured according to their classification as either a **core**, **notable** or **non-critical** constraint. The constraints were selected based on extensive stakeholder consultations and literature review. Data is the core constraint for intelligence solutions, cost and capability are the core constraints for infrastructure technologies and the core constraints for data collection are cost and capability.

		Data	Connectivity	Access	Cost	Expertise	Capability
Data	IoT Devices						
	Drone Technology						
	Satellite						
Infrastructure	Cloud and Edge						
	Distributed ledger						
Intelligence	Data Analytics						
	AI						

APPENDIX 4: **TECHNOLOGY APPLICATIONS**

The table below outlines the technologies which underlie the layers of our analysis. It indicates the forms they take which can be leveraged by solution developers in the agricultural value chain and the descriptions or applications of these forms.

Data Collection: IoT Devices

IoT DEVICE	APPLICATION
Radio Frequency Identification	Cold chains, perishable products
Wireless Sensor Network	LPWA, Agriculture and crops
Machine-to-Machine System	Mobile applications

Data Collection: Drone Technology

DRONE	APPLICATIONS
Agricultural Imaging	Provides aerial view of crops
Seed-Planting	Gathers and processes data to determine the number of seeds required in the fields
Cloud Seeding	Autonomous drones

Data Collection: Satellites

SATELLITE SOLUTION	APPLICATIONS
Satellite Imagery Data	Spectral, spatial, and temporal range of the satellite imagery
Remote Sensing	A process where satellite imagery data is matched with on the ground samples to create condition estimates at various spatial scales

Infrastructure: Distributed ledger Technology

DISTRIBUTED LEDGER DESIGN	APPLICATIONS
Private	Ledger participation and transacting is limited to known participants
Public	Ledger participation and transacting is open to anyone

Intelligence: Data Analytics

ANALYTIC MODEL	APPLICATIONS
Descriptive	Program Evaluation Review Technique (PERT), Queuing theory, Activity-based costing (ABC)
Predictive	Time series analysis, discriminant analysis, dynamic systems
Diagnostic	Network description, Pareto classification schemes
Prescriptive	Classical optimization, stochastic programming, multicriteria decision-making

APPENDIX 5: **INNOVATIONS IN ARTIFICIAL INTELLIGENCE**

Artificial intelligence and automation technologies are advancing at breakneck speed and across multiple domains. This is revolutionizing what these technologies can do and the impacts they will have on society. There are five key drivers:

- ***Hardware acceleration:*** AI algorithms require significant processing power for training. Rapid increases in the computational power of hardware has pushed the frontier of AI research forward. This is underpinned by the availability of more and more powerful Graphical Processing Units (a computer hardware) that are well suited to training AI. At the same time the cost of computational power continues to fall which widens who undertakes research and decreases the funds needed to support research.

- ***AI democratization:*** AI research and development is no longer restricted to a select group of academics and researchers. Innovations in cloud computing such as AIaaS and plug-and-play tools for AI such as APIs make it easier to develop AI and include AI services in existing solutions. The hype around AI has also stimulated public interest and seen the emergence of many open source, educational materials.

- ***New regulatory efforts:*** There is no global consensus on appropriate AI regulation or mechanisms for enforcing AI regulation. China, the European Union and the United States of America are however pioneering the regulation of AI such as the EU's 8 guidelines for Ethical AI, however these principles are not universal.[108] This highlights rising global recognition of the importance of the technology.

- ***Algorithmic innovation:*** Innovations in hardware and connectivity have rapidly pushed the frontier of AI innovation forwards. AI models are becoming larger and more capable of completing a wider range of tasks, as discussed below.

- ***Economic volatility:*** Many years of low interest rates since the 2008 crisis drove substantial amounts of money into frontier technologies in stock markets and by venture capitalists. This stimulated significant interest and innovation, however recent economic downturns have seen the withdrawal of capital from higher-risk, frontier technology ventures.

The four areas of algorithmic innovation may reveal the direction of AI development and its relationship with the agriculture sector. The areas are contained in the table below and their implications are explored after the table.

[108] The EU principles are - human agency and oversight, technical robustness and safety, privacy and data governance, transparency, diversity, non-discrimination and fairness, societal and environmental well-being and accountability.

Transfer Learning

Transfer learning allows for the 'transfer' of knowledge between AI algorithms performing similar tasks. This can drastically reduce the amount of training data that innovators need to collect to train new models, and has led to the emergence of 'pre-trained' models. For example, a computer vision algorithm that is used to classify the pest present in an image of a plant may only require 10,000 images in training, if these images are used to 'fine-tune' an algorithm that was historically pre-trained for image classification using millions of images. Pre-trained image classification algorithms are widely available and are often trained using open datasets. Similar benefits can be seen when modeling languages with scarce machine readable data that share similar underlying features with languages with significant machine readable data. Transfer learning underpins the importance of investing in openly-accessible, and widely relevant training datasets.

