

Improving nutrition and health data to and from remote regions

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INTRODUCTION

There is a real possibility, particularly in sub-Saharan Africa, that the sustainable development targets on nutrition may not be achieved. While the global prevalence of undernourishment has remained slightly below 11 percent since 2015, in Africa, hunger is increasing in almost all subregions (FAO et al., 2019). Sub-Saharan Africa has the highest prevalence of undernourishment globally, at 22.8 percent, equivalent to 239 million people (FAO et al., 2019). It is home to 27 of the 41 countries globally that have high rates of all three forms of malnutrition – overweight, micronutrient deficiency and stunting (Development Initiatives, 2018). More than 40 percent of stunted children live in Africa, and sub-Saharan Africa is the only region in the world to have seen an increase in the number of stunted children over the last two decades (UNICEF, WHO and World Bank Group, 2020).

Sub-Saharan Africa is not only experiencing high malnutrition rates, but many regions also lack the current, accurate and reliable data on nutrition and health that could help to forge effective solutions to reducing malnutrition (Development Initiatives, 2018). Such data are critical to determining if policies and interventions are working and to improving them.

There are some nationally representative sources of household and individual nutrition and health data, such as the United States Agency for International Development's Demographic and Health Surveys (DHS)¹ and the United Nations Children's Fund's (UNICEF) Multiple Indicator Cluster Surveys,² but these are rare. When they do exist, however, they are commonly cross-sectional and infrequently collected, as they are extremely expensive. Subnational surveys, such as those conducted to assess humanitarian interventions, are rarely representative, so are difficult to use beyond their immediate goals or to merge with each other to develop broader databases. Other sources of information that are common in more affluent areas, such as the administrative data collected when interacting with public services, are also scarce in remote and poor regions, where access to public services is limited.

1 <https://dhsprogram.com/data/>

2 <https://mics.unicef.org/>

The resulting infrequent household-level data can seriously misrepresent the nature of shocks, coping strategies, seasonality and nutrition-security status of individuals within households, with implications for how practitioners and policymakers assess conditions, allocate resources and judge the impact of interventions aimed at improving welfare. It has long been acknowledged that point observations of households do not accurately characterize the dynamic reality of their members and this has been highlighted in a number of recent papers.

For example, Brown, Ravallion and de Walle (2019) find that many underweight women and malnourished children in Africa live in households that are not among the poorest, while Bevis, Naschold and Rao (2019) find that the seasonal nutritional dynamics are heterogeneous across individuals within households.

In addition to their high cost and often inaccurate representation of the nutritional reality of individuals and populations, common methods for collecting data in sub-Saharan Africa are often extractive. The data are recorded, sent out of the community and anonymized without providing any direct benefit to those being surveyed and at risk of or suffering from malnutrition, for example, by providing nutritional advice or nutrition support tailored to a participant's responses.³ In a few cases, a surveyed community may receive a presentation on findings from a development project, or a government may reallocate resources in response to the information collected. However, even then, there is little effort to ensure that the survey respondents benefit directly from the data they provide.

At the same time, the nutrition community has identified education and behavioural change as cornerstones to improving nutrition, while research has shown that linking self-tracking with tailored advice can be an effective method of improving behaviour and impacting health indicators (Mummah et al., 2017; Payne et al., 2015; Sternfeld et al., 2009; Sullivan and Lachman, 2017). The current norms associated with data-collection in development settings neglect an important opportunity to help improve health and nutrition by providing respondents with information on their progress against benchmarks.

There have been several efforts to improve the availability of health and nutritional data and/or reduce the cost of collection. In lower-income settings, most efforts are focused on standardizing and improving the quality of existing methods (for example, the DHS, the World Bank's Living Standards Measurement Survey⁴ and the inter-agency Standardized Monitoring and Assessment of Relief and Transitions, or SMART initiative).⁵ However, these exercises continue to rely on enumerators for data-collection, which are too expensive for the higher-frequency individual-level surveys required to accurately track health and nutrition dynamics. In higher-income settings, firms and researchers are using browser- or smartphone-based applications that simultaneously collect, track and return information to the user at little to no cost to them. Indeed, such applications can be used to deliver customized messaging and recommendations in response to information recorded by the user, which, as mentioned, have been shown to generate positive behavioural changes in some settings. However, these tools generally require internet connectivity at the time of data-collection and depend on literacy, both of which make them unsuitable for remote environments in low-income countries (Bell et al., 2017).

