Chapter 8
Digital Agricultural Extension for Development

Raissa Fabregas, Tomoko Harigaya, Michael Kremer, and Ravindra Ramrattan

1 The Challenge

More than two billion people globally live in smallholder farming households, comprising a large proportion of the world's poor. Smallholder farm yields are estimated to reach only 25–50% of the potential in many parts of the world (Koo, 2014; Das, 2012). Increasing agricultural production is a necessity for meeting the growing demand for food in decades to come (World Bank, 2007), but the scope for expanding cropland is limited as ecological risks from deforestation and loss of biodiversity loom large (Lambin et al., 2013; Zabel et al., 2019). Raising agricultural productivity is, therefore, a critical component of improving the economic well-being of millions of people in developing countries. Simple technologies can significantly increase yields, and an increasing body of evidence suggests that access to agricultural advice can help farmers to improve their productivity. Yet, a vast

Ravindra Ramrattan lost his life in the 2013 attack on the Wastegate mall in Nairobi. During his professional career he contributed to several projects related to digital agriculture and digital finance for development. We remember him not only for his contributions in this area, but also for his curiosity, humor and kindness, which are sorely missed.

R. Fabregas (✉)
School of Public Affairs, The University of Texas at Austin, Austin, TX, USA
e-mail: rfabregas@utexas.edu

T. Harigaya
Senior Researcher, Precision Agriculture for Development (PAD), Boston, MA, USA

M. Kremer
University Professor in Economics and the College and the Harris School of Public Policy (Recipient of 2019 Nobel Prize for Economics), University of Chicago, Chicago, IL, USA

R. Ramrattan *(deceased)*
Ravindra Ramrattan wrote this book while at Kenya

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majority of smallholder farmers do not have access to science-based agricultural information (Fabregas et al., 2019).

The rapid spread of mobile phones and other digital technologies present new opportunities to make quality agricultural information accessible at scale to farmers in developing countries (see Fig. 8.1). This chapter discusses why market failures

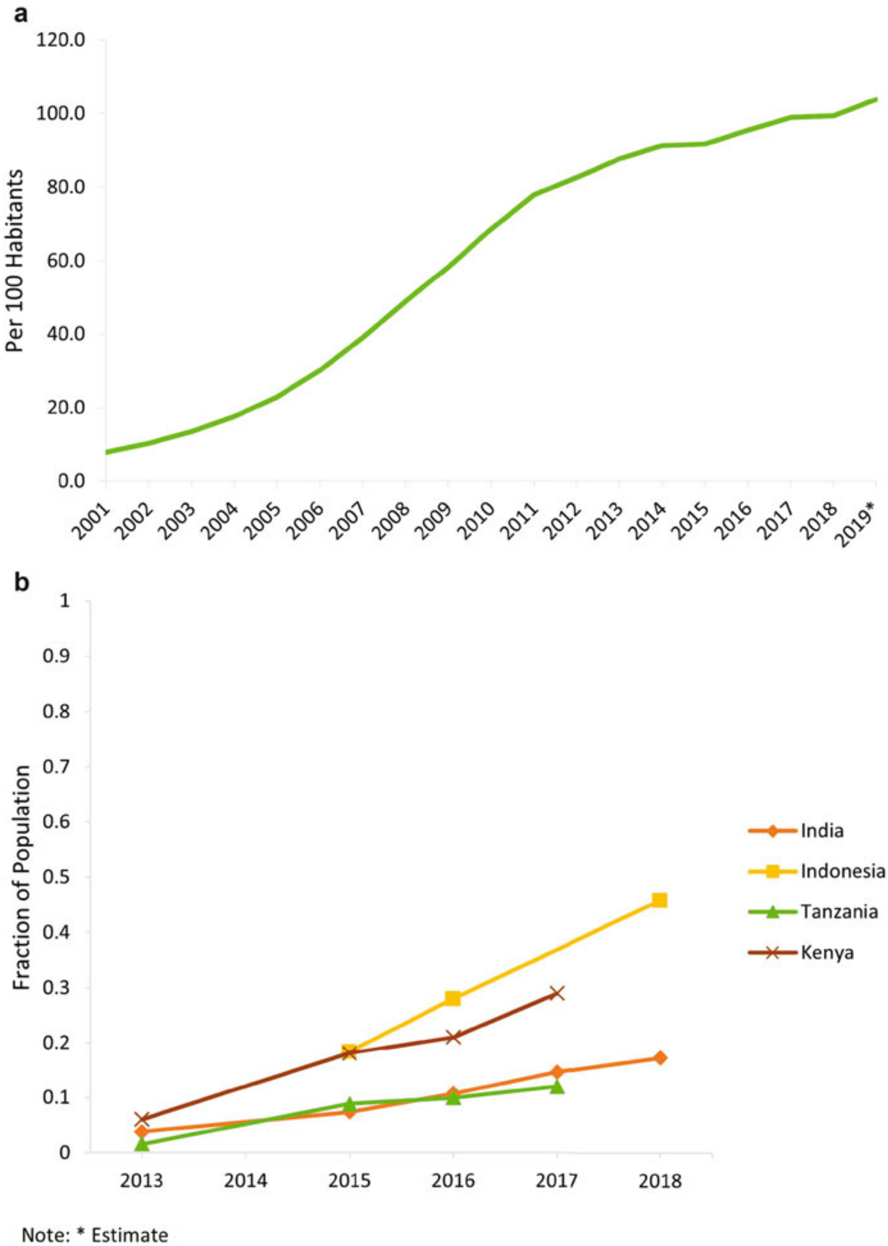

Fig. 8.1 Penetration of mobile phones in developing countries (**a**) Shows mobile cellular subscriptions in the developing world per 100 inhabitants (2001–2019). (**b**) Shows the share of population who reports owning a smartphone. (Source: Financial Inclusion Insights, finclusion.org)

Box 8.1: From Research to Practice at Scale: Precision Agriculture for Development (https://precisionag.org)

Precision Development (PxD), a global nonprofit that provides actionable information to enable smallholder farmers to improve their wellbeing, was conceptualized and formed based on a series of research projects in India and Kenya conducted by academic researchers. PxD continues to learn, innovate, and scale its services, using technology, behavioral sciences, human-centered design, and experimentation (Illustration 8.1).

Illustration 8.1

and service delivery shortfalls undermine the creation and optimal flow of agricultural information and reviews ways in which digital innovations can overcome these barriers. We draw insights from existing evidence and use illustrative examples across geographies to highlight practical considerations and lessons learned through the iteration of these services. Many of these lessons come from our experience with Precision Development (PxD), a global nonprofit providing actionable information to smallholder farmers via mobile phones (see Box 8.1).

1.1 What Limits Access to Agricultural Information?

Many farmers have vast amounts of agricultural knowledge that has been transmitted throughout generations. Yet, the existence of new agricultural technologies and changes in farm conditions – from soil degradation, to market conditions – require ongoing learning and experimentation to optimize productivity. Farmers in developed countries have access to a wide range of technological developments – from high-density soil testing and moisture sensors to satellite and drone imagining – capable of gathering precise information about their farms and which enable them to apply inputs more efficiently. However, an overwhelming majority of smallholder farmers in developing countries do not have access to these technologies, and many would find it unprofitable to use them. Even relatively simple technologies, such as soil chemistry analyses, are well beyond the means of many smallholders. Additionally, experimenting with inputs in isolation is complicated because individual results are noisy and farmers may not know which dimensions to prioritize for experimentation (Hanna et al., 2014).

Several factors explain why the private sector often lacks sufficient incentives to create and offer appropriate information to farmers at the optimal scale. Information is generally a non-rival and non-excludable good. Once information is created, it can be easily shared with others at a very low cost. For example, a buyer of agricultural advice could share this information with many other farmers. If sellers of information cannot recover their investment costs, they will be unlikely to create it. Moreover, uncertainty on the part of buyers regarding the value of a particular piece of information may limit their demand.

