MSI
A TETRA TECH COMPANY

Remote Monitoring: Considerations for Practitioners based on Recent Literature

By Jacob Patterson-Stein and Christine Canavan

The COVID-19 pandemic has forced a reexamination of how data are collected as part of Third-Party Monitoring (TPM). At a time when most mobile phones have over a dozen sensors built into their hardware, what may feel like drastic changes in data collection now are, in the long view, largely part of a move toward remote monitoring as the primary source of development data. From publicly available satellite data to monitor cultural heritage sites to using mobile phone meta-data to understand travel patterns, a growing literature explores the trade-offs in using remote data to track, monitor, and assess development activities.

As a leader in TPM, Management Systems International (MSI) has summarized various approaches for using remote data for TPM. This summary highlights the tools that should be considered by TPM practitioners, followed by a summary of the pros and cons, and relevant examples from recent literature. The final section depicts a summary decision tree for considering what approach may be most relevant. Remote monitoring, like any data collection effort, needs to be contextually relevant, culturally sensitive, and technically rigorous. The decision tree and overall review of tools is a starting point for practitioners to consider what approach or combination of approaches will work best for their TPM activities.

Approaches to Remote TPM

There are two general categories of remote monitoring: remote data collection and remote sensing. Remote data collection is built on many of the same assumptions and methods as in-person qualitative or structured survey work, but there is no direct engagement between researchers or enumerators and respondents. In contrast, remote sensing broadly observes behaviors or activities using satellites, in-situ measurement devices, or drones. A key distinction between the two approaches is that remote sensing relies largely on observation, whereas remote data collection is self-reported.

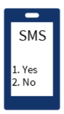
This paper was prepared by MSI staff to contribute to the discussion and understanding of the important development challenges facing policymakers and practitioners

Remote Data Collection

The reviewed literature identifies five main approaches for remote data collection. Each approach assumes mobile phone coverage, with some requiring internet or mobile data. Basic feature phones and, increasingly, smart phones are accessible in almost every country, including low- and middle-income countries (Taylor and Silver 2019). This paper reviews the following approaches:

INTERACTIVE VOICE RESPONSE (IVR): Delivers questions via audio recordings while respondents reply via the keypad or through simple audio responses. This approach can include outgoing calls or a hotline that collects incoming responses from participants who dial-in. The approach requires a roster of phone numbers.

COMPUTER ASSISTED TELEPHONE INTERVIEWS (CATI): A remote, interviewer-assisted approach that involves administering a structured survey via telephone. This approach is most similar to implementing a survey face-to-face as it involves talking to respondents. The approach requires a roster of phone numbers.



SHORT MESSAGE SERVICE (SMS): A text-based survey sent remotely to mobile phones with respondents answering questions via the touchpad. There is no human engagement. The approach requires a roster of phone numbers.

MOBILE INSTANT MESSAGE (MIM) AND SOCIAL MEDIA GROUPS: The use of mobile text, photo, and video applications, and social media to collect observations and open text responses to TPM-facilitated questions and moderated discussions. Platforms such as WhatsApp can be used to facilitate group discussions or hold daily check-ins with a group of participants. Moderated social media groups can serve a similar role, with facilitated questions posed to the group.

ONLINE SURVEY: Respondents directly engage with a structured survey instrument via an internet connected computer or mobile device without interviewer assistance. No human engagement is needed. Users can either be targeted through email or SMS, or the survey link can be promoted through social or other media.

Remote Tools, Local Context

As with any data collection effort, local context should drive the approach. If a roster of phone numbers is not available, random digit dialing may be an option to develop such a roster. This approach was used in Afghanistan to develop a sample of potential respondents for an IVR survey (Leo et al, 2015) In other cases, agreements with local mobile carriers may provide a sample of respondents for a remote survey. However, as Leo et al. (2015) note, the number of national carriers, costs to coordinate with carriers, and variation in carrier subscription can make this approach logistically difficult and costly.

