

# Info Note

## Collecting development data with mobile phones: Key considerations from a review of the evidence

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### KEY MESSAGES

- Growth in mobile phone access and ownership presents an opportunity to collect more data, more frequently, from more people, and for less money.
- There are multiple ways to collect data with mobile phones (SMS, voice calls, etc.), each with particular strengths and weaknesses.
- The best mode of data collection depends on the characteristics of the target population (e.g. literacy, network access, acceptability of using mobile phones, etc.) and of the data to be collected (e.g. quantitative vs. qualitative, number of questions, sensitivity of information, etc.).

The Sustainable Development Goals (SDGs) set ambitious, comprehensive and explicit development targets that aim to bolster recent gains in human well-being, while slowing or reversing trends in environmental degradation. Progress against these targets will be monitored by collecting information on more than 200 indicators, necessitating data collection at unprecedented spatial and temporal resolution.

Data collection for many of the selected indicators relies on household surveys, typically conducted in-person by trained enumerators. However, reliance on physical visits to sites limits the extent of data collection that is possible due to transportation cost and time, poor infrastructure, security and health risks, among other factors. The consequence is that the most vulnerable areas are often undersampled, leaving large gaps in our ability to track progress toward the global goals and adaptively manage interventions.

Mobile phones have emerged as a natural tool for monitoring at large spatial scale and high temporal fidelity. Phone subscriptions are increasing rapidly throughout the developing world (Table 1). In Sub-Saharan Africa, approximately 43% of the population was connected in 2015, and is expected to reach 54% by

2020 (GSMA 2016). This increase in mobile phone ownership is not restricted to affluent or urban populations, but has also occurred among the rural poor, women (Figure 1), and populations that are traditionally difficult to reach, such as internally displaced persons (Mock *et al.* 2016).

*Table 1: Mobile penetration rates, 2015, for select regions (ITU 2016)*

	Mobiles per 100 ppl	Penetration rate (%)	Growth in Mobile Subs. 2010-2015 (%)
<b>Sub-Saharan Africa</b>	55	43	6
<b>South Asia</b>	70	47	9
<b>Middle East &amp; North Africa</b>	96	57	3
<b>East Asia Pacific</b>	74	62	4.5
<b>Latin America &amp; Carribean</b>	100	68	4.8

The proliferation of mobile phones, service providers, and survey platforms has allowed digital data collection to take off in sectors including health, the environment, and food security. However, changing the way data is collected (the “mode”) can significantly affect the resulting data and inferences (Dabelan *et al.* 2016). In this brief we review the current evidence on mobile data collection, assess the options for monitoring development indicators with mobile devices, and lay out key considerations for use.



*Figure 1: Phones owned by women in Kitui, Kenya, where nearly 80% reported ownership. Photo: S. Chesterman*

## Modes of mobile data collection

Mobile data collection has come of age rapidly over the past ten years. Initially and still most frequently, mobile data collections simply substitute paper for mobile devices during surveys. That is, the mode of interviewing remains the same but data collection and aggregation are done with electronic devices. This change, from paper to electronic-based data collection, offers benefits in terms of data quality and reduced time-lags between data collection, analysis and use. Data collection on mobile devices is now becoming more ubiquitous, supplementing and in some cases replacing traditional civil data collection and registration systems. This is reflected in the support the United Nations Economic Commission for Africa provides to member states to transition their National Statistical Systems to mobile-based platforms.

Surveyors have now started attempting to reach and connect directly to households through mobile phones. These efforts seek to replace face-to-face interviews with voice calls from live operators, SMS messages, or through pre-recorded messages (Box 1) to enable the more frequent collection of more data, from more people, for a lower cost.

Box 1. Modes of mobile data collection.

<b>CAPI</b>	<b>Computer Assisted Personnel Interviewing</b> - data collected on tablets or mobile phones using interactive software, saved and sent electronically to a central server using mobile phone network
<b>CATI</b>	<b>Computer Assisted Telephone Interview</b> – live voice calls usually administered from a call centre to respondents' mobile phones or land lines
<b>GPRS</b>	<b>General Packet Radio Service</b> –transmits data similar to SMS but without limits on the number of characters or transmission size
<b>IVR</b>	<b>Interactive Voice Response</b> – during a voice call computers detect voice and touch tones completed by the respondent during a phone call, and a response is made with a pre-recorded or dynamically generated audio
<b>SMS</b>	<b>Short Messaging Service</b> - text of up to 160 characters in length, suitable for any phone type
<b>USSD</b>	<b>Unstructured Supplemental Service Data</b> - is a protocol used by cellular telephones to communicate messages of up to 182 characters in length with the service provider's computers
<b>VOX</b>	<b>Live Voice Calls</b> – usually conducted from a call centre to respondents' mobile phones.