Since many aspects of agricultural extension can be considered a public good, public provision is common in many countries (Anderson & Feder, 2004). Governments in developing countries spend millions of dollars every year creating agricultural knowledge and delivering extension services. Typical delivery approaches involve in-person visits and community events such as "farming workshops" and "field days" where technologies and input use are demonstrated (BenYishay & Mobarak, 2019; Emerick & Dar, 2020; Fabregas et al., 2017; Kondylis et al., 2017; Mueller & Zhu, 2021). However, scaling these services effectively poses a number of challenges. Foremost, in-person extension is often expensive, severely limiting its reach. Developing country governments maintain networks of over one million extension agents (Anderson & Feder, 2007), but ratios of farmers to extension agents generally remain high, leaving a majority of smallholders without adequate access to their services and information. Public extension services may also be affected by bureaucratic problems that limit the accountability of frontline information providers. Moreover, there are concerns that the most disadvantaged, including the poorest and women farmers, are often neglected (Saito et al., 1994; Cunguara & Moder, 2011). Other oft-used technologies, like radio, can reach farmers at scale, but these media make it difficult to tailor recommendations to local conditions.

In addition to service delivery challenges, generating agricultural content tailored to local conditions and the specific needs of individual farmers can be costly to produce (see Box 8.2). In many instances this leads to extension services providing blanket recommendations across large geographic areas. Cost-related considerations may also hamper the regular updating of dynamic conditions: in such cases advisory content quickly becomes obsolete. Finally, many extension systems focus on agronomic recommendations developed to maximize crop yields. However, farmers may optimize adoption decisions to maximize returns to investment (ROI), rather than crop yields, under real-world constraints, such as liquidity, transportation costs and expected market conditions, In addition, farmer's ROI calculation is influenced by individual characteristics such as risk and taste preferences. These considerations are rarely accounted for by traditional extension services.

Box 8.2: Why Do Smallholders Lack Weather Information?
Contributed by Hannah Timmis, Precision Development

Smallholders face substantial risk from fluctuations in the weather, and climate change only increases this risk. Weather unpredictability affects agricultural incomes directly, by varying the amount and quality of outputs produced from a given bundle of inputs and, indirectly, by compelling farmers to adopt costly risk mitigation strategies such as intercropping (Cole & Xiong, 2017). Accurate weather forecasts reduce this risk by enabling farmers to optimize their production based on future meteorological conditions. In India, for example, smallholders that live in areas with better seasonal forecasts calibrate their planting-stage investments to predicted rainfall and have higher profits on average (Rosenzweig & Udry, 2019). Despite these benefits, accurate forecasts are frequently unavailable in developing countries due to a combination of market and institutional failures. Producing a high-quality forecast involves large fixed costs. Global weather prediction models, which are operated by specialized meteorological centers, run many times a day and generate vast quantities of data. Forecast providers must access, assimilate, analyze, and disseminate this information, and some also deploy limited area models. The process is capital-intensive: high-performance computing, rapid data transmission systems, and highly skilled staff are all required. Yet, once the forecast is created, anyone can access and use the information at near-zero marginal cost. These production characteristics mean that basic weather forecasts are under-supplied by the market.

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Box 8.2 (continued)

Hence, by international agreement, national governments are responsible for weather forecasting. Members of the UN World Meteorological Organisation, which comprise 193 countries and territories, maintain dedicated public providers called National Meteorological and Hydrological Services (NMHS). The problem is that the capability of NMHS varies enormously. Many public agencies in developing countries frequently suffer from under-funding, failing infrastructure, outdated equipment, and inadequate expertise (Webster, 2013). The result is that valuable weather information does not reach the right people at the right time.

A case study from Pakistan illustrates the issue. In 2010, northern Pakistan suffered devastating floods, which killed 2000 people and destroyed $US500M in agricultural output. Researchers at Georgia Tech subsequently showed that the floods were predictable 8–10 days in advance if available data had been analyzed at the time (Webster et al., 2011). Yet, Pakistan's NMHS issued no warning.

1.2 The Potential of Digital Agriculture

The widespread adoption of mobile phones, combined with the advances in agricultural measurement and computational technologies presents new opportunities to address the barriers to making relevant information available for smallholder farmers. Information and communication technologies (ICT) and mobile phones, in particular, allow for low-cost, timely, and customized information delivery at scale. This medium can be particularly useful for the delivery of dynamic information which requires continuous updates, for example, weather information and market prices. Digital technologies also present comparative advantages for delivering information to farmers in remote areas with poor infrastructure, conflict-affected areas beyond the reach of in-person extension services, and in contexts affected by natural disasters in which the delivery of time-sensitive information can be life-saving.

Two features in particular make digital extension a promising area of innovation. First, ICT and other digital technologies allow for two-way communication with farmers. This can be leveraged to collect information about local conditions, farmers' backgrounds, and experiences with inputs. For most smallholder farmers, deploying hardware/sensor-based precision agriculture technologies would be prohibitively expensive. Mobile phone communication can facilitate information transmission in which farmers can ask specific questions and request information valuable to them. Even with recent technological efforts to reduce the cost of delivering precision agriculture in developing countries (Jain et al., 2019), there are many potential gains from collecting information directly from farmers. For instance, if data is collected at sufficient scale, it would enable extension systems to aggregate information more effectively, which in turn would allow for the generation of better recommendations to be made available to everyone in the system. Once aggregated, the information about individual's farm conditions could also be used to solve other informational frictions in supply markets. For example, it could be used to identify pest-prone areas or improve understanding of demand for inputs.

Second, digital extension can exercise large economies of scale to generate analytical insights and improve customization. In turn, the iteration of these insights and improvements can progressively increase impacts over time. Digital platforms generate large volumes of user data which can be utilized for constant experimentation and adjustments at low cost. The addition of more users and generation of more data allow for faster experimentation and advanced analytics – for example, through the use of machine learning – leading to faster improvements in the quality of customization and the magnitude of potential impacts. The progressive increase in returns to scale implicit in digital systems suggests that systems operating at scale, and leveraging data for constant learning, will likely derive the largest impacts.

Despite the potential of digital extension services many implementation challenges remain. For instance, many existing agricultural mobile-based systems are based on one-way, "push-only" approaches that focus on broadcasting one specific type of information (e.g., prices, specific recommendations for a crop, etc.). Not all information is useful, actionable, or accessible. The value of information depends on context. For example, advice on basic agronomic techniques is likely to be irrelevant for experienced farmers. Similarly, farmers who confront markets with constraints in the supply of labor may not adopt labor-intensive technologies. Operationalizing active two-way communication with farmers in a way that allows systems to learn about their needs could vastly improve the usefulness of the recommendations farmers receive. Moreover, relevant information uploaded to a digital platform may still not reach many smallholder populations in the absence of a user-centered design that facilitates access and comprehension for farmers across linguistic groups and takes into account low levels of literacy.

Similarly, cheap information delivery tools do not solve constraints in creating local and dynamic agricultural information. Few systems leverage experimentation or information created by farmers themselves or have mechanisms capable of facilitating local information creation. Finally, the current landscape of mobile-based agricultural information platforms is diverse, fragmented, and uneven in quality. Most ICT-based services only reach a few thousand farmers, and there has been little coordination to avoid duplication of information creation or to maximize gains from sharing. There are high fixed costs in setting up these systems – particularly with regard to information generation, software creation, establishing trust with farmers – which suggests that small-scale approaches are likely to be suboptimal.

Fully realizing the potential of digital agricultural extension will require addressing these issues through concerted efforts to develop and test a range of approaches. Successfully addressing these challenges will require interdisciplinary collaboration that incorporates lessons and insights from behavioral and data sciences, agriculture, economics, and engineering.

2 Implementing Mobile Phone-Based Agricultural Extension Services

Mobile-phone based agricultural extension services vary in the complexity of the design and the types of technologies used. In this section, we briefly discuss existing evidence on the impacts of current ICT-based extension approaches (see existing reviews for a more detailed scan of the literature, e.g., Aker, 2011; Nakasone et al., 2014; Aker et al., 2016; Fabregas et al., 2019). We then discuss selected aspects of implementation that are key to successful deployment.

2.1 Current Approaches via Mobile Devices

2.1.1 Services That Rely on Text Messages

Basic mobile devices with call and texting capabilities only are still the most common type of phone handset used in developing countries, and text messaging is still the cheapest way to reach people in many parts of the world. Text messages, or short message services (SMS), allow for written messages of 160 characters, which can be sent in bulk and broadcast in near real time to hundreds of thousands of people. This ability to reach farmers in resource-poor areas at very low cost makes text messaging an attractive option for closing information gaps.