In many cases, a combination of methods may yield the best results (Greenleaf et al. 2017). For example, in South Sudan, face-to-face interviews were combined with mobile phone follow-up interviews to capture recurrent household data (Demombynes, Gubbins, and Romeo 2013). Sending SMS reminders ahead of CATI calls can improve response rates (Kasy and Sautmann 2019, Morse et al. 2016).

Sampling and Remote Data Collection

Sampling poses challenges for remote monitoring. Because sampling frames for remote data collection exclude individuals without access to, or willingness to use, appropriate technologies, they are not representative of the broader population. Unobservable differences between respondents willing to answer the phone or respond to a text and those who cannot or prefer not to respond to a remotely applied survey likely exist and can skew analysis. Researchers need to consider potential sample biases when selecting a remote data collection method. Highet et al. (2017) note that mobile phone access, mobile data usage, and text message usage vary by gender and age, with women less likely to have mobile access and to use mobile data. World Bank research also suggests that younger populations are more likely to respond to SMS surveys (see Ballivian et al. 2015 and Du et al. 2013). The literature on MIM for TPM is limited, but the same sampling challenges are likely to apply. In contexts where smart phone use is concentrated among youths or people with more education, MIM and social media groups may present serious TPM design and analytical concerns.

Mobile Data Requirements May be a Burden

Mobile data requirements must also be considered. While SMS surveys can generally be designed such that the TPM implementer bears the messaging costs, online surveys and mobile instant messaging and social media groups often require access to mobile data. Mobile instant messaging and social media groups give TPM implementers the ability to collect observations from people on the ground or allow for focus group-style discussions, but can be difficult to manage (Raftree 2017, Kaufman and Peil 2019). Platforms such as WhatsApp do not always protect participant identities, with some practitioners developing their own chat platforms to engage with respondents anonymously (Richards 2019).

These issues are summarized in Table 1 below. While not an exhaustive review of the pros and cons of each remote data collection approach, the table highlights issues raised in the literature and provides a starting point for weighing which mode or modes to use.

APPROACH	STRENGTHS	LIMITATIONS	IT REQUIREMENTS	GENERAL COSTS (USD CURRENT)	EXAMPLE
IVR	• No variation in application of questionnaire • Low cost • No literacy constraint • Easy to contact large sample • Rapid deployment, rapid responses • Anonymous • Can be run at any time of the day • Respondents can initiate contact	• Low response rates (<20%) • High attrition • No ability to capture respondent feedback or open-ended questions • Limited language options • Responses tend to differ compared to in-person interviews • Binary and five-point Likert questions work best	• Local phone plan • IVR survey software platform • Local phone	• $7-9 per completed questionnaire • IVR platform license fee <$500	• Somalia to collect household food security data (Dette et al. 2016). • The World Bank used IVR to survey re-settled refugees in Afghanistan (Krishnan et al. 2018).
CATI	• Low cost compared to face-to-face surveys • No literacy constraint • Potential for adapting to multiple languages if the interviewer team has capacity. • Responses are generally similar to in-person interviews • Easy to engage respondents and clarify questions • Binary, and five-point Likert, and brief open text questions permissible	• Low response rates (<50%) • High attrition • Inter-rater reliability concerns • Requires a trained team of interviewers	• Phones • Headsets for making calls • Online or tablet survey software	• $5-20 per completed questionnaire	• The World Bank used CATI for real-time monitoring in Liberia during the Ebola outbreak (Etang and Himelin 2020). • Applied in Lebanon to capture population data (Mahfoud 2014).
SMS	• No variation in application of questionnaire • Low cost • Easy to contact large sample • Rapid deployment, rapid responses • Anonymous • Can be run at any time of the day • Can easily provide mobile credit incentive	• Literacy constraint • Low response rate (<20%) • Very high attrition due to change in numbers between survey rounds for longitudinal surveys • No ability to capture respondent feedback or open-ended questions. • Responses tend to differ compared to in-person interviews • No more than 10 questions recommended • Binary and five-point Likert questions work best • Potential age and gender bias	• Local phone plan • SMS survey software • Local phone	• $1-6 per respondent for a 10-question survey • SMS platform license fee <$200	• UNICEF used SMS surveys for real time monitoring in multiple conflict and post-conflict countries to track health, education, and household income data (Wexler and Yang 2018). • SMS messages were used in Liberia to track and monitor Ebola (Feng et al. 2018)