The characteristics of each mode of mobile data collection determine the conditions where it can be most useful and when it has the potential to provide high quality information (Table 2). For example, voice calls are most effective when the interviewer expects questions could be interpreted in multiple ways and may require clarifications from the respondent due to the complexity of questions or the length of the survey. However, voice operator surveys can also be more costly in terms of establishment and

operation. Alternatively, SMS surveys are relatively cheap and fast to set up by comparison to call centres, but they tend to limit the length and complexity of the surveys that can be administered. Furthermore, SMS relies on literacy of participants, while voice calls do not. Cultural norms, such as women having no or limited access to a phone, can limit the utility of all modes of mobile data collection to particular contexts. These examples highlight just a few of the many constraints that affect implementation and ultimately the quantity, quality and kind of information gathered with mobile devices. Unfortunately, because of the rapid pace of technological development there are few rigorous studies that explore all the potential confounding factors and trade-offs offered by each mode of mobile data collection (but see bibliography below for many of the studies available). The challenge for implementers, therefore, is to use first principles to consider and adapt for factors that might affect the reliability and validity of data collected before embarking on surveys with mobile technologies (see Box 2 for suggestions).

Table 2: Constraints for mobile data collection by mode. (Compiled from GSMA 2013, Demombynes et al. 2013, Tommy & Eldon 2016, Toninelli et al. 2015, Dabelen et al. 2016, and Adams et al. 2015)

Constraint	SMS	Voice	IVR	USSD	Mobile internet
Literacy required	✓	✗	✗✓	✓	✓
Supports multiple response options	✗	✓	✗✓	✓	✓
Limited number of questions (<15)	✓	✗	✓	✗✓	✗
Able to verify answers	✗	✓	✗	✗	✓
Requires a reliable network signal	✗	✓	✓	✓	✗✓
Self administered	✓	✗	✓	✗	✗✓
Suitable on all phone types	✓	✓	✓	✗	✗
Sensitivity of questions	✗	✗✓	✗	✗	✓
Real time communication	✗	✓	✓	✓	✗✓
Third party support required	✗✓	✗	✓	✓	✗
Ability to save data	✓	✗✓	✗	✓	✓
Supports visual aids	✗	✗	✗	✗	✓
Language support	✗	✓	✓	✓	✗
Verification of respondent	✗	✓	✗	✓	✗

## The promise of mobile data

The utility and limits of each mobile survey mode are still being defined empirically, yet best practices are emerging (mVAM 2017). In general, decisions around monitoring systems must optimize among three factors: *scale*, *accuracy* and *cost*. Typically only two of these factors can be maximized simultaneously since accurate and cheap

monitoring usually cannot be done at scale (e.g. collecting soil samples in the field to measure soil carbon) while monitoring that is at scale and accurate cannot be cheap (e.g. launching a satellite to monitor deforestation). Remote data collection with mobile devices can challenge this paradigm, allowing users to maximize all three. Here we describe evidence to support this assertion but call attention to limitations to help the next user collect meaningful data.

### **Mobile devices allow users to reach scale**

The recent growth in phone subscriptions in developing countries (Table 1) allows greater connectivity with the target populations for development monitoring and reduces the potential for sampling bias. Sampling bias when using mobile devices can arise when only a fraction of the population uses mobile phones and this subpopulation may not have the same characteristics or behaviors as the population of interest. However, the risk of sampling bias from conducting surveys via mobile may be decreasing due to the increased uptake of the technology. For example, in rural Kenya 70-90% of women report having access to mobile phones (Hachhethu *et al.* in prep). Furthermore, the risks of sampling bias depends on the subject of the questionnaire. For instance again in rural Kenya, while mobile phone ownership indeed correlated with higher wealth, there was no correlation with differences in nutritional status indicators (Lamanna *et al.* in review).

Mobile devices not only let users reach more people, they can also help surveyors to reach them more frequently. A challenge with panel surveys (i.e. repeated surveys of the same individual) is loss of participants over time (i.e. attrition), which often negatively affects data quality. However, the rate of attrition depends on the survey mode (Dillon 2012, Hoogeveen *et al.* 2014). This was illustrated by a trial of mobile technologies in Honduras and Peru, which found that voice surveys had the lowest attrition in repeat monitoring versus IVR and SMS for data on household status (Gallup 2012). The same study also found statistically significant differences between IVR and SMS responses compared to traditional face-to-face responses, whereas there were no significant differences with voice calls.