This simple text messaging technology, however, has a number of limitations. First, there is limited scope for communicating complex information sending too many messages can annoy farmers (IDinsight, 2019) or overload cognitive capacity, potentially leading farmers to pay little attention to message content. Even in instances where farmers are eager to receive messages, illiteracy may limit the effectiveness of written information. Second, poorer farmers with low mobile literacy may find a significant barrier to direct two-way communication, especially in contexts where users pay for outgoing text messages. In particular, collecting accurate location data from farmers via text messaging, and tailoring information accordingly, poses a big challenge (see Box 8.3).

Existing evidence suggests that text messages can have modest, but positive effects on the likelihood of a farmer adopting recommended agricultural technologies. A text-message extension program offered to sugar cane farmers in Kenya found positive yield impacts in one trial but no effects in a second trial (Casaburi et al., 2019b). In Ecuador, text messages to potato farmers increased knowledge and self-reported adoption of integrated soil management practices (Larochelle et al., 2019). Similarly, delivering price information via SMS resulted in better farmer outcomes in Peru and India (Nakasone, 2013; Courtois & Subervie, 2015), but did not affect average crop prices obtained by farmers in Colombia and India (Camacho & Conover, 2011; Fafchamps & Minten, 2012). The existing evidence base offers limited insights on the heterogeneity of treatment effects. Are effects sensitive to the local conditions and the specific design features, or varying findings across studies are merely driven by sampling variation and imprecise impact estimates due to small samples? A meta-analysis of six experimental evaluations of text message services encouraging farmers to adopt an input to reduce soil acidity, implemented by three different organizations with thousands of smallholder maize farmers in Kenya and Rwanda, found that farmers who received texts were 19% more likely to follow the agricultural advice (Fabregas et al., 2021). While some of the individual experiments had statistically significant impacts and others did not, one cannot reject the hypothesis that the effects were the same across contexts. These results also suggest that one needs to be cautious when interpreting sources of impact heterogeneity across different studies.

Another key consideration for policy is how impacts compare to the costs of the programs. Since the marginal costs of sending an SMS is extremely low, even small effects can be cost-effective. While SMS is a well-known and simple technology widely used for digital extension, there are a number of opportunities that deserve further exploration. First, it is important to understand the extent to which more effective message design can increase impacts. Here, insights from marketing and behavioral economics could be useful. Second, when and how frequently messages should be targeted. Third, how to develop systems to collect farmer information through text message. All of these approaches require more experimentation.

Box 8.3: Customizing Advice to Farmers' Location via Text Message

A group of researchers working in Kenya, including several of the authors of this case study, partnered with a public entity, a social enterprise and an NGO to evaluate SMS-based agricultural services that recommended a specific type of input for acidic soils (Fabregas et al., 2021).

The government-run program recommended farmers first to test their soils to learn about the soil acidity of their plot before following the advice. However, individual soil testing can be prohibitively expensive for most smallholder farmers (approximately $20USD at the time of the study). Even though local recommendations could be generated using the available data on local soil tests in the region and shared directly with farmers through their phones, such customization required information about a farmer's location.

Establishing user locations faced a number of challenges. First, most smallholder farmers in rural Kenya do not have GPS-enabled smartphones. Therefore, potential users had to be people for whom information on location already existed (e.g., because they had already participated in other programs,

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Box 8.3 (continued)
and this had already been collected), or information about their location had to be collected through text message questionnaires. Second, many developing countries lack precisely defined physical addresses (Union, 2012). Collecting precise location information about specific farmers seemed almost impossible. In this particular case, the smallest unit that farmers could report uniformly was their village. However, village name spellings were not consistent and user text entry was often error-prone. Moreover, no GIS maps existed at the village level. At the end, data could only be reliably collected at a higher level of aggregation like the ward or sublocation.

The research team experimented with a number of solutions. In one project, farmers were recruited through partner organizations that already had information about farmers' locations. In a second project, participants were recruited through agricultural shops. Clients of these shops were invited to enroll into the agricultural extension program, and shopkeepers provided support in filling out a text-message questionnaire that asked farmers about their physical location.

These models have trade-offs. Recruiting through a partner organization lowers the cost of user acquisition, but the scale and the target farmer population are determined by the partner's reach. In contrast, coordinating a recruitment process through local agents can be costly and limited in scalability. A more scalable approach may be to partner with mobile network operators and use the data on cell tower locations. However, as discussed in the next subsection, there is often a large fixed cost in negotiating these agreements. As the adoption of GPS-enabled devices increases, more opportunities to gather farmers' locations at low cost and at scale will likely emerge.

2.1.2 Services That Rely on Interactive Voice Responses (IVR)

A second technology operating in basic phones which we highlight is interactive voice responses (IVR). This technology allows computers to interact with humans through voice. Several developing countries, including India, Madagascar, and Ethiopia already operate IVR phone-based government extension systems. These systems usually allow farmers to listen to prerecorded information and to record new questions (Fig. 8.2). This approach is likely to be more inclusive of users with low levels of literacy, though it requires users to listen to audio-recorded messages. It can also be more expensive to operate than text-based systems. Cole and Fernando (2021) evaluate an IVR mobile advisory system that provides agricultural advice to cotton and cumin farmers in India. The intervention increased self-reported adoption of recommended seeds, though it had no impact on the adoption of other inputs like pesticides or fertilizers.

2.1.3 More Advanced Technologies: Smartphones and Tablets

Smartphones and tablets offer new possibilities for sharing information and learning. For example, farmers could watch videos demonstrating new agricultural techniques or take pictures of pests affecting their crops and either request automatic identification and recommendations or raise questions with agronomists (Olson, 2018). Farmers could play with apps to better understand the risks associated with certain crops (Tjernström et al., 2019). However, access to smartphones and tablet devices is still limited in some parts of the world, and it may require innovative delivery approaches to reach scale, including engaging agricultural extension officers, agrodealers, and other local agents with familiarity with smartphones.

To date, a number of video-based interventions for farmers have also been found to have positive impacts at changing knowledge and self-reported farmer practices (Gandhi et al., 2007; Fu & Akter, 2016; Van Campenhout et al., 2018). Measured impacts on crop yields have been mixed, with some projects documenting null effects (Udry, 2019; Van Campenhout et al., 2019) and others documenting positive impacts (Van Campenhout et al., 2018; Arouna et al., 2019). However, a recent meta-analysis combining the effects of these existing projects suggests that, on average, yields increased by 4% as a result of these types of programs (Fabregas et al., 2019).

2.2 Implementation: Technological Considerations

Deploying mobile phone-based solutions requires coordination with a number of stakeholders including government, agricultural agencies, communications regulatory bodies, and local telco companies. In this section, we discuss key technological considerations for setting up and scaling a digital agricultural extension service.

2.2.1 Technology Infrastructure

Several options for technology infrastructure are available in most countries. These options include working directly with mobile network operators (MNOs), working through a mobile aggregator, or working with an existing mobile solutions provider. Negotiating individually with each MNO can be time-consuming and difficult. In contrast, many aggregators have an infrastructure and partnerships that allow them to send messages to subscribers across MNOs within a country, but regulations on mobile communications and the nascent market environment for aggregators vary across countries. Finally, mobile solutions providers may offer additional