MIM	• Low cost • Allows for qualitative data collection such as focus group-style discussions • Can be run at any time of the day • User-driven, which can improve engagement with questions	• Literacy constraint • Difficult to manage if groups become large • Anonymity may be difficult to maintain • May require well-targeted, relevant content to elicit responses • Potential gender and youth bias • Platforms may be banned in TPM countries	• Phone or computer with relevant applications loaded	• Free, with some pay schemes for upgraded business features	• WhatsApp was used in Syria to monitor attacks on health services in real time (Elamein 2017) • UNDP is using a WhatsApp messaging project to share news about COVID-19 (UNDP 2020)
ONLINE SURVEY	• No variation in application of questionnaire • Low cost • Easy to contact a large sample via email, social media, or SMS to share survey link • Multiple question types • Easy to track respondents via meta data • Possible to provide online incentive	• Some evidence that medium (computer vs. mobile phone) affects responses • Literacy constraint • Low response rate (<20%) • Requires internet connectivity • Potential age and gender bias	• Survey platform (free and licensed options exist)	• Basic survey platforms are free, but proprietary license costs vary.	• Used to survey donor staff in Afghanistan, Somalia, South Sudan, and Turkey/Jordan (Steets et al. 2016)

Remote Sensing and Other Observation Approaches

Remote sensing is ideal in situations where prior in-person work entailed tracking and validating the existence of development activities, ensuring functionality, or observing changes over time that do not involve perceptions. In rural Kenya, sensors on water borehole pumps were installed to broadcast pump functionality data, which allowed for real-time tracking of breakdowns in drought-prone areas (Turman-Bryant et al. 2019). A similar study in Nairobi combined real-time sensor tracking with predictive modelling to improve targeting of toilet repairs which replaced the use of in-person monitors to regularly assess toilets (Turman-Bryant, et al 2019). For many remote sensing approaches, data are combined with classification algorithms to process and interpret findings. Machine learning may be critical in some cases to make the large amount of data generated comprehensible (Quinn et al. 2018). As shown in Table 2, remote sensing for TPM solves some access problems, but comes with limitations that need to be carefully assessed, as well.

The remote sensing approaches identified in the literature are summarized below:

IN-SITU SENSORS: SENSORS are placed at a site to track an activity, such as water flow, particulate concentration, seismic activity, number of entries/exits, or acoustics. Size, power source, and memory capacity vary. Some in-situ sensors can broadcast data over satellite or cellular networks, while others require periodic, on-site data downloads.

EARTH OBSERVATION/SATELLITE DATA: Collected by national and international bodies, data are recorded at a near-constant rate from the earth's surface. Publicly available data on nighttime light, precipitation, road construction, forest and vegetation cover, and land use are easily accessible.

UAV: Generally, user-controlled small aerial vehicles that can capture images, apply light detection and ranging (LiDAR), and assist in capturing geo-spatial information from several hundred to several thousand feet high.

META-DATA: Call detail records (CDRs) can provide basic information on all communication flows over a network, such where and when calls and text messages originated.

All the approaches above avoid active engagement with the TPM subject. This may be valuable in cases where repeated assessments can alter behavior or present a danger to the person or place being monitored. Each approach monitors actual rather than reported activity. For example, in India, in-situ sensors measuring latrine use recorded much lower use than when a human observers were present (Clasen et al. 2012).

Sampling is Still an Issue for Remote Sensing

The challenge of sample selection is applicable to remote sensing and other remote observation approaches. In-situ sensors must be installed or placed at the relevant monitoring site. This may pose a risk to the installation team, but site selection may also over- or under-represent certain populations, behaviors, or phenomena. Satellite data are less prone to such limitations, but are less able to observe relevant indoor behavior. The challenges of cloud cover or, in some cases, temporal coverage can also affect sampling and availability for satellite data.