Unless approaches to collecting nutrition and health data – especially for hard-to-reach communities – become less expensive or users invest more heavily in data-collection, inadequate data will continue to impede the efforts of governments and development practitioners to effectively monitor nutrition-related catastrophes or assess the performance of nutrition and health programmes. Furthermore, without tools for tracking individual performance, caregivers may not be able to accurately assess their own performance against recommendations provided by nutritionists and programme agents. Ultimately, this lack of data will determine how well we will be able to achieve global nutrition and health targets.

³ There is one exception: there is an ethical norm practiced by many survey teams and ethics committees to ensure that any participating child found to be suffering from malnutrition be provided with the means to access appropriate medical attention.

⁴ <http://surveys.worldbank.org>

⁵ <https://smartmethodology.org/about-smart/>

PROPOSED SOLUTION

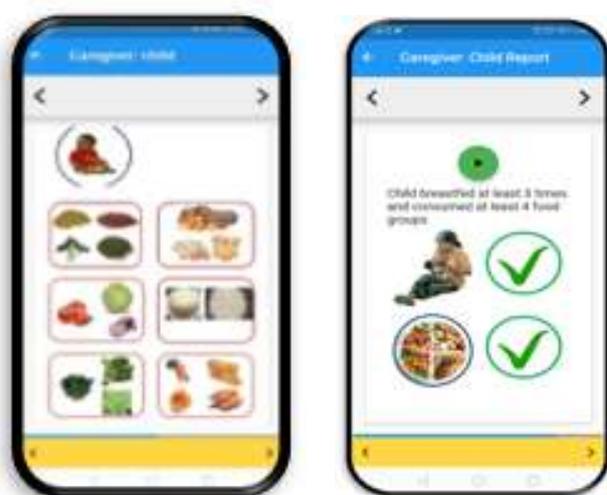
A team of researchers at the International Livestock Research Institute (ILRI) and the Food, Agriculture and Natural Resources Policy Analysis Network (FANRPAN) have partnered with 190 women and 22 community health volunteers (CHVs) in rural Samburu County, Kenya, to tackle the health information gap faced by policymakers, researchers and individuals interested in tracking the consumption and health information of caregivers and their children at high frequency, over time.

Our goals are to reduce the cost of collecting and disseminating information in remote regions, to improve the nutritional and health data available about and for pastoral and other isolated populations and to develop a methodology for responsive, high-frequency data-collection that will contribute to better health and nutrition policies and interventions. To this end, we have developed a smartphone-accessible health information tool for caregivers of young children in remote regions. The smartphone application (app) – called Mbiotisho, which roughly translates as “our health/nutrition” in the Samburu language – uses a simple audio-

and icon-based interface to help the caregivers, many of whom are illiterate and have no experience of smartphones, report their own and their children’s consumption and health status. The caregivers, in turn, receive reports on status and trends in the information they report, along with recommendations based on those reports.

Reporting is undertaken by the caregivers on themselves and/or their children as much or as little as they like. The caregiver begins by selecting an icon indicating who she is reporting on and then faces a sequence of questions with related response options, all based on audio messaging in the local language and sets of icons that were identified and agreed by researchers and caregivers. Through the app, the caregivers can record information for the previous 24 hours on: the consumption of foods from 16 food groups (Kennedy, Ballard and Dop, 2013; WHO, 2008); food security as captured by the reduced coping strategy index (Maxwell and Caldwell, 2008); incidence of clinical symptoms, such as cough, diarrhoea and cough; health care-seeking behaviour; and, in the case of children, source and treatment of water and mid-upper arm circumference (MUAC). The caregivers were trained on how to report on each of these indicators and, in the case of MUAC, how to collect a photo of the reading for verification. The left panel in Figure 1 provides an example of the app interface used by caregivers to report the food groups consumed by an index child over the previous 24 hours.

Figure 1. EXAMPLE OF PROCESSES USED IN THE MBIOTISHO CAREGIVER APPLICATION



Note:

The left panel shows the process for collecting 24-hour recall of consumption by food group for the child. The right panel is an example of feedback given to a caregiver with a child aged 12–24 months.

Source: ILRI and FANRPAN

In addition to being stored on the device until it can be synced to the server and accessed remotely, the information recorded by the caregivers is also processed directly on the caregiver's mobile device, which then provides customized recommendations to the caregiver through a series of images and pre-recorded messaging. One such audio message reminds caregivers of children between 12 and 24 months of the importance of complementary feeding and compares the caregiver's reports on child feeding with recommended practices. The right-hand panel of Figure 1 provides an example of the feedback a caregiver might receive.