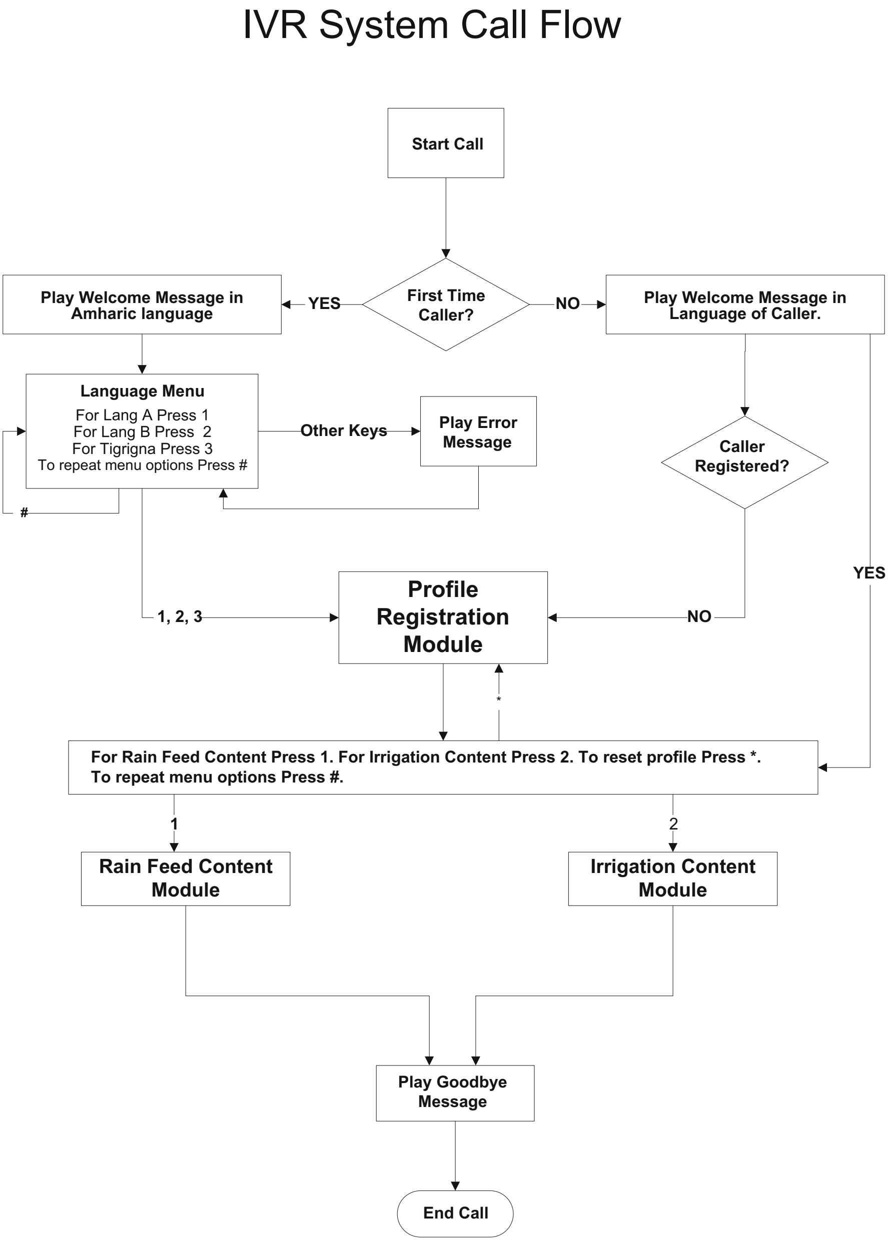

Fig. 8.2 An example call flow of an existing IVR-based agricultural information service. This figure illustrates the IVR menu structure for an existing IVR-based agricultural information service. A caller is first asked to select a language and answer a few profiling questions before being taken to the menu of agricultural content organized by irrigation access. (Source: PxD)

services such as dashboards for easy monitoring and a team of engineers to build customized service features. Below are some key considerations when considering these different options.

User Protection Mobile phone subscribers receive many spam messages and calls. In some countries, unsolicited messaging in the absence of a user opting in to a service is prohibited or regulated. Noncompliance can result in the service being shut down or penalized. Even in the absence of such regulations, the opt-out right needs be considered as part of the user protection measure. A simple process that allows users to choose whether and when to opt out can reduce annoyance. Telecommunications authorities can also decide whether certain emergencies – such as severe pest outbreaks – warrant sending unsolicited messages.

Data Security and Privacy Two-way digital agricultural extension systems can accumulate a large volume of private data about smallholder farmers. This often includes phone numbers, as well as more detailed information about a farmer's location, crop selection, and input usage, and may include sensitive information such as exact plot locations, agricultural sales, and credit history. Privacy protection for service users needs to be handled carefully. Some countries have data protection and security regulations that restrict how and where data about individual citizens can be stored and accessed. One must also consider obtaining consent from farmers to use their data for analysis or to share their information with third parties. It may be practical in some cases to obtain consent from users as they register into the service. However, with low mobile literacy among smallholder farmers, providing sufficient information and obtaining informed consent via digital messages can be difficult.

Access to Mobile Data Mobile communications data owned by MNOs contain rich information about farmers, which can be used to improve the quality of a digital advisory service. For example, cell tower data provides user location information; call and message logs can be used to identify social networks or predict mobile literacy (Björkegren, 2019); and user profile and phone settings reveal user preference. Aggregators often do not have access to this kind of granular user-level data. More importantly, when a digital agricultural extension service is launched, usage data provides real-time feedback about demand for service and information. Whether working with MNOs or through aggregators, access to the basic usage data (e.g., whether the message was received, why it was not received, etc.) can contribute to building a robust monitoring and evaluation system as well as capacity to engage in rapid testing and iterative development.

2.2.2 Implementation Model: Product Considerations

A host of operational decisions need to be considered in setting up a digital agricultural extension service. How does one optimally recruit farmers? What types of implementing organizations make good partners? What are adequate revenue

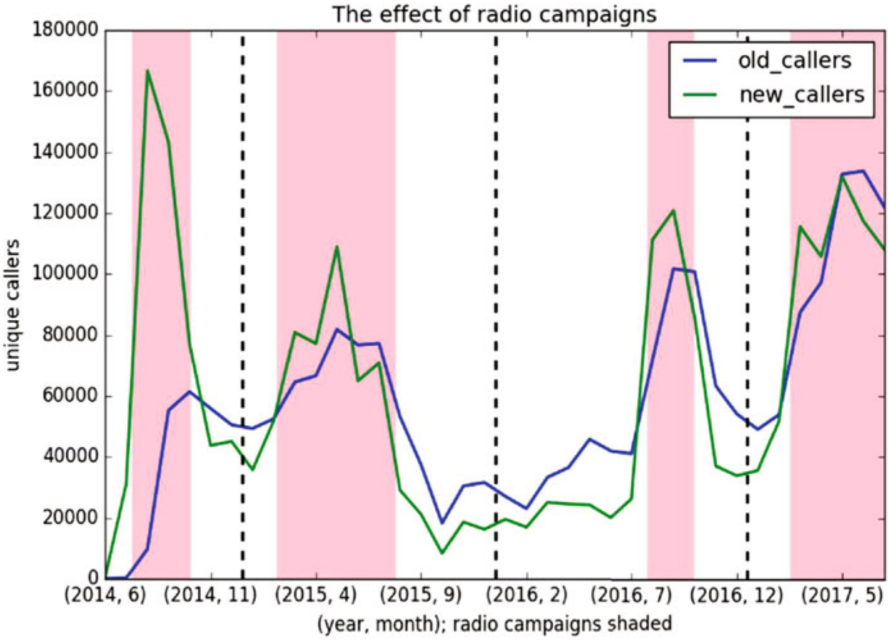

Fig. 8.3 Trends in access to a national agricultural hotline service. This graph illustrates how a mass radio campaign generated spikes in calls to a large public agricultural hotline service, serving as an effective tool to recruit farmers to digital agricultural advisory services. (Source: PxD)

models and financial paths to scale? Not all of these questions need to be answered right away, and implementation models may evolve as questions are answered through piloting and incremental scaling.

Customer Acquisition Farmer recruitment and partner selection are key design elements in the implementation of a digital agricultural advisory service. These decisions will affect the scale, density, and target farmer population as well as the scope of feasible customization and the cost of service delivery per farmer. Databases of farmer phone numbers may be available through – among others – government agencies, NGOs, and farmer associations. Some implementers already have valuable and detailed information about farmers (e.g., location, gender, primary crops, etc.), although they might work with a limited number of individuals. Alternatively, mass campaigns via radio advertisements and posters in village centers may be feasible. For example, a large public agricultural hotline service saw spikes in call volumes immediately after hotline numbers were broadcast via radio programs (Fig. 8.3). The cost per user acquisition through radio campaigns in this setting was $0.29/user in 2019.

