Inclusively Advancing Agri-Food Systems through AI and Automation

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This document presents a subset of the full study on Inclusively Advancing Agri-Food Systems Through AI and Automation, focusing on **why AI and automation matters for small-scale producers in low and middle-income countries.**

INTRODUCTION

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

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

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

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

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

The full study aims to provide a compass to stakeholders navigating the complexities of these issues. As the application of these technologies among SSPs is still in the early stages, it is difficult to predict what their net impact will be, and almost impossible to do this quantitatively without significant investment in primary impact data collection.

This document makes the case that AI and automation will be hugely transformative for small-scale producers in low and middle income countries. It lays out the landscape of use cases, underlying technologies and delivery models of AI and automation solutions in agri-food systems.

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

METHODOLOGY

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

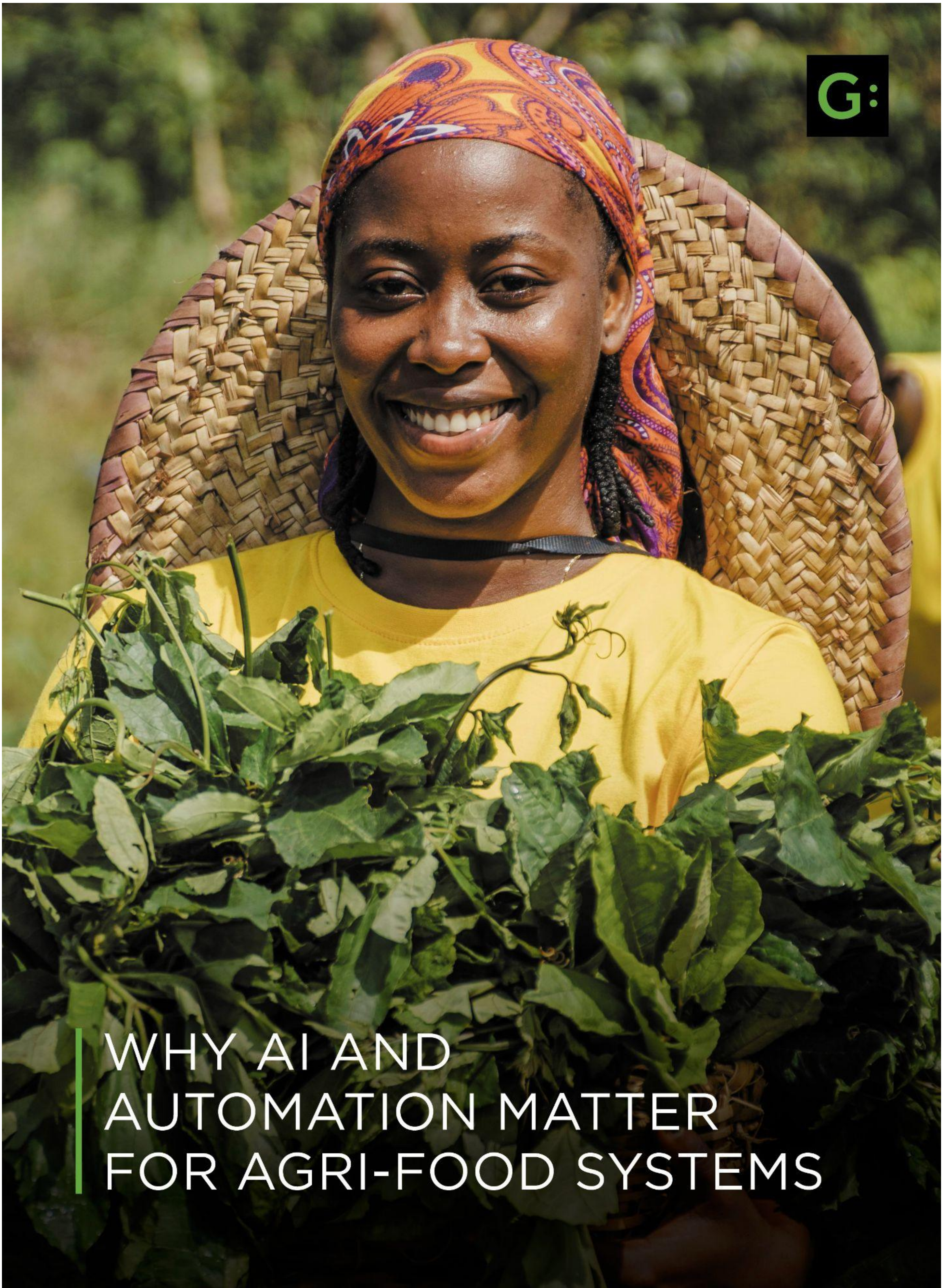
The stakeholder engagement phase collected information through targeted stakeholder interviews across the agri-food, technology and development ecosystem. These included interviews with agricultural policymakers and program officers, agricultural practitioners, impact investors, AgTech providers, and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