Another recommendation illustrates the level and trends in the child's MUAC records and instructs the caregiver to contact a CHV if the MUAC falls below the 125mm threshold for moderate acute malnutrition. We hope that caregivers will use this information to benefit themselves and their children, either by adjusting their behaviour or by contacting their local CHV when the child's health is in jeopardy.

IMPLEMENTATION

The project obtained research approvals from Kenya's National Commission for Science, Technology and Innovation and ILRI's Institutional Research Ethics Committee. Pre-piloting was performed with CHVs and caregivers in Lolmolog, Kenya, to test the feasibility of the processes, improve the user interface and develop a training curriculum. Over three weeks in July and August 2019, we tested and iterated and retested every aspect of the app. Our main finding was that caregivers could and would participate in the activities, at least in the short term, and that they were enthusiastic about the process, especially the tracking features.

The 12-month pilot project was launched on 17 October 2019. Its primary objective is to determine whether caregivers will collect information reliably and accurately over the period. To assess the accuracy of the caregiver-collected data, we will compare it with data collected by CHVs on the same individuals at the same time. A secondary objective is to test if the caregivers adjust their behaviour in response to the tracking and recommendations provided by the tool. To provide an empirical strategy for causal inference, we launched the tracking and recommendation features of the application one month after data-collection started.

The pilot project was launched in four community health units (CHUs) in the pastoral region of Samburu County, selected to provide variation in remoteness and access to infrastructure, caregiver literacy levels, nutritional status and experience with mobile phones. The community health extension worker of each CHU selected five CHVs to participate in the study. Each CHV then provided a roster of caregivers that they supported and that met the project's eligibility criteria: participants needed to be of childbearing age and the primary caregiver of at least one child between 5 and 47 months of age at the time of selection.

For CHVs with sufficient rosters, five caregivers with children aged less than 24 months and four caregivers with children over 24 months old were randomly selected to participate. For about half of the CHVs, their caseload contained fewer eligible caregivers than our target number of caregivers per CHV. In those cases, the extension worker helped the CHVs to identify additional caregivers within their area. Two additional CHVs from the largest CHU, each with five caregivers, were added to the sample by the same process, in response to our concern that two of the CHVs there might not perform well.

In total, all 190 caregivers and 22 CHVs were invited to and participated in training on the project's objectives, phone use and how to use the Mbiotisho app. All participants were provided with phones, small solar chargers for them and monthly mobile-phone data bundles for submitting records. The caregivers were invited to participate as much or as little as they liked and are paid KES 20 (about USD 0.20) per submission. The app limits the caregivers' contributions to a maximum of once every 24 hours for themselves and their index child.

The CHVs' project activities were developed to integrate easily into their existing monthly work schedule, during which they visit each caregiver in their caseload and log the caregiver's pregnancy status, attendance at antenatal care, child MUAC and child immunization. They can include nutrition education. We also asked the CHVs to conduct a survey – the benchmark data – from the participants during those monthly visits and to provide any technical

support the caregivers needed over the duration of the project. In most cases, the technical support entails helping the caregiver deal with the quirks of smartphones, such as accepting or rejecting app updates, but can also include responding to questions the caregiver has on the intention behind a question, or even reinstalling the app if the phone has been accidentally reset or the app uninstalled. The CHVs are paid a stipend of KES 3 000 (USD 30) per month by the project for this additional work.

After the training sessions were completed, the CHVs asked each caregiver if they consented to participate in the study. All 190 consented and were enrolled in the study by the CHVs, who then collected basic demographic information. At his point, one caregiver dropped out of the study. The participating caregivers range from 15 to 61 years of age and most have little or no formal education, are illiterate and have no experience of smartphones (Table 1). The children participating in the programme are nearly two years of age, on average, but there were participants as young as 5 months and as old as 47 months at the time of registration.⁶

Table 1. DEMOGRAPHIC COMPOSITION OF THE STUDY PARTICIPANTS

	No.	Mean	Standard deviation	Minimum	Maximum
Caregiver					
Age (years)	189	27.2	7.5	15	61
Female	189	1.00			
Any formal education	189	48%			
Can read	189	48%			
Has used a smartphone	189	11%			
Index child					
Age (months)	189	20.7	10.8	5	47
Female	189	51%			
In a feeding program	189	6%			

Source: ILRI and FANRPAN.