Ethical Considerations and Remote Sensing

The guidelines used in face-to-face data collection and human-based observation to protect human subjects (informed consent, do no harm, protection of identifiable information) are also applicable to remote data collection. However, remote sensing presents an ethical challenge in that respondents or participants often cannot give consent. Although many countries do not regulate the use of remote sensing, practitioners must ensure the privacy and risk of people living near a TPM site (Stöcker et al. 2012).

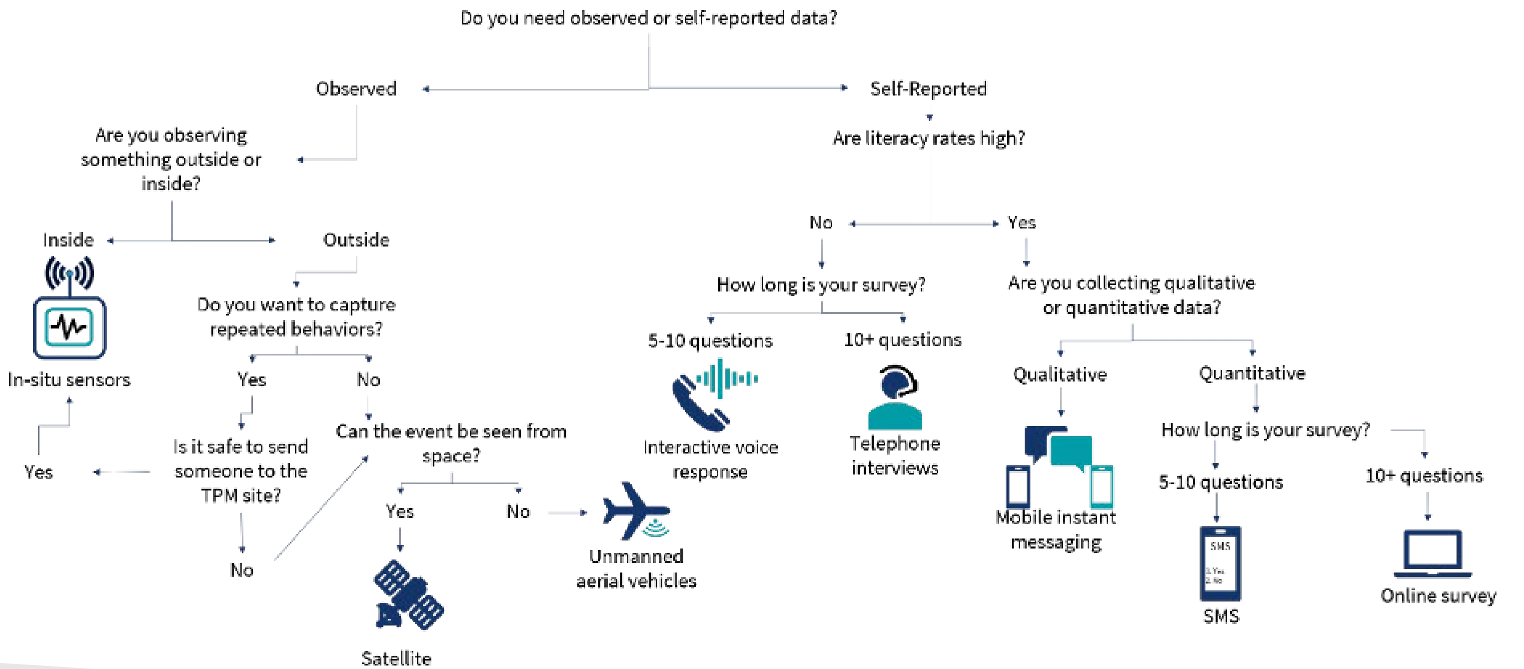
Table 2: Remote Sensing Approaches

APPROACH	STRENGTHS	LIMITATIONS	IT REQUIREMENTS	GENERAL COSTS (USD CURRENT)	EXAMPLE
IN-SITU SENSORS	• Continuously capture localized behavior (e.g., cookstove use) • Some sensors broadcast data, which removes the need to revisit sites • No enumerator bias in monitoring of recurring events or usage • Possible to obtain consent from participants prior to sensor installation	• Sensors have to be installed • Theft • Battery life • Memory limits for non-transmitting sensors	• Local phone plan or satellite connection for transmitting sensors • Software for conversion of sensor data to readable format	• Prices vary from <$50 to $600	• Used in Syria to capture acoustic sounds correlated with Russian bombing to develop an early warning system (Hala 2018) • Deployed in Indonesia to monitor handwashing practices (Thomas 2013)
SATELLITE	• Regular time series that is comparable across periods and locations • Global coverage • Many free sources • Ability to make observations in conflict and remote locations • Data are easy to map and visualize	• Data stored in formats that require special software and/or skills to access and interpret • Small changes on the ground are not always observable • Some sources may require agreements or licenses • No consent	• High bandwidth internet connection • Free, open source software	• Generally low, some datasets require license access	• USAID used satellite data to evaluate road construction in the West Bank (BenYishay 2019) • Satellite data were used to track the scale of modern slavery in the "Brick Belt" countries across South Asia (Boyd et al. 2018) • Researchers used satellite data to map, count, and categorize IDP settlements around the world (Quinn et al. 2018)