Agronomic Content A vast body of agronomic sciences research and crop modeling informs evolving insights on new productivity-enhancing technologies and practices. However, the rigor of evidence supporting the use and impact of new technologies varies widely. Institutional willingness to take risks with recommendations and relative openness to incorporating new technologies into extension services may vary widely by implementing agency. For instance, government agencies might provide agricultural information that is agronomically correct but too technical to be adequately used by target farmers (Cole & Sharma, 2017; Fabregas et al., 2021). In vetting agricultural content, we emphasize the importance of considering farmer's profitability calculations in real-farm settings, and the potential risks associated with any technology. For example, customized advice generated by complex crop models may benefit from an empirical validation to corroborate whether customization, in fact, improves profitability among targeted farmers.

Costs and Financing of Digital Agricultural Systems Mobile phones offer a low-cost means to reach smallholder farmers with information at scale. Moreover, the low marginal costs of distribution suggest that there can be high returns to scale. For instance, PxD's average cost of service has dramatically decreased from $5.20 per farmer per year in 2017 (serving approximately 345 K farmers) to $1.55 in 2019 (serving 3.53 M farmers).[1] Despite the very low marginal cost of scaling the service, however, setting up a digital agricultural system in a new setting might require nontrivial upfront capital.

There are several potential financing models for digital agricultural services. Many for-profit service providers in digital agriculture charge farmers a subscription fee. However, economic theory suggests that markets for information will often perform poorly and, therefore, financing models that solely rely on charging fees directly to farmers are likely to exclude a large proportion of smallholders who might still find these services valuable (Fabregas et al., 2019). Market failures arise because information differs from most other goods: it is non-rival (e.g., once created many people can benefit from it at minimal marginal distribution costs), it is non-excludable or partly excludable (e.g., once an individual has access they can share with many others), and there often exists asymmetric information in the market (e.g., buyers do not know the value of information sold to them). These features might suppress farmers' willingness to pay for information services and also make it difficult for service providers to recoup their costs, limiting their incentives to invest in generating informational products.

Limited empirical data suggests that farmer's willingness to pay varies widely across settings, but farmers are sensitive to prices. The IVR service in India studied by Cole and Fernando (2021) found that, despite a high rate of engagement, the average price which farmers were willing to pay was $2 when the cost of provision for a 9-month subscription for that particular service was $7. The percentage of farmers who took an offer at a randomly selected price varied from 6.7% at $4.13 to 85% at $0.68. In a study in rural Ghana, most farmers were willing to pay a low

[1] These estimates are based on PAD's total operating cost and the total number of farmers served across all initiatives, and the initiative-specific cost per farmer varies widely by the design of the service, partnership arrangement, and the scale at which it is operating.

price for digital information service ($0.10/month), but they were highly sensitive to price increases (Hidrobo et al., 2020). In a study of willingness to pay for local soil information in western Kenya, farmers were not willing to pay the full cost of local soil tests, but the aggregate valuation of all farmers for a given soil test in an area exceeded the cost of soil testing and distributing this information. This potentially makes investment in this information worthwhile from a social standpoint (Fabregas et al., 2017).

Other commercial models might help address some of these issues. A freemium model in which users receive free access to a basic service and pay for advanced features may increase access while still generating revenues. Alternatively, revenues may be raised from value-chain players with an aligned incentive to increase farmer productivity (e.g., contract farming companies, large agricultural corporations with corporate social responsibility). Overall, the above market failures provide a rationale for some public sector involvement in financially supporting these services.

Other Costs to Farmers Even in the absence of direct fees to use a digital agricultural service, farmers may face indirect (pecuniary and nonpecuniary) costs of accessing these services. For instance, phone signals can be weak and unreliable in remote areas; farmers may incur transportation costs to access electricity for charging phones; and some MNOs require a minimum phone credit to receive calls. In addition, challenges with mobile phone access and digital literacy may present greater barriers for marginalized populations, such as women and the poorest. Expanding digital agricultural services among those who may face high costs and barriers to access them will require a deliberate effort for the developer to address their specific barriers and meet their specific needs.

3 Iterative Development

Developing a user-centered service requires an iterative process guided by frequent user feedback. A variety of methods and approaches can be used to test, evaluate, and iterate the design of digital agricultural extension services to improve service delivery and impact (see Box 8.4).

3.1 Approaches

Human-Centered Design Approach Agricultural recommendations developed by scientists and experts are often technical and difficult to understand. Given the limited volume of content which a typical digital message can deliver at one time, the comprehensibility and actionability of a message are likely to be a critical driver of impact. The exact content of messages can be tested and iterated with target farmers through in-person or telephonic focus group discussions, interviews, and observations, before launching rigorous testing. For instance, one could share the messages with a small number of farmers and ask them to explain the recommendation to ensure that agricultural words used in the message are locally appropriate; farmers may be asked to call into an IVR service and interact with the system so that the developer team can observe the pain points in the interface.

Monitoring Implementation quality can be assessed by monitoring key performance metrics, such as user engagement, user satisfaction, or perceptions. Monitoring these outcomes can provide valuable information about program's aspects that may or may not be working well. For example, low user engagement suggests that the system might be failing to deliver agricultural information to a large number of farmers. Similarly, low user satisfaction can indicate that farmers are unlikely to utilize the service and the agricultural information it provides. Obtaining feedback from farmers and iterating on design may help identify and reduce any potential barriers. However, merely monitoring engagement and satisfaction does not tell us whether the service impacts farmer behavior and outcomes.

Box 8.4: Iterative Development of Customized Fertilizer Advice, PxD India

The Government of India invests a large amount of resources in soil testing of farmers' fields and distributing Soil Health Cards (SHCs). SHCs are physical soil report cards which provide detailed soil nutrient information and customized fertilizer recommendations. However, information presented in SHCs is highly technical and difficult for farmers to understand. For instance, previous research in Bihar shows that nearly 70% of farmers with sufficiently nutrient soils wrongly believed that SHCs recommended relevant fertilizer application (Fishman et al., 2016).

To address this challenge, in 2017 a research team set out to develop a digital support tool for SHCs. The team conducted a series of focus group discussions in Gujarat, India, followed by a "lab-in-the-field" experiment to develop and test supplemental materials including an audio aid for SHCs. Approximately 600 farmers across 12 villages were randomly assigned to be presented with (i) a (hypothetical) SHC only, (ii) a SHC with an audio aid, (iii) a SHC with a video clip, or (iv) a SHC with an agronomist on hand to explain the SHC. The SHC was presented as something for a farmer's friend. Farmers in groups (ii)–(iv) were also given a simplified SHC with fertilizer recommendations converted into a familiar local unit. The field team visited farmers door to door and administered short surveys at the beginning of the visit, after the SHC was presented, and after the supplementary materials were presented. The team found that all of the supplementary materials dramatically increased the proportion of farmers who understood the SHC

(continued)

Box 8.4 (continued)
content from 8 to over 40% and the level of trust in SHC recommendations by 5–7 percentage points (Cole & Sharma, 2017).

In the following season, researchers evaluated the impact of customized fertilizer recommendations on fertilizer application and yields among 1585 cotton farmers in Gujarat. Half of the farmers received a basic digital advisory service with weekly push calls on topics including planting, weeding, and pesticides, while the other half of treated farmers also received customized fertilizer recommendations via visual aids and weekly push calls. At the end of the first season, treated farmers reported more than two- to five-fold increases in the likelihood of using profitability-enhancing fertilizers, when compared to farmers in the control group (Cole et al., 2020). On aggregate, this intervention narrowed the gap between recommended and actual fertilizer use by 0.08 standard deviations.

The positive effects on fertilizer application, where previous efforts had failed, attest to the importance of an iterative approach. Despite the large impact on fertilizer adoption, the study observed no impact on self-reported cotton yields or satellite-based yields. Unfortunately, in the year of the trial, Gujarat had a historically low rainfall, potentially suppressing returns to fertilizers. This confounding factor highlights challenges associated with rigorously measuring agricultural impacts.

