Emerging Technologies and Approaches

in Monitoring, Evaluation, Research, and Learning for International Development Programs

Kerry Bruce, Valentine J. Gandhi, and Joris Vandelanotte

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Authors: Kerry Bruce, Valentine J. Gandhi, and Joris Vandelanotte

Abstract

Emerging technology is making monitoring, evaluation, research and learning (MERL) more precise and enriching data. However, this evolution is so rapid that it can be difficult to stay informed about the field overall. This paper presents examples of emerging technology that are most often used in MERL for development programs, describes the pros and cons of their use, and discusses technology and ethics concerns that practitioners should keep in mind. The paper covers new types of data sources (application data, sensor data, and drones), new ways to store data (distributed ledger technology and the cloud), and new ways to analyze data (text analytics and supervised and unsupervised learning).

Background

In this paper, we provide an overview of how emerging technologies and approaches are being developed, tested, and used for monitoring, evaluation, research, and learning (MERL) in international development and humanitarian programs. We also review the potential of these technologies and approaches to improve MERL practice, and we note some current barriers and challenges to the use of these technologies for MERL.

We hypothesize that emerging technology is revolutionizing the types of data that can be collected and accessed and how it can be stored, processed, and used for better MERL. These improved data streams may lead to potentially transformational changes in the ways development programs are delivered. However, research and documentation on the use of these technologies is required so MERL practitioners can better understand where, when, why, how, and for which populations the use of these technologies and approaches is appropriate.

In the international development space, the main purposes for MERL data collection and use are, broadly:

- Researching and consulting for program design.
- Measuring progress toward project or program goals.
- Demonstrating accountability to donors, peers, and program participants.
- Evaluating the impact of program interventions and approaches.
- Improving implementation methods for ongoing programs.
- Learning what is working, why, how, where, when, and for whom.
- Sharing results, learning and new methods, approaches, and good practices.

Traditionally, ***monitoring data*** has been collected actively at set times in a project life cycle to measure progress toward achieving project goals and objectives. Monitoring sometimes focuses on accountability and understanding whether a planned action has occurred (for example how many people were trained). It may include more complex indicators and outcome measurements that use several layers of analysis or employ instruments to understand a situation holistically (for example, the Organizational Performance Index[1], the treatment cascade for HIV monitoring,[2] or the use of nighttime lights to monitor economic development.[3]

Evaluation, by comparison, generally occurs more episodically and looks more deeply at a project's outcomes (and sometimes impact) over time. While examples of continuous and real-time evaluation are more common now than previously,[4,5] most commissioned evaluation looks at a project's or activity's process or performance at a point in time (for example, at midterm or endline). The purpose of evaluation is to improve the delivery of a project.

[1] Rachel Dubois et al. (2019). "The Organizational Performance Index: A new method for measuring international civil society capacity development outcomes," Performance Improvement Quarterly 31, No. 4: 381. Accessed September 20, 2019. https://doi.org/10.1002/piq.21282

[2] "PEPFAR 2019 Country Operational Plan Guidance for all PEPFAR Countries" (2019). Accessed September 10, 2019. https://www.state.gov/wp-content/uploads/2019/08/PEPFAR-Fiscal-Year-2019-Country-Operational-Plan-Guidance.pdf

[3] Douglas M. Addison and Benjamin P. Stewart (2015). "Nighttime lights revisited: the use of nighttime lights data as a proxy for economic variables," Policy Research Working Paper Series 7496. The World Bank.

[4] Riccardo Polastro (2012). "Real Time Evaluations: Contributing to system-wide learning and accountability." Accessed September 20, 2019. http://odihpn.org/magazine/real-time-evaluations-contributing-to-system-wide-learning-and-accountability

[5] John Cosgrave, Ben Ramalingam, and Tony Beck (2009). "Real-time evaluations of humanitarian action: An ALNAP Guide — Pilot Version," London: ALNAP/ODI. Accessed September 20, 2019. https://www.alnap.org/help-library/real-time-evaluations-of-humanitarian-action-an-alnap-guide

Research generally aims to create generalizable knowledge on a given topic. The definition used by the National Institutes of Health (the Common Rule) is: "Research means a systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge."[6] While many monitoring and evaluation (M&E) approaches use research methods, the intent of most M&E exercises is to better understand a project to improve implementation rather than to create generalizable knowledge.

USAID defines learning as "… the intentional process of generating, capturing, sharing, and analyzing information and knowledge from a wide range of sources to inform decisions and adapt programs to be more effective."[7] Learning uses products from monitoring, evaluation, and research to understand how a program is operating.

Digitization of existing data sets and data collection, and emerging hardware, software, and approaches to data analysis allow for the collection, processing, merging, storage, and analysis of continuous and increasing volumes of quantitative and qualitative data for MERL activities. This is changing how MERL is conducted and, in some cases, who performs this work. These developments have spurred discussion about whether the international development and humanitarian aid sectors could and should incorporate these tools and processes into MERL, in what circumstances, and for what purposes. New disciplines entering the MERL field (for example, software development and data science), are bringing new ideas and ways of working.