UAV	• Ability to observe small scale activities that are unobservable by satellite • High-resolution, 3D images can be captured • Provides researcher access to otherwise inaccessible observation points	• Image data may require classification algorithms to use at scale • Ethical concerns about privacy given high resolution imagery • History of targeted UAV strikes in some contexts may add sensitivity to deploying drones for TPM • Limited fly time a challenge for some models	• UAV • Open source statistical software for image classification	• $500-$25,000 for a UAV	• Used in Indonesia to monitor conservation efforts (Koh and Wich 2012) • Multiple use cases for agricultural monitoring (CRS 2019)

APPROACH	STRENGTHS	LIMITATIONS	IT REQUIREMENTS	GENERAL COSTS (USD CURRENT)	EXAMPLE
META DATA	• Large scale observation possible • Ability to capture connections between people within network • Provides approximate location information	• Serious privacy concerns given that no consent is provided and personal information is shared • No ability to capture information beyond a limited number of meta-fields • Requires cooperation and coordination with local mobile service providers • Real time monitoring may not be feasible	• Monitoring software used in some cases	• Unknown	• Used in Rwanda to predict poverty and wealth (Blumenstock et al. 2015). • In Boston and Rio de Janeiro, call detail records were used to track travel over time (Colak 2014)

Decision Tree

The following tree provides a starting point for navigating the various approaches presented in this paper. For TPM activities that are transferring existing face-to-face data collection to a remote approach, there may be additional logistical considerations. The time to train, deploy, and scale each of these approaches will vary by country, what is being monitored, and the TPM team itself.



Bibliography

Acumen Fund. "The Lean Data Field Guide." *New York* (2015).

Andres, Luis et al. "A Review of In-Situ and Remote Sensing Technologies to Monitor Water and Sanitation Interventions." *Water* 10, 6 (2018): 756.

Android Developers. "Sensors Overview: Android Developers." Android Developers, 2020. Accessed March 31, 2020. https://developer.android.com/guide/topics/sensors/sensors_overview.

Ballivian, Amparo, João Pedro Azevedo, and Will Durbin. "Using Mobile Phones for High-Frequency Data Collection." *Mobile Research Methods* 21 (2015).

Barbosa, Sérgio and Stefania Milan. "Do not Harm in Private Chat Apps: Ethical Issues for Research on and with WhatsApp." *Westminster Papers in Communication and Culture* 14, 1 (2019).

BenYishay, Ariel. "Evaluation of the Infrastructure Needs Program II." *AidData, William & Mary*. https://www. aiddata. org/publications/evaluation-of-usaid-west-bank-gaza-infrastructure- needs-program (2019).