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

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

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

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



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.[7] 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.

[7] 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.

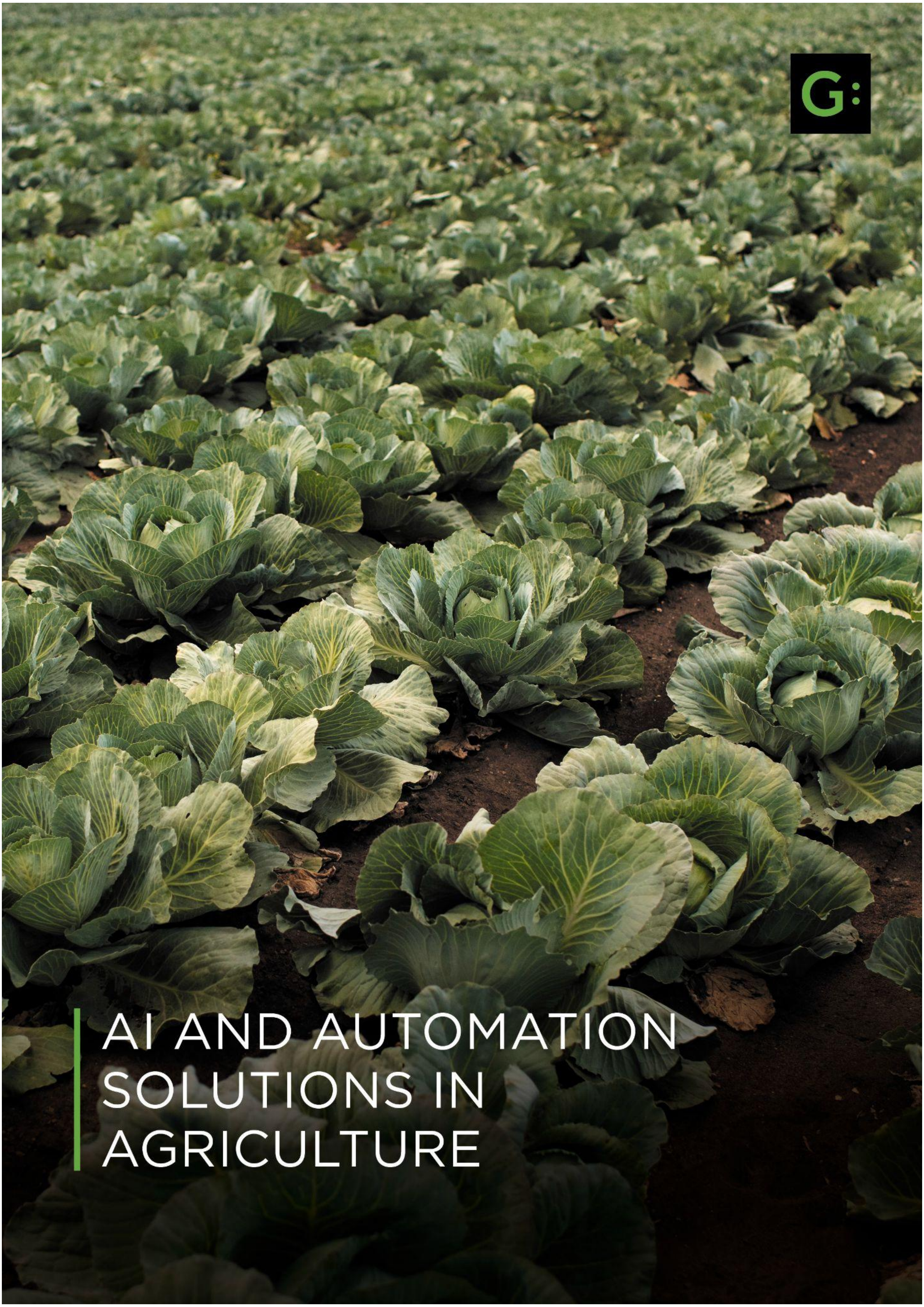
The very capabilities that give AI its transformative potential also introduce significant risk. For example, if an AI system is trained to complete a particular task using biased or incomplete training data, the system is likely to reproduce or exacerbate biases inherent in that data. Moreover, AI processes 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 tend to be SSPs in LMICs.	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
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[8] 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.