### **Mobile-based surveys generate accurate data**

While the ability to reach the appropriate scale for monitoring is important, the ability to collect accurate information is critical. Accuracy may be affected when collecting data with mobile devices for many reasons such as social stigma or even boredom. Recent experimental evidence shows that voice calling produces similar data compared to face-to-face interviewing for various indicators including nutrition, welfare status, food security, microfinance and economic development (Lamanna *et al.* 2017, Etang-Ndip *et al.* 2015, Bauer *et al.*

2014, Garlick *et al.* 2015). However, the accuracy of data collected via mobile technologies can be affected by the nature of the questions, and the length of the survey. For example, in rural Kenya, there was no difference in dietary diversity for women when measured via voice calls or in face-to-face interviews; yet, dietary diversity for infants was much higher when reported via voice calls, suggesting that collecting data on infant care and feeding may be more sensitive to mode than adult nutrition (Lamanna *et al.* in review). In a study of food security in a refugee camp in Sudan, data collected via SMS closely matched face-to-face interview data, but only for the shorter five question indicator; the longer ten question indicator showed large differences (Bauer *et al.* 2014). It is important to note that bias in measurement may not invalidate the use of the technology for a specific indicator. If the bias is consistent (precise), then oftentimes the technology can still be used for monitoring purposes over time (e.g. Heckman 1979).

### **Mobile-base data collection is cost effective**

Other monitoring approaches can collect accurate data at scale, but rarely are they cost effective. So far, remote data collection via mobile phones seems to offer a significant saving versus traditional face-to-face surveys, which is the standard approach for monitoring social change (Cassidy 2014). Even voice-based calls, the most expensive of mobile approaches, are far more cost efficient than in-person interviews. For example, in a study in Peru voice-calls were only 60% of the costs of face-to-face interviews while SMS was 80% less than that of face to face interviews (Ballivian *et al.* 2015). Similar reductions were found in Kenya, where voice calls were approximately 5 USD per survey vs. 16 USD per face-to-face surveys (Hachhethu *et al.* in prep). Reduced costs may allow programs to either collect data on additional respondents or redirect monitoring funds towards other programming (Dillon 2012).

## **Conclusions**

Mobile data collection is changing rapidly due to technological advances, increases in mobile subscriptions and increased adoption by organizations, NGOs and governments alike. Best practice guidelines are emerging which can serve as a target to achieve data quality. However, there are still large gaps in the evidence given the diversity of social contexts, modes, and indicators of interest. With careful planning, field testing and innovation, mobile technologies and surveys offer a nearly unparalleled opportunity to understand people's circumstances and changes in populations for a wide range of applications and under a wide range of conditions. Finally, as the approach is similar to existing methods, it offers easy and acceptable adaptations to the current paradigm of household surveys for monitoring development.

Box 2: Which mode is fit for purpose? Examples for indicators of climate change, agriculture and nutrition.