Blatt, Amy J. "Ethics and Privacy Issues in the Use of GIS." *Journal of Map & Geography Libraries* 8, 1 (2012): 80-84.

Blumenstock, Joshua, Gabriel Cadamuro, and Robert On. "Predicting Poverty and Wealth from Mobile Phone Metadata." *Science* 350, 6264 (2015): 1073-1076.

Bolton, Laura. "Interactive Voice Response in Humanitarian Contexts." (2018). Accessed March 31, 2020. https://assets.publishing.service.gov.uk/media/5c6bd962e5274a72b6ba06de/495_Interactive_Voice_Response_in_Humanitarian_Contexts__1_.pdf.

Boyd, Doreen S. et al. "Slavery from Space: Demonstrating the Role for Satellite Remote Sensing to Inform Evidence-Based Action Related to UN SDG Number 8." *ISPRS journal of photogrammetry and remote sensing* 142 (2018): 380-388.

Building Markets. "What's the point…if nothing changes: Current Practices and Future Opportunities to Improve Remote Monitoring and Evaluation in Syria." June 2018. https://reliefweb.int/sites/reliefweb.int/files/resources/practices_and_opportunities_to_improve_remote_me_in_syria_2018.pdf.

Catholic Relief Services. "Unmanned Aerial Vehicles (UAVs): Walking vs. Flying - A Comparison." CRS. 2019. Accessed March 31, 2020. https://www.crs.org/sites/default/files/tools-research/uavs_-_walking_vs_flying_-_benin_study.pdf.

Clasen, Thomas et al. "Making Sanitation Count: Developing and Testing a Device for Assessing Latrine Use in Low-Income Settings." *Environmental Science & Technology* 46, 6 (2012): 3295-3303.

Çolak, Serdar et al. "Analyzing Cell Phone Location Data for Urban Travel: Current Methods, Limitations, and Opportunities." *Transportation Research Record* 2526, 1 (2015): 126-135.

Cook, S.L., M. Sha, J. Murphy, and C.Q Lau. *Technology Options for Engaging Respondents in Self-Administered Questionnaires and Remote Interviewing*. RTI Press, 2016.

Crews, Kelley A. and Stephen J. Walsh. “Remote Sensing and the Social Sciences,” In *The SAGE Handbook of Remote Sensing*, T. Warner, M. Nellis, and G. Foody, 437-445. London: SAGE Publications, 2009.

Demombynes, Gabriel, Paul Gubbins, and Alessandro Romeo. *Challenges and Opportunities of Mobile Phone-Based Data Collection: Evidence from South Sudan.* The World Bank, 2013.

Desai, Raj M. et al., eds. From *Summits to Solutions: Innovations in Implementing the Sustainable Development Goals*. Brookings Institution Press, 2018.

De Sy, Veronique et al. “Synergies of Multiple Remote Sensing Data Sources for REDD+ Monitoring.”Current Opinion in *Environmental Sustainability* 4, 6 (2012): 696-706.

Dette, Rahel, Julia Steets, and Elias Sagmeister. “Technologies for Monitoring in Insecure Environments.” DFID, 2016. https://www.gppi.net/media/SAVE__2016__Toolkit_on_Technologies_for_Monitoring_in_Insecure_Environments.pdf.

Du, Xiaozhen, et al. “mHealth Series: Text Messaging Data Collection of infant and young Child Feeding Practice in rural China–A Feasibility Study.” *Journal of global health* 3, 2 (2013).

Elamein, Mohamed, et al. “Attacks against Health Care in Syria, 2015-16: Results from a Real-Time Reporting Tool.” *The Lancet* 390, 10109 (2017): 2278-2286.

Etang, Alvin and Kristen Himelein. “Monitoring the Ebola Crisis Using Mobile Phone Surveys.” *Data Collection in Fragile States*,” 15-31. Palgrave Macmillan, Cham, 2020.