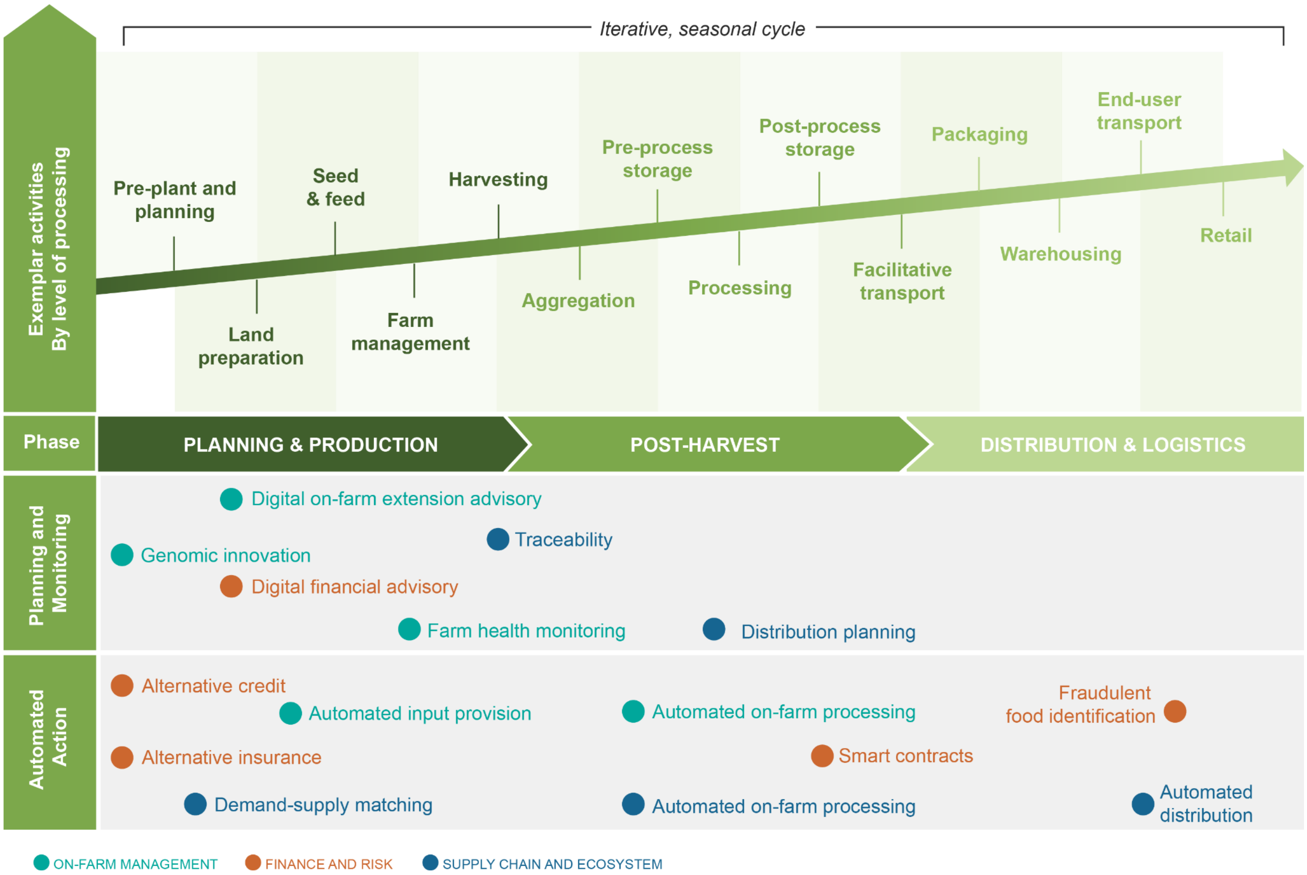
- **Finance and risk management solutions** use AI and automation technologies to expand agri-food stakeholders' access to financial products and services, such as payments, credit and insurance. Access to these services continues to be particularly difficult for SSPs, who typically lack credit profiles 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.