Foundation Models and Transformers[109]

Foundation models refer to a family of AI models that are developed using extremely broad datasets and are built on deep learning and transfer learning algorithms. Foundation models can be reused as the basis for many applications in areas with similar tasks. For example, GPT-3 is a language based foundation model that can be quickly adjusted from predicting a sentence, to answering a question, to then translating a sentence. This model was trained with almost all of the text data available on the internet, amounting to 45 Terabytes. Various foundational models are emerging in broad domains such as language, image and video, and sometimes where combining these data types. Their first emergence in language arguably transformed research in the field, with exploration into the role of foundation models in industry application such as health now being hypothesized. The 'transformer' - a powerful AI architecture which was first published by Google in 2017 for use in language - underpins many of these foundation models. The GPT-3 transformer - and many other foundational models - are so large and require so much data to train that they are out of reach for ordinary researchers, or are not publicly accessible for experimentation. This may locate frontier AI innovation in big-tech.

Human in the Loop (HITL)[110]

Large models can have rare, undesirable behaviors. Models trained with small datasets may also struggle to perform well. HITL is a suite of potential mechanisms for managing these challenges by introducing interaction between humans and the AI to increase the precision and safety of the AI outputs. HITL solutions integrate domain experts into the training, data labeling and validation of model outcomes. Curating and adjusting the 'curriculum' used by the AI and providing focused and incremental feedback to the AI on its performance can help the AI to learn to produce more desirable results. Some AI researchers believe that HITL is well suited for complex domains such as health where there is uncertain and incomplete data from a diverse range of sources, and where the problems that are being solved may benefit from introducing the experience of huma experts to fill in gaps or deal with complex data. HITL solutions may come to be important in the agricultural sector given the need for precise advisory services with a complex range of variables and data, and the poor quality of data available in LMICs.

Knowledge Graphs

Knowledge graphs are powerful data structures that can effectively store and classify data from a variety of sources, and store the relationships that exist between these data. These graphs help to break down information silos and improve research by allowing the collation of data regardless of source and type. Knowledge graphs can then be queried and used in training AI systems that use a variety of data. Knowledge graphs are leveraged across a wide range of sectors including health, banking and retail. Knowledge graphs in agriculture may be an important mechanism for collating various data from a variety of sources, and making it usable in frontier technology solutions.

Innovations in AI are occurring faster than ever which may see the emergence of larger algorithms that can perform a variety of tasks with numerous data types, or are suited to operating in specific domains such as in agriculture. There are two key changes occurring:

- ***AI is accelerating in its functionality.*** It appears likely that AI research will continue to deliver larger algorithms that have wider functionality than the task specific algorithms that are commonly used in AgTech solutions today. These algorithms can be reshaped to perform a single task with even less training data. We also see models using multiple data formats and may come to see algorithms with industry specific

109 Cornell University. 2022. *On the Opportunities and Risks of Foundation Models.* Available here.
110 Artificial Intelligence Review. 2022. *Human-in-the-loop machine learning: a state of the art.* Available here.

intelligence - in agriculture we may see a foundation model and knowledge base to draw on. It is difficult to predict the use cases that will emerge from these new capabilities without further research.

- ***AI has been opening up in terms of access.*** There are falling barriers to expertise requirements for AI with the emergence of AIaaS, increasing opportunity to repurpose other data-sets, and openly accessible algorithms

Emerging risks due to the rapid acceleration of AI innovation and barriers to participating in the frontier of AI innovation may spill-over into the agricultural sector. Frontier AI innovation and the AI agenda appears to be located in big-tech firms. These firms - while admirable in the quality of their research - are subject to competitive pressures which may influence how this research is undertaken. The growing complexity of algorithms and volumes of data they ingest may create increasing complexity in evaluating the quality and safety of their outputs. This is of particular concern in complex systems where poor outputs may have a meaningful, negative impact on users such as SSPs. In addition, AI systems will become increasingly able to mimic people on digital channels and may expose less digitally literate people to fraud risk. This will require greater knowledge of how to regulate these systems, and how to strengthen people’s ability to interact safely with online channels. This broader ethical and safety concern highlights the need for strengthening global consensus on AI ethics and responsible AI. These fields are nascent, which may underpin the reason why there has been little consideration of AI ethics’ intersection with agriculture.

CONTACT US

digital@genesis-analytics.com
+27 11 994 7000

www.genesis-analytics.com

USAID FROM THE AMERICAN PEOPLE

BILL & MELINDA GATES foundation

DigitalFrontiers SCALING DIGITAL DEVELOPMENT

G:ENESIS UNLOCKING VALUE