Feng, Shuo, Karen A. Grépin, and Rumi Chunara. “Tracking Health Seeking Behavior during an Ebola Outbreak via Mobile Phones and SMS.” *NPJ digital medicine* 1, 1 (2018): 1-8.

Greenleaf, Abigail R., et al. “Building the Evidence Base for Remote Data Collection in Low-and Middle-Income Countries: Comparing Reliability and Accuracy across Survey Modalities.” *Journal of Medical Internet Research* 19, 5 (2017): e140.

Hala Systems. Sentry Presentation. Accessed March 31, 2020. https://drive.google.com/file/d/1KDGJnt8_wC_ymIK_GfjG3LfTogD22nQA/view.

Hansch, Steve, et al. “Findings in Monitoring and Evaluations Practices During Humanitarian Emergencies.” (2015).

Ham, Youngjib, et al. “Visual Monitoring of Civil Infrastructure Systems via Camera-Equipped Unmanned Aerial Vehicles (UAVs): A Review of Related Works.” *Visualization in Engineering* 4, 1 (2016): 1.

Highet, Catherine, Hannah Skelly, and Alexandra Tyers. “Gender and Information Communication Technology (ICT) Toolkit.” (2019). https://www.usaid.gov/sites/default/files/documents/15396/Gender_and_ICT_Toolkit.pdf

Hoogeveen, Johannes, et al. “Collecting High Frequency Panel Data in Africa Using Mobile Phone Interviews.” *Canadian Journal of Development Studies/Revue canadienne d’études du développement* 35, 1 (2014): 186-207.

Kamel Boulos, N. Maged, Dean M. Giustini, and Steve Wheeler. “Instagram and WhatsApp in Health and Healthcare: An Overview.” *Future Internet* 8, 3 (2016): 37.

Kasy, Maximilian and Anja Sautmann. “Adaptive Treatment Assignment in Experiments for Policy Choice.” (2019). https://maxkasy.github.io/home/files/papers/adaptiveexperimentspolicy.pdf

Kaufmann, Katja and Corinna Peil. “The Mobile Instant Messaging Interview (MIMI): Using WhatsApp To Enhance Self-Reporting and Explore Media Usage In Situ.” *Mobile Media & Communication* (2019): 2050157919852392.

Koh, Lian Pin and Serge A. Wich. “Dawn of Drone Ecology: low-Cost Autonomous Aerial Vehicles for Conservation.” *Tropical Conservation Science* 5, 2 (2012): 121-132.

Kopper, Sarah and Anja Sautmann. “Best Practices for Conducting Phone Surveys.” Abdul Latif Jameel Poverty Action Lab (J-PAL). March 20, 2020, Accessed March 21, 2020. https://www.povertyactionlab.org/blog/3-20-20/best-practices-conducting-phone-surveys.

Krishnan, Nandini, Christina Wieser, and Thea Yde-Jensen. *Afghanistan World Bank Phone Survey of Afghan Returnees : Methodology and Representativeness* (English). Washington, D.C. : World Bank Group, 2018. Accessed March 30, 2020. http://documents.worldbank.org/curated/en/298881533562809348/Afghanistan-World-Bank-Phone-Survey-of-Afghan-Returnees-Methodology-and-Representativeness

Levin, Noam, et al. “World Heritage in Danger: Big data and remote sensing can help protect sites in conflict zones.” *Global environmental change* 55 (2019): 97-104.

Leo, Benjamin, et al. “Do mobile phone surveys work in poor countries?” *Center for Global Development Working Paper* 398 (2015).

Mahfoud, Ziyad, et al. “Cell Phone and Face-To-Face Interview Responses in Population-Based Surveys: How do they Compare?” *Field methods* 27, 1 (2015): 39-54.

Morrow, Nathan, et al. “Knowing Just in Time: Use Cases for Mobile Surveys in the humanitarian World.” *Procedia engineering* 159 (2016): 210-216.

Morse, Ben, et al. “Patterns of Demand for Non-Ebola Health Services during and after the Ebola Outbreak: Panel Survey Evidence from Monrovia, Liberia.” *BMJ Global Health* 1, 1 (2016): e000007.