[8] 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.[9] 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.

[9] 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,[10] SMS and IVR.[11] 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.

[10] 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.

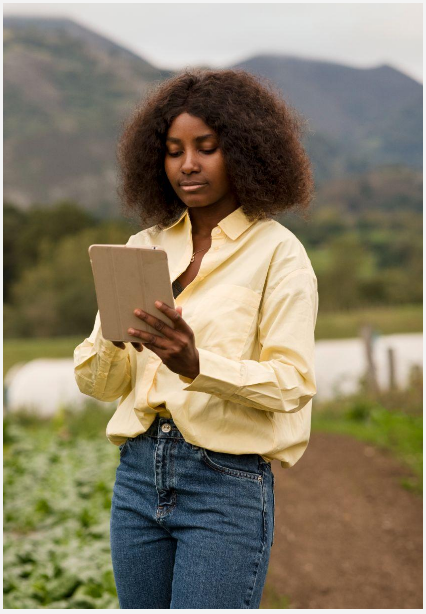
[11] Interactive Voice Response (IVR) is an automated system that allows users to access "call center-type" information without speaking to an agent. The user dials a phone number, and a menu is recited automatically over the phone. The caller uses the number keypad or speech recognition technology to 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.[12] 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

[12] 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.[13] 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.

13 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.[14] 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

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

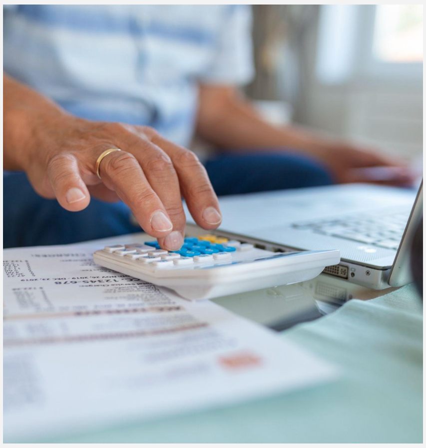
profiles, SMS data or social media activity. This data is then analyzed via machine learning techniques, which conduct near-instant risk assessments of whether an applicant is creditworthy. For example, a psychometric profile that indicates a more risk-averse personality may increase a calculated credit 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.[15]

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

[15] 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.

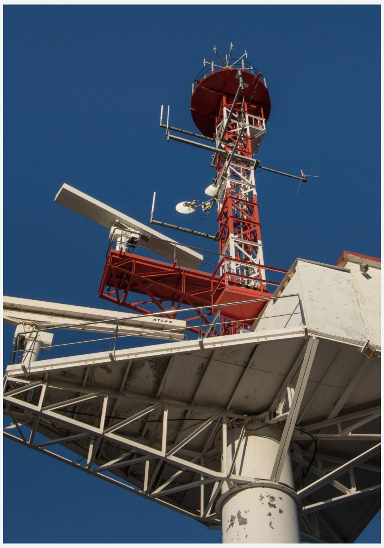
costs. Data may be collected from satellites, weather stations and/or local cameras. For example, satellite imagery can be used to identify if the farm is in a flood zone and, using the data that has been gathered, AI can predict the likelihood of loss by flooding. The data can also be used to determine 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

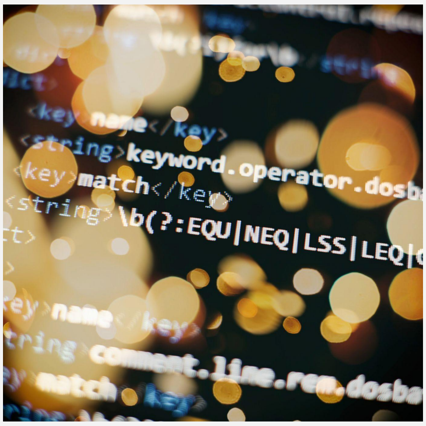
Traceability systems provide verified information about the journey of a product across the supply chain. For SSPs, this can enable access to new markets and drive more transparent pricing. For example, wholesale buyers and end consumers may demand supply chain standards with respect to labor protections, 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[16] 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,