Indicator	Target respondent	Need to verify respondent ?	Annual frequency of collection	No. Of Qs	Range of response options	Clarifications required	Social question sensitivity (1 low – 5 high)	Recommendation	Data collection examples (Mode   theme   location) (** in reference list)	Summary notes
<b>Climate change</b>										
Onset of rains	Household	No	1-2	1	Binary, categorical or numeric	Yes	1	SMS	SMS   Rainfall levels   India (Department of Agriculture 2014)	Real-time data upload and accuracy of rainfall data compared to traditional data structures.
Household water storage	Household	No	1	1	Binary, categorical or numeric	Yes	1	SMS or Voice	<a href="#">SMS   Rainwater monitoring in specific areas through the SMART Schools Program (SSP)   Philippines</a> (Smart 2009)	The rainfall data was sent via SMS to SMART Inc. to be put online as principle data collected for that region of the Philippines. Data used to assess levels of rainfall and give rise to an early warning systems.
Pests and disease	Household	No	1-2	3	Binary, categorical or numeric	Yes	1	Voice or SMS	<a href="#">SMS and Picture   Disease control and diagnosis in Cassava crops   Uganda</a> (Quinn 2013)	Goal is to improve crop yields of smallholder farmers through effective and real-time diagnostic tools that enable smallholders to assess and mitigate damage to their crops. System is used as a wider diagnostics tool for problem areas and relief services.
<b>Agriculture</b>										
Irrigated land	Household	No	1-2	1	Binary, Numeric	No	1	SMS or IVR	<a href="#">SMS   Crop-specific Irrigation information provided by USAID, DAI and MEC   Morocco</a> (Soukrel 2013)	Program provides specific information on irrigation practices for each individual farmer and crop based on individual water needs. Has resulted in up to 60% water saving.
Yield	Household	No	1-2	1	Numeric	No	1	SMS or IVR	<a href="#">SMS   Survey to Maize Farmers   Tanzania</a> (Harvest Choice 2014)	SMS-based sample (1000 farmers) of Tanzanian maize farmers compared to the Tanzanian Agricultural Census sample (52,000 households) of maize farmers
Livestock productivity	Household	No	1	>1	Numeric	No	1	Voice or SMS	<a href="#">SMS   Milk yield   Kenya</a> (Omondi <i>et al.</i> 2016)	Ng'ombe Planner rolled out to 475 farmers in 19 project sites. The application allows farmers to record feeding, watering and milk production sales.
Input prices	Extension officer	No	1	1	Numeric	Yes	1	SMS or USSD	<a href="#">SMS   Market functionality and food availability   Sierra Leone, Liberia</a> (Geopoll 2015)	Survey concluded that Ebola significantly affected stock availability, market operations, and agricultural activities.
Progress out of poverty (PPI)	Household	No	1	10	Binary, categorical & numeric	Yes	3	Voice or SMS	<a href="#">SMS   Agricultural inputs   Kenya</a> (Graameen Foundation 2013) Voice   Dietary diversity   Kenya (Lamanna <i>et al.</i> 2017)	SMS survey to assess PPI. Results were compared to a follow-up survey conducted in person and concluded small sample size, and significant communication errors were found in PPI terminology such as 'pots'.
<b>Nutrition</b>										
Household dietary diversity score (HDDS)	Household	No	1 or less	12	Binary	Yes	1	Voice or SMS	<a href="#">Face to Face mobile data collection   Dietary Diversity   Burkina Faso, Burundi, DRC, Ethiopia and Malawi</a> (Kamanzi <i>et al.</i> 2012)	Testing of a digital data collection tool for dietary diversity
Household food insecurity access scale (HFIAS)	Household	No	1 or less	9	Categorical	Yes	2	Voice	Voice   Household Hunger Scale (HHS)   South Sudan (Demombynes <i>et al.</i> 2013)	Food security situation worsened between rounds 2 and 3 of the survey.
Food consumption score (FCS)	Individual	Yes	1 or less	9	Numeric & binary	Yes	1	SMS	<a href="#">SMS   FCS   Eastern DRC</a> (Bauer <i>et al.</i> 2014)  <a href="#">World Bank Listening to Africa</a> (Croke <i>et al.</i> 2012)  Voice   Food Consumption Score   Sudan (FCS) (Mock <i>et al.</i> 2016)	FCS text data tended to produce lower estimates of the prevalence of 'borderline' food insecurity than the face to face comparator survey
Infant and young child feeding (IYCF)	Caregivers	Yes	1 or less	8	Binary, Categorical & Numeric	Yes	4	Voice or SMS	SMS   IYCF   China (Du <i>et al.</i> 2013)  <a href="#">SMS   Malnutrition   Nigeria</a> (Nutrition RapidSMS 2016)	SMS suitable for simple answers, such as 'was your child breastfed yesterday during the day or at night?'  Number of food groups reported was significantly higher in face-to-face surveys than in the text messaging surveys.
Minimum dietary diversity for women (MDD-W)	Women of rep. age	No	1 or less	10	Binary	Yes	1	Voice	Voice   Dietary diversity   Kenya (Lamanna <i>et al.</i> 2017)	F2F and VOX comparison from 1600 households. VOX modality gave comparable accuracy on results for women's dietary diversity indicators but not for infant and young child feeding indicators.
Water, Sanitation and Hygiene (WASH)	Caregivers	Yes	1 or less	6	Binary, Categorical & Numeric	No	3	SMS	<a href="#">SMS   mWASH   Somalia</a> (UNICEF 2015)	SMS-based Q&A sessions on hygiene and sanitation reached 104,358 registered participants.

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<sup>1</sup> References with \*\* are studies cited in Box 2

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### Research led by



*This brief summarizes a stock taking exercise on the question, 'Can mobile devices be used to monitor climate, agriculture and nutrition linkages?' The research was funded by UK Aid through the Innovative Metrics and Methods for Agriculture and Nutrition Action (IMMANA) and was undertaken by the Surveillance of Climate-smart Agriculture for Nutrition (SCAN) project team, which is mapped under the CCAFS Partnerships for Scaling (P4S) project (<http://p4s.ccafs.cgiar.org>). **Sabrina Chesterman** is an independent consultant and research fellow with the World Agroforestry Centre (ICRAF). **Christine Lamanna** is a Decision Scientist with ICRAF in Nairobi, Kenya. **Sofia Kalamatianou** is a Researcher with IMMANA in London, UK. **Todd Rosenstock** ([t.rosenstock@cgiar.org](mailto:t.rosenstock@cgiar.org)) is an Environmental Scientist and Country Representative for the Democratic Republic of the Congo with ICRAF. He leads the SCAN and P4S projects.*

## CCAFS and Info Notes

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