Continuous Experimentation Continuous A/B tests can be designed to answer a range of operational and product design questions. For example, one can use insights from behavioral sciences to experiment with different ways of framing a particular message or message contents to test influences on farmer behavior or the timing and frequency of messages to optimize user engagement (Fabregas et al., 2021). These rapid experiments on systems and tweaks in message design often focus on intermediate outcomes that are easy to measure: administrative data on system usage or self-reported outcomes on adoption, knowledge, comprehension, information sharing, and trust in the system. These outcomes can be used to optimize user experience. Experimenting with large sample sizes is necessary for detecting small effects and for harnessing the benefits of economies of scale in learning. For example, one could compare several experimental arms at once or use big data analysis to draw insights on heterogeneity or uncover other patterns in the data to inform service design, impact, and scope for improvements. We note that these design improvements may not add up linearly: user experience may drastically improve and lead to better outcomes when a number of tweaks remove major pain points at once. Therefore, testing the aggregate effect of many design improvements together, rather than individually, can be an effective way to approach product improvement. The effectiveness and targeting of messages might be significantly improved over time, when feedback loops and iterative learning tools are integrated into operations at scale (see Box 8.5). Indeed, evaluating too early may underestimate long-run impacts.

Impact Evaluations Because impact can vary significantly by context and product design, building local evidence on the impact of a service can be important. However, implementing experimental evaluations to measure impact on downstream outcomes, such as yields and profits, can be complex and costly. In many instances, the effect sizes that would make these types of programs cost-effective are small, and detecting these effects in a study might require large sample sizes. Evaluations that have low statistical power are unlikely to detect effects that would still be considered cost-effective. Hence, large-scale evaluations may be suited to settings in which access to behavior and yield outcomes for a large number of farmers is accessible at low cost. For instance, in Kenya and Mozambique researchers worked with agribusinesses that regularly buy crops from farmers. Therefore, they could use a large sample of size of administrative data on yields (crop sales collected by these companies) to determine impacts on productivity (Axmann et al., 2018; Casaburi et al., 2019b).

Localization vs. Generalizability Experiments designed to understand the impact mechanism of an intervention – why the intervention works – can often generate more generalizable insights than experiments that only assess whether or not an intervention works. Understanding *why* helps us formulate a broader conceptual model about conditions and constraints under which a particular intervention is likely to be effective. We iterate and refine the conceptual model and our understanding about farmer behaviors as we gather observations from similar experiments across multiple contexts with varying constraints. These broader lessons constitute global public goods that can inform policy and practice. In this sense, there is likely a large social value in experimenting and making results widely available.

3.2 Data and Measurement Issues

An effective feedback and iteration system leverages administrative outcome data while supplementing it with additional data collection. In addition, available advanced technologies, such as remote sensing, might be used to improve the cost-efficiency of outcome measurements over time.

Administrative Data on Usage System usage data can provide reliable information about user engagement: however, not all systems offer this option. Pickup and listening rates for a push call service can offer insights on the amount of information each user accessed. However, it is often difficult for a service provider to obtain data on whether SMS advisory messages were opened by recipients.

Measurement on Input Adoption and Agricultural Practices Phone surveys, delivered via voice calls or text messages, allow for high-frequency data collection at a much lower cost than traditional in-person methods. However, low response rates and selection in attrition are common. For example, farmers who are more satisfied with the service might be more likely to provide feedback or more likely to respond to a phone survey. These biases in outcome data would make it difficult to draw appropriate inferences in A/B tests.

Simply measuring increases in farmers' knowledge or self-reported adoption of inputs or practices has a number of limitations. For instance, knowledge may not necessarily translate into any behavior change. Self-reports on whether farmers followed recommendations could lead to a biased estimation of effects. For example, farmers who received the service might overreport using suggested practices because of experimenter demand effects, or farmers' might fail to report using inputs if they believe that it might make them more likely to receive a program. A comparison of self-reported and administrative data use for four studies in Kenya found that the measured impact of mobile phone messages using self-reported data exceeded the impacts measured through administrative data (Fabregas et al., 2021).

To address concerns around experimenter demand effects, administrative data on purchases from input sellers could be used to measure farmer behavior. For instance, the text message program that encouraged farmers in East Africa to use locally appropriate inputs used both administrative data from input sellers and data from redemption of electronic discount coupons to understand whether farmers were more likely to purchase recommended inputs (Fabregas et al., 2021).

Yield Measurement Researchers might be most interested in estimating effects on farm profits or yields. However, the measurement of profits requires detailed data and assumptions about input and labor use and costs. Impacts on yields are often imprecisely estimated since it is often difficult for farmers to report yields precisely, and yields are dependent on a number of other environmental factors, such as seasonal rainfall. Moreover, small impacts on farmer behavior are likely to translate to modest improvements in yields, which might be difficult to detect.

A potentially promising approach for obtaining multiple seasons of yield data at limited cost (outside of contract farming settings) would be to obtain GPS location information for farmers' plots and then assess yields over multiple years using satellite data. Recent studies demonstrate a strong correlation between satellite yield measurements, crop cut data, and full plot harvests (Burke & Lobell, 2017; Lambert et al., 2018). An ongoing evaluation in India suggests that satellite yield measurements can reduce standard errors in estimates of treatment effects by over 50% when compared to farmer-reported data (Cole et al., 2020). This can substantially improve statistical power to detect impact (Fig. 8.4).

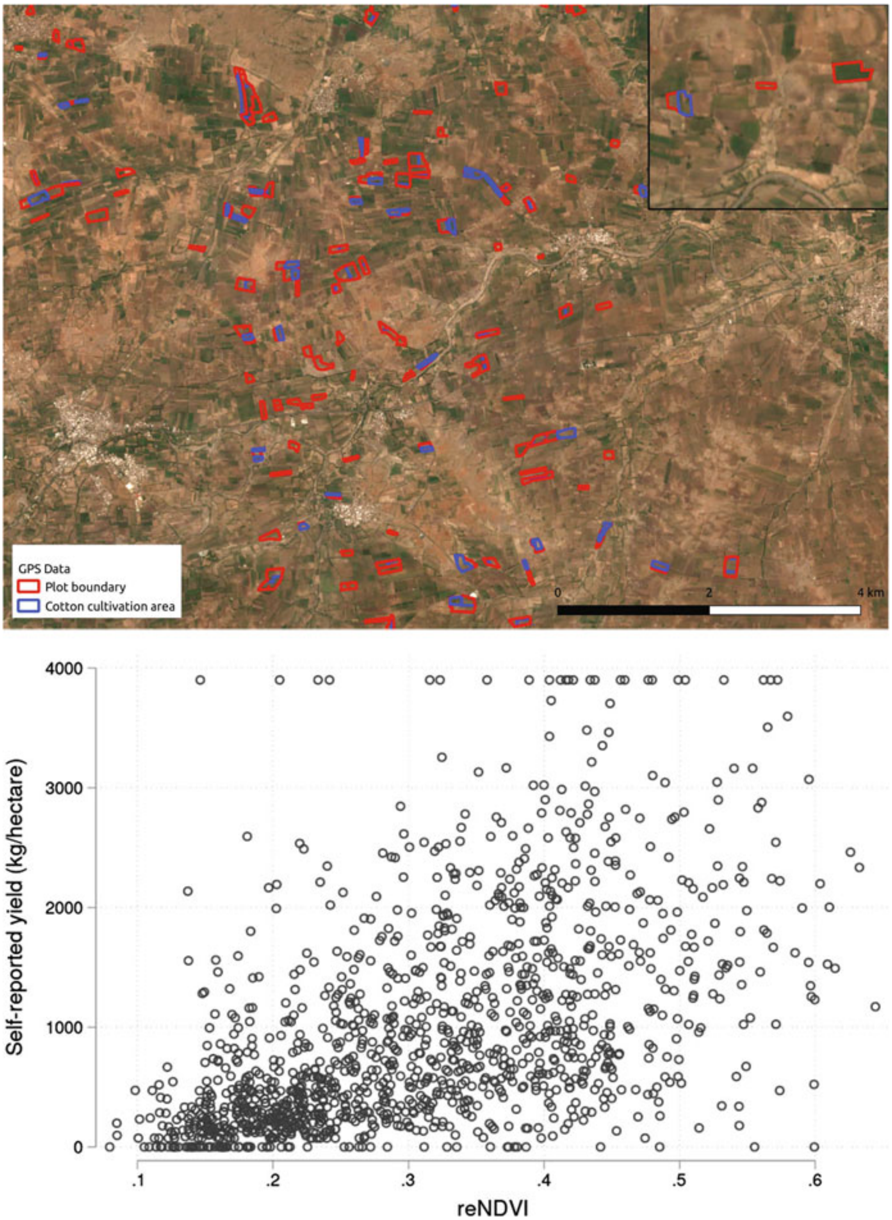

Fig. 8.4 Satellite-based yield measurement (**a**) Plot boundary data collected via Garmin; (**b**) Satellite-based (reNDVI) vs. self-reported yields. Cole et al. (2020) use satellite-based yield measures to evaluate the effect of customized fertilizer recommendations among cotton farmers in Gujarat, India. They collected plot boundary data using a Garmin GPS hand device (Panel a). Panel b illustrates the positive correlation between vegetation index and self-reported yield measurements. They calculate vegetation index values "*by taking the median value of each VI pixel contained in each sample plot for 5 Sentinel-2 images from 2018 . . . [and taking] the maximum value across the 5 satellite images*"