Table 2. SUMMARY STATISTICS ON CONSUMPTION FROM NOVEMBER-DECEMBER 2019 CHECK-UPS

	No.	Obs.	Mean	Std. dev.	Min.	Std. dev.
Caregiver (N=182)						
Minimum Dietary Diversity for Women (MDD-W) ^a	173	248	3.10	1.37	1	7
MDD-W ≥ 5 ^b	173	248	15%			
Reduced Coping Strategy Index (rCSI) ^c	173	248	4.87	3.08	0	8
Number of meals in the last 24 hours	173	248	3.70	1.45	0	9
Child						
Minimum Dietary Diversity Score (MDDS, 6-24 months) ^d	168	236	2.66	1.46	0	6
MDDS ≥ 4 (6-24 months) ^e	168	236	23%			
Reduced Coping Strategy Index (rCSI) ^c	168	236	2.37	2.14	0	5
Number of meals in the last 24 hours (age ≥12 months)	168	236	3.32	1.63	0	9
Child is nursing (age <24 months)	99	139	78%			
Child is nursing (age <12 months)	38	57	100%			

Notes: (a) MDD-W is calculated by summing the number of food groups consumed in the previous 24 hours from a menu of 10 food groups. It has a range of 0-10. See FAO and FHI 360 (2016) for more information on the index, its construction and objectives. (b) It is recommended that women maintain a MDDS of five or greater (FAO and FHI 360, 2016). (c) rCSI is calculated by summing the weighted responses to a set of five questions on coping strategies utilized by the household in the last 24 hours. It has a range of 0-50. See Maxwell and Caldwell (2008) for more information on the five questions, the weights used and the characteristics of the index. (d) MDDS is calculated by summing the number of food groups consumed in the last 24 hours from a menu of seven food groups. It has a range of 0-7. See WHO (2008) for more information on the index, its construction and objectives. (e) It is recommended that children maintain a MDDS of four or greater (WHO, 2008).

Source: ILRI and FANRPAN.

⁶ These figures reflect our sampling frame, which included children that would be between 6 and 48 months at the start of data collection.

While the data-collection component of the project had only been running for two months as of 1 January 2020, to provide some indication of the data that will be collected over the remainder of the pilot, we include summary statistics from the initial CHV check-ups that took place in November and December 2019 (Table 2).

Only 15 percent of women and 19 percent of children in the survey sample meet the recommended thresholds for MDD-W and MDDS, respectively, indicating lower-than-recommended dietary diversity for both groups. At the same time, 100 percent of children under 12 months and 78 percent of children under 24 months continue to breastfeed, as is recommended.

DISCUSSION AND CONCLUSION

Although it is too early in the study to assess the data quality or behavioural responses to the tracking features, the caregivers are successfully using the tool to collect, submit and receive information. In December 2019, the first full month after training, caregivers completed and submitted 1 607 caregiver check-ups, 1 573 child check-ups and 322 child MUAC check-ups. The study will continue with data-collection by both caregivers and CHVs and we will soon begin a rigorous comparison of the two sets of data.

Beyond the assessment of data quality, we aim to learn about and provide guidance on the appropriate frequency for collecting specific types of data and to understand data-collection errors that may result from caregiver-collected data. For example, MUAC should be recorded at a frequency that reflects its dynamics, but also frequently enough to control for the errors introduced by the caregivers in their collection and recording process. What that frequency is will be identified by comparing the monthly data collected by the CHVs with the higher-frequency data collected by the caregivers. We will also explore how best to dynamically adjust frequency, question sequence and information provided to caregivers in response to their records and to reflect sudden changes in indicators, environmental shocks or outbreaks of common diseases (such as cholera, malaria and COVID-19).

This pilot phase will be followed by validation through further testing at two additional sites in Kenya and one other country. These additional locations will provide information on the tool's applicability in different food environments and cultures. The comparison will also expand beyond the current scope to include a cost-comparison with other conventional methods of data-collection, a critical factor for upscaling.

An important feature of the tool is that it provides tracking and tailored recommendations to the caregiver in near-real time, potentially helping her make better consumption decisions. Indeed, requests for additional functionality in this regard have constituted a considerable portion of comments received from the caregivers to date. There is a possibility of extending the tailored advice to include more sophisticated logic and related recommendations. Furthermore, because the data are often uploaded soon after collection, the tool could be used by programmes to facilitate the provision of appropriate care and support to the households in response to acute events. The availability of the data in near-real time could expedite programmatic response by both humanitarian and government agencies. Such efforts to upscale the tool will be conditional on the results of the assessments of data quality.

Ultimately, we see the use of this tool allowing communities to take responsibility for their nutrition and health outcomes, with government and non-state agencies providing the necessary support. Its use could be extended to other community-based development initiatives beyond nutrition and health, for example, early-warning systems, where near-real-time data-collection and dissemination are important elements.

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