[16] *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

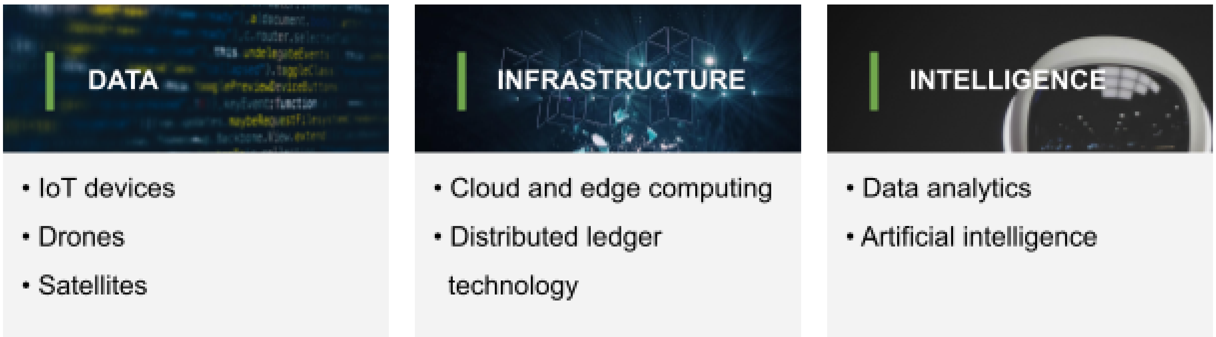
PAY-FOR-USE PLATFORM ENABLING ACCESS TO MACHINERY

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.[17]

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.[18] 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[19], 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

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

18 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.

19 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[20] 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.[21] 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.[22]

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.[23,24] 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.

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20 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.

21 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.)

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

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

24 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.[25]

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.[26]

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.*[27] Significant research has been undertaken to improve the ability of distributed

[25] The Digital Supply Chain. 2022. *The cloud, platforms, and digital twins - Enablers of the digital supply chain.*
[26] COMPASS '18: Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies. 2018. *GreenApps: A Platform For Cellular Edge Applications.* Available here.
[27] 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.[28] [29]

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.[30] 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.

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

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

30 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.[31] 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.

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[31] 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.[32 33]

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

32 Springer Handbook of Geographic Information. 2012. GIS in Agriculture
33 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[34],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.[35] 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

[34] When delivered through foundation models this is at the expense of model size which may create new access barriers as discussed in the appendix.
[35] 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'.[36] 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[37], 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.

[36] Gates Notes. 2023. *The Age of AI has begun*. Available here.
[37] 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.[38] 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.[39]

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.

[38] IBM, 2023. What is Quantum Computing? Available here.
[39] 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.[40] 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.[41] 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.

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[40] World Bank. 2020. *Scaling Up Disruptive Agricultural Technologies in Africa.* Available here

[41] 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[42]	Number of SSPs (in millions)	Mobile broadband connections[43] (% penetration)[44]	Mobile ownership[45] (1-100)	AI readiness indicator[46]	Capacity for innovation (ranking 1–7)[47]
India	200	140[48]	61	59.7	56.11	4.5
Kenya	136	7.5[49]	75	58.9	45.54	4.7
Nigeria	87	38[50]	69	56.3	35.15	3.9
South Africa	73	2[51]	151	75.5	48.24	4.9
Malawi	42	2[52]	37	38.2	24.85	3.3
Ethiopia	42	12[53]	50	37.2	27.95	3.5
Bangladesh	39	15[54]	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,

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

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.[56]

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.[57] 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.[58]

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

55 AGRA. 2021. *The Role of VBAs is Crucial to Vision for Inclusive Agricultural Transformation, says AGRA President*. Available here
56 Harper, nd, *The Digital Acceleration of Africa's Green Revolution*, available here
57 ResearchGate. 2019. *Agriculture Extension System in India: A Meta-analysis.* Available here Stakeholder interviews. 2022
58 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[59] 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.[60] 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

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[59] AgFunder News. 2022. *Farmers have been burned by agtech too often. Here's how to win back their trust.* Available here

[60] 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.[61] 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.

[61] ThinkAg. 2022. *The Platform*. Available here.

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