Box 8.5: Learning Through Feedback and Experimentation in a Government Agency

The use of mobile technologies in the public sector is usually discussed in the context of addressing traditional government failures, such as limited accountability and incentives for public-sector workers (Dal Bó et al., 2021; Callen et al., 2020; Muralidharan et al., 2020). To date, most mobile phone-based agricultural extension services rarely rely on public sector workers for delivery. Instead, the potential of these services lies in the large volume of user feedback data for rapid assessment, experimentation, and iterations. However, the government may face a new type of capacity constraints in leveraging the available data to monitor and improve the design of technology-based services. The example described in this box demonstrates that these constraints exist, but that they can be overcome.

An (anonymous) government agency has been operating an IVR-based agricultural information service for several years. When a farmer calls into the system through a toll-free number, the automated hotline service starts with a language selection and questions on farmer location and other characteristics for the first-time users. Only after this is completed, it takes farmers to the menu selection with a variety of agricultural topics for more than 20 crops. The system had been accessed by nearly three million farmers by mid-2017, but only a small fraction of farmers called back after the first try.

A research team conducted a diagnostic assessment of the system in 2017, in which they analyzed the existing administrative data on system usage to understand usage patterns and identify potential issues with the system (PxD, 2018). This exercise was followed by a series of in-person design sessions with farmers, where researchers observed farmers calling navigating the system in real to identify pain points. Additionally, a phone survey of users was conducted to assess the accuracy of farmer profiling data collected by the IVR service. This assessment revealed that the service was losing a nontrivial number of farmers in every required menu selection. The insights from the diagnostic assessment led to a number of ideas for system design improvements. The research team and the government agency started regular meetings to brainstorm ideas and agreed to implement A/B tests to experiment with different solutions. Over the following 2 years, 13 A/B tests were implemented, 6 of which have shown to significantly increase the likelihood of farmers successfully accessing agricultural content.

Selected insights from the diagnostic assessment and system tweaks for A/B testing

(continued)

Box 8.5 (continued)

Observation	Recommended system tweaks
Majority of first-time callers do not complete the registration and drop from the call	Remove registration questions for the first-time callers and postpone them to a later call
Majority of users select the menu option by pressing #1 on the keypad	Rotate the menu option seasonally to keep the most relevant topic as the first option
Many users do not press any key after a question; the system hangs up if no response	Add menu replay twice if no option is selected, before the application hangs up Add pause in between options for language menu Slow down the speed of recording
Most farmers don't access agricultural content	Add push call explaining how to use IVR service

4 Innovations to Improve Impacts

In this section, we discuss selected areas of innovation that offer significant potential for improving impacts for farmers.

4.1 Customization

Agricultural information can be customized across a range of dimensions. First, optimal agricultural practices vary widely in line with local conditions. For example, several field experiments have demonstrated a large spatial variation in yields and yield responses to inputs (Zingore et al., 2007; Seo et al., 2009; Suri, 2011; Tittonell & Giller, 2013), and agronomic research provides strong evidence that the nutrient composition in a particular soil informs which set of fertilizers, and quantities, thereof, will be optimal for maximizing yields (Sapkota et al., 2014). Second, the benefits farmers derive from advice are, in part, based on the applicability of the advice relative to real-time changes in the local environment, such as weather and pest outbreaks. Studies suggest that weather forecasts affect farmer investment decisions (Pandey, 1998; Chisadza et al., 2020) and that accurate forecasts increase farm profitability (Rosenzweig & Udry, 2019). Third, both the appropriateness of agricultural content and optimal message design may vary by farmer characteristics, such as land size and access to storage, as well as gender, age, and other individual characteristics.

The key challenge, across different types of customization, is to generate and gather relevant local data at scale (see Box 8.6 for some resources). In some cases, there is insufficient coordination and poor incentives among stakeholders to direct resources toward data generation. In other cases, the cost of collecting and aggregating local data and/or packaging it in a way that is accessible and easy to understand may act as barriers to scaling up.

Box 8.6: Examples of Publicly Available Remote Sensing Data Sources

Global Precipitation Measurement (GPM) Data – https://gpm.nasa.gov/data

The global precipitation measurement (GPM) mission, initiated by NASA and the Japan Aerospace Exploration Agency (JAXA), is an international network of satellites that provide global data on rain and snow fall. In the agricultural context, this data can be applied to analyze and forecast changes in water resources and, thereby, food security.

Sentinel-2 – https://sentinel.esa.int/web/sentinel/missions/sentinel-2

Sentinel-2 is an imaging mission dedicated to Europe's Copernicus program. The mission aims at monitoring variability in land surface conditions, including vegetation and soil and water cover, while also observing inland waterways and coastal areas. Publicly available data includes coverage of all continental land surfaces (including inland waters) between latitudes 84°N and 56°S, all coastal waters up to at least 20 km from the shore, all islands greater than 100 km^2, all EU islands, the Mediterranean Sea, and all closed seas (e.g., the Caspian Sea).

Google Earth Engine – https://developers.google.com/earth-engine/datasets/

Google Earth Engine combines a massive catalog of more than 40 years of historical imagery and scientific datasets with APIs and other analysis tools. The data catalog is organized into three categories, each with their own subcategories: climate and weather (surface temperature, climate, atmospheric, weather); imagery (Landsat, sentinel, MODIS, high-resolution imagery); and geophysical (terrain, land cover, cropland, other geophysical data).

Landsat – https://landsat.gsfc.nasa.gov/

The Landsat series of earth observation satellites is a joint NASA/US geological survey program that has continuously acquired images of the Earth's land surface since 1972. Landsat 8 is the latest mission with moderate-resolution (15–100 m, depending on spectral frequency) measurements of the Earth's terrestrial and polar regions in the visible, near-infrared, short wave infrared, and thermal infrared going back to 2013.

MODIS – https://modis.gsfc.nasa.gov/

(continued)

Box 8.6 (continued)

MODIS (Moderate Resolution Imaging Spectroradiometer) is an instrument that has been launched on the Terra (1999) and Aqua (2002) NASA satellites. It has a good temporal resolution, imaging the whole earth every 1 or 2 days. This makes it suitable to track large scale trends over time. For agriculture in particular, NDVI (normalized difference vegetation index) products can be useful, providing insight into vegetation changes over time. One MODIS-based NDVI product is MOD13A1.

The European Centre for Medium-Range Weather Forecasts (ECMWF) – https://www.ecmwf.int/en/forecasts/datasets

ECMWF is a European intergovernmental organization which generates medium, extended, and long-range forecasts using its own comprehensive earth system model and conducts research to improve forecasting skills.

Radiant MLHub – https://www.mlhub.earth/#home

Radiant MLHub is an open library for geospatial training data to advance machine learning applications on earth observations. It aims to be a repository of data and trained models for development. Currently, it has smallholder crop classification data but plans to add global land cover in the future.

Consultative Group on International Agricultural Research (CGIAR) Data Resources – https://bigdata.cgiar.org/wp-content/uploads/2020/05/Webinar-Slides-_-Secondary-Data-for-Crop-Modeling-2020-_-Presented.pdf

These slides for the CGIAR webinar: *Secondary data for crop modeling: Filling data gaps under lockdowns* include links to various data resources. Dataset topics include weather, soil properties, cropping calendar, management practices, evaluation data, phone surveys, household surveys, and satellite remote sensing.