Ozler, Berk and P. Facundo Cuevas. “Reducing Attrition in Phone Surveys.” Development Impact Blog, World Bank, November 21, 2019, Accessed March 30, 2020. https://blogs.worldbank.org/impactevaluations/reducing-attrition-phone-surveys.

Quinn, John A., et al. “Humanitarian Applications of Machine Learning with Remote-Sensing Data: Review and Case Study in Refugee Settlement Mapping.” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376, 2128 (2018): 20170363.

Raftree, Linda. “IVR, Facebook and WhatsApp: Tech and M&E at AfrEA.” *MERL Tech* April 7, 2017. Accessed March 31, 2020. https://merltech.org/ivr-facebook-and-whatsapp-tech-and-me-at- afrea/.

Richards, Cathy. “Messaging Platforms: Best Practices, Costs, Security, and Privacy.” MERL Tech October 2, 2019. Accessed March 31, 2020. http://merltech.org/messaging-platforms-best-practices-costs-security-and-privacy/.

“Sensors Overview: Android Developers.” Android Developers. Accessed March 31, 2020. https://developer.android.com/guide/topics/sensors/sensors_overview.

Steets, Julia, Elias Sagmeister, and Lotte Ruppert. “Eyes and Ears on the Ground: Monitoring Aid in Insecure Environments.” *Global Public Policy Institute* (2016).

Stöcker, Claudia, et al. “Review of the Current State of UAV Regulations.” *Remote sensing* 9, 5 (2017): 459.

Taylor, Kyle, and Laura Silver. “Smartphone ownership is growing rapidly around the world, but not always equally.” *Pew Research Center* (2019).

Thomas, Evan A. and Kay Mattson. “Instrumented Monitoring with Traditional Public Health Evaluation Methods: An Application to a Water, Sanitation and Hygiene Program in Jakarta, Indonesia.” Portland, Mercy Corps, 2013.

Turman-Bryant, Nick, et al. “Improved Drought Resilience through Continuous Water Service Monitoring and Specialized Institutions: A Longitudinal Analysis of Water Service Delivery Across Motorized Boreholes in Northern Kenya.” *Sustainability* 11, 11 (2019): 3046.

_____. “Toilet Alarms: A Novel Application of Latrine Sensors and Machine Learning for Optimizing Sanitation Services in Informal Settlements.” *Development Engineering* 5 (2020): 100052.

UNDP. “COVID-19: WHO, UNICEF and UNDP Partner with WhatsApp to Get Real Time Health Information to Billions around the World.” March 27, 2020. Accessed March 30, 2020. https://www.undp.org/content/undp/en/home/news-centre/news/2020/COVID-19_WHO_UNICEF_UNDP_Partner_with_WhatsApp_to_Get_Real_Time_Health_Information_to_Billions_around_the_World.html.

UN Global Pulse. “Using Machine Learning to Analyse Radio Content in Uganda.” September 2017. https://beta.unglobalpulse.org/wp-content/uploads/2017/09/Radio-Analysis-Report_Preview.pdf.

“Using WhatsApp to Improve Family Health.” Every1Mobile, December 19, 2018. Accessed March 30, 2020. www.every1mobile.com/whatsapp/.

Watts, Adam C., Vincent G. Ambrosia, and Everett A. Hinkley. “Unmanned Aircraft Systems in Remote Sensing and Scientific Research: Classification and Considerations of Use.” *Remote Sensing* 4, 6 (2012): 1671-1692.

Wexler, Raquel and Ye Wang. "UNICEF looks to scale real-time monitoring systems with open source tech to 110 countries by 2021." *UNICEF Office of Innovation*, November 13, 2018. Accessed March 31, 2020, https://www.unicef.org/innovation/stories/unicef-looks-scale-real-time-monitoring-systems-open-source-tech-110-countries-2021.

World Bank. *The Web of Transport Corridors in South Asia*. Washington, DC: World Bank Group, 2018.