Crowdsourcing The two-way nature of digital communication presents opportunities for aggregating relevant, real-time information through crowdsourcing. For example, a pest hotline can be used to identify pest outbreaks at an early stage, allowing faster detection of local outbreaks and alerting farmers in at-risk areas about pest prevention and management recommendations. Moreover, a "Yelp"-like system of customer service ratings could reduce information asymmetry in input markets (Hasanain et al., 2019). A small but growing literature suggests that crowdsourcing can be used successfully to reduce information scarcity in a variety of settings (Bailard & Livingston, 2014; Jame et al., 2016). However, evidence of its use and utility among smallholder farmer populations is scarce.

The relative advantage of using crowdsourcing to collect information is dependent in large part on whether a sufficiently large number of farmers contribute information with sufficient accuracy. There is ample room for research in this space to advance our understanding of technology design and (financial and nonfinancial) incentives for farmers to contribute high-quality information. A risk linked to crowdsourcing that requires attention in the design process is a potential data gap for less technology-adept farmers. If the needs and preferences of less technologically proficient or literate farmers are different from those who contribute information to the system, the resulting customization may result in making the information provided *less* relevant.

Data-Driven Customization A key advantage of digital agriculture is its ability to improve the quality of customized advice by using the data it generates. For example, in settings in which extensive data on farmer characteristics is available, analysis of large platform data may reveal differential patterns in system usage by farmer characteristics. These patterns could then be tested in A/B tests to inform systems and service iteration and improvements (see Box 8.5). Furthermore, when agricultural outcome data is available at large scale, customized recommendations based on agronomic trials or a crop model can be empirically validated in real farm settings and improved through subsequent experiments.

4.2 *Using Digital Technology to Facilitate Social Learning*

A large volume of literature suggests that social learning – learning from the experience of other farmers – is key to facilitating optimal technology adoption among farmers (Munshi, 2004; Bandiera & Rasul, 2006; Conley & Udry, 2010). Existing evidence suggests that mobile phone-based agricultural information services can generate information spillovers. For instance, in India, farmers who had not received the piloted services in the trial increased interactions with, and learned from others, who had (Cole & Fernando, 2021). Furthermore, directing the flow of information via mobiles phones can also affect existing dynamics of information networks (Fernando, 2021).

Beyond the diffusion of agricultural information through existing mechanisms, advanced communications technologies offer scope for increasing and directing the flow of information among farmers to facilitate more efficient learning. First, digital messages can be designed to spur conversations about agricultural practices and inputs within existing networks. Moreover, a farmer's beliefs about a particular input or practice may be influenced by the experience and beliefs of others. With or without novel information, increasing conversations about a particular input can potentially accelerate learning among farmers. Second, the two-way character of digital communications technology allows farmers to exchange information and learn from experts and other farmers beyond their networks of friends and neighbors. It is common in a radio program to solicit questions from listeners and broadcast responses as a way of facilitating learning. With digital technology, this type of learning can happen much more locally and in real time.

An important consideration when using digital tools to accelerate learning among farmers is the potential presence of behavioral factors in learning. Existing literature suggests that individuals confront a range of barriers when communicating factual information, experience, and perceptions and in interpreting information shared by others (e.g., Benjamin et al., 2016; Breza et al., 2018; Eyster et al., 2018). For example, if farmers who have had a bad experience with a new input talk more about their experience than those who had successful experiences with the same input, there may be convergence on an inaccurate belief that the input is ineffective. Given the nascent nature of these innovations, rigorous experimentation, assessment, and iteration – as discussed in the earlier section – will be critical for advancing the development of digital social learning tools capable of amplifying the impact of digital agricultural extension.

4.3 Digital Support for Existing Extension Systems

Digital agricultural extension can complement traditional extension systems. While many governments in developing countries maintain a network of extension workers, the evidence base on their impact on farmer outcomes is limited. (Anderson & Feder, 2004). Agricultural extension workers are difficult to monitor and incentivize: many tasks involve working independently, often in remote communities, with limited supervision. In addition, a lack of resources and poor institutional capacity limits the availability of training and technical support to extension workers. There are three broad mechanisms through which digital technology can potentially improve in-person extension services.

Extension for Extensionists Extension workers could be supported with better resources made available through digital devices. For example, extension agents could access detailed localized information through smartphones and could receive reminders to use appropriate messages for farmers based on the stage of the local agricultural season or to communicate important developments such as pest outbreaks, adverse weather conditions, or market disruptions. In a recent meta-analysis which estimated a positive impact of digital agricultural extension on farmer yields (Fabregas et al., 2019), four of the seven impact estimates were derived from an "indirect" model in which digital advice was delivered to farmers via extension agents or field officers.

Communication Between Farmers and Extension Workers Digital technology can facilitate communication between farmers and extension workers. An IVR system could aggregate local information to service commonly asked questions and equip extension workers with relevant information and recommendations. This could help extension workers determine which content is relevant for farmers in their area. Extension workers could also notify farmers about activities such as farmer field days or demonstration plots. Many extension workers already use digital communication channels, such as WhatsApp, to exchange information among themselves. However, these are nascent developments, and a dearth of rigorous evidence makes this a fertile area for future research.

Performance Management There is growing evidence on the use of mobile phones to help improve motivation and accountability of public-sector workers in developing countries, and a number of new initiatives have been successful at scaling up (e.g., Dimagi's CommCare, a data collection platform for frontline health workers). A study in Paraguay showed that increased monitoring of agricultural extension workers through the use of GPS-equipped mobile phones resulted in a 22% increase in the likelihood of visiting a given farmer over 7 days (Dal Bó et al., 2021). Calling beneficiaries to verify the delivery of cash transfers to farmers in Telangana, India, reduced nondelivery of the transfer by 8% (Muralidharan et al., 2020). In Pakistan, a smart-phone app to track activities of health facility inspectors increased the likelihood of rural health clinic inspection by 74% (Callen et al., 2020). In addition to increasing the effectiveness of monitoring, a mobile phone-based app that allows self-tracking has been shown to harness intrinsic motivation, and was associated with a 24% increase in performance (Lee, 2018).

5 Lessons Learned

In this chapter we discuss a number of issues that practitioners and researchers would need to consider when working with digital agricultural extension technologies. We provided insights from our work with several initiatives, implemented in different countries by a variety of organizations. While existing evidence suggests that these approaches can have positive impacts, delivering on the full promise of digital agriculture will require sustained iteration and testing. Moreover, as more sophisticated mobile technologies improve and are adopted over time, several more opportunities will open up.

While we identified a number of promising areas for future study throughout the chapter, we failed to discuss other important topics in digital agricultural extension. First, digital technologies can also help improve supply chains more widely. For instance, a hotline offered by a sugar company that contracted with sugarcane farmers led to an improvement in the delivery of inputs because farmers could report problems (Casaburi et al., 2019a). A system for agricultural supply dealers could be used to give better recommendations to farmers and gather data on which items to stock while facilitating price comparisons for farmers. Second, digital approaches might be particularly important during emergencies. Information could quickly get out (e.g., pests or weather shocks), but they could also help governments and other agencies gather information directly from farmers about critical needs. Third, crowdsourced information can be useful for a variety of purposes beyond agriculture. There might be complementarities with other sectors, or new ways of generating impacts, where data are responsibly shared for a variety of purposes.

We conclude by encouraging readers to actively engage with user needs and the constraints people face on the ground but also by having clear conceptual models or theories of change that can help guide the development and implementation of these technologies.

Discussion Questions

1. What are the trade-offs between improving customization and reaching scale in digital agricultural extension? What drives the trade-offs?
2. How could farmers who do not own a mobile device or do not own smartphones benefit from digital extension approaches?
3. Many development interventions follow the three-stage process – pilot, evaluate, and scale – but digital interventions may benefit from scaling quickly. What are the potential benefits and costs of this strategy? How do you ensure that the service delivers impacts to farmers?
4. Should digital agricultural extension services focus on solutions for basic phones because they would generate large benefits for the majority of poor smallholder farmers now or leverage the power of smartphones to create solutions that would generate large benefits in the future?
5. What are the potential distributional implications of digital agricultural extension?
6. Oftentimes agricultural information requires sending information about probabilities (e.g., the likelihood of rainfall) or potential risks. What are strategies to convey this information in an intuitive way to populations with low levels of education?

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