Practitioners from the wider MERL field ask questions like the following:

- **How might these new forms of data provide more actionable information for program managers and decision-makers?**
- **How might digitization of MERL processes replace current practices? What are the implications?**
- **Will these new technologies replace MERL practitioners with data scientists or automation?**
- **What ethical questions arise with these new technologies and their potential uses when working with vulnerable populations and their data?**
- **Can these new approaches allow for the full range of MERL practices to be conducted, and will they contribute to better decisions, resource allocation, and impact?**

[6] "3014 - NIH Human Research Protection Program," National Institutes of Health (2005). Accessed October 27, 2019. https://policymanual.nih.gov/3014
[7] "Learning," USAID Learning Lab. Accessed October 27, 2019. https://usaidlearninglab.org/cla-component/learning

Emerging Technologies and Their Potential for MERL

This paper discusses three key trends in emerging technology for MERL. First, we examine new types of data sources and data collection methods, including where the data is, how it can be accessed, and what it is useful for. Second, we look at new methods of data storage and organization and how they are changing options for MERL practice. Finally we look at new methods of data analysis that are relatively nascent in MERL practice and that suggest ways of working that may become common in the future. We focus on how MERL practitioners might make best use of these technologies in the next decade and highlight additional research and ethical scrutiny that may be required before they are used more extensively for MERL.

New Kinds of Data Sources

Below we discuss three new types of data sources: application data, sensor data, and drones (unmanned aerial vehicles) and drone data.

Application Data

Application data is composed of the data trails that users of software applications leave behind when they use devices such as smartphones and the Internet. The most ubiquitous data comes from web and mobile applications; smartphone users normally use several applications multiple times per day. Application data is increasing around the world as more people access the Internet and the mobile web via smartphones. Applications are mainly used to collect data such as demographics and location or monitor behavior and interactions or time use.[8] Applications produce metadata such as the time and place of use, and in some cases provide information about a person's contacts, social network, preferences, and behaviors. They may also provide data about a service delivered or requested.

Incorporating application-generated data into MERL

Data generated through web or mobile applications can be active or passive. An example of active data collection is a survey or reporting application that respondents use regularly to provide information about, for example, a program or health or education activities, or to provide feedback on a program. Another type of active collection is tagging data to categorize it, making it more accessible or searchable.

[8] Borja B. Garcia, Jo Welford, and Brett Smith (2015). "Using a smartphone app in qualitative research: the good, the bad and the ugly," Sage Pub Journal, 16, No. 5: 508–525, https://doi.org/10.1177/1468794115593335

Passive data collection through an application often occurs without a person's knowledge, gathering specific information about perceptions, interests, and behaviors. It can reveal how often someone performs an action (makes a financial transaction, places a phone call, visits a health care provider). Some believe passive data collection is more objective than active data collection because the process does not cause a person to feel observed or pressured to follow social norms. This data can help gain insights into whether a program is having its intended effect (see text box). If an organization owns or has rights to the application, access to the data is immediate and unfettered.

Using Application Data to Monitor Learning

RTI developed the Tangerine® application to assess early grade reading ability in a developing country setting. Data from the application helps RTI monitor the efficacy of programs it implements.

Challenges and Constraints in Using Application Data

Technological. The passive data that applications produce is not always accessible to those who want to use it. One example is metadata generated by the mobile money wallets of savings groups, especially in sub-Saharan Africa. While mobile money providers can access the data (how much people are saving, where they are located, how often they transact),[9] MERL practitioners rely on reporting provided by these groups. Data from applications like mobile wallets, crop report mobile applications,[10] or health care worker reporting applications,[11,12] could be useful to implementers of education, health, or agricultural programs — but those implementers do not have access. Application data may be available to those who own or build an application that collects the data. However without advance planning and agreement on how to use it, much of the data collected through applications will not be utilized or could be used in unethical ways.

Methodological and behavioral. Active reporting through applications (as opposed to passive collection of data during everyday use) is much less frequent and generally must be enforced to be effective. While reporting through applications can increase the speed at which data is received, it may be incomplete and present biased results.

Socio-political, legal, and ethical. Ethically, MERL practitioners must disclose to users how they will use data from non-reporting applications — and obtain their consent. Especially under data privacy regulations such as the General Data Protection Regulation,[13] any data collected on citizens of the European Union (and perhaps other countries in the future) must be removed at the user's request. Maintaining systems that can address such requests may be too onerous for development and humanitarian agencies.

[9] Bonnie Brusky et al. (2018). "Protecting Saving Groups Reached Through High Tech Channels: Guidance from the New Client Protection Principles for a Digital Savings Project," UN Capital Development. Accessed January 17, 2020. https://grameenfoundation.org/documents/Microlead-Protecting-Savings-Groups-Case-Study.pdf

[10] Shannon McCrocklin (November 19, 2019). "Mobile Phone Apps For Farmers In Sub-Saharan Africa," GeoPoll. Accessed January 20, 2020. https://www.geopoll.com/blog/mobile-apps-farmers-africa/

[11] Gahizi Emmanuel and Emmanuel AWR (2018). "A Mobile Application System for Community Health Workers: A Review," Global Journal of Research and Review, 5, No. 2:11: 1–7. https://www.imedpub.com/articles/a-mobile-application-system-for-community-health-workers-a-review.pdf

[12] Lakshmi Gopalakrishnan et al., in addition to the CAS Evaluation Consortium (January 2020). "Using mHealth to improve health care delivery in India: A qualitative examination of the perspectives of community health workers and beneficiaries" (2020). National Center for Biotechnology Information. PLoS ONE 15, No. 1 (2020) https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0227451

[13] The European Union General Data Protection Regulation, European Union. Accessed October 30, 2019, https://gdpr-info.eu/

Sensor Data

Sensors are instruments that detect changes in the physical environment. For example, rainfall sensors are activated in the presence of precipitation. Sensors are embedded in many common objects, such as smartphones; smart watches and fitness trackers; and radio frequency identification technology.[14] Sensors can detect changes in movement, light, temperature, volume, and composition (such as of soil, water, or air). They have gained popularity in recent years because they are small and can be relatively inexpensive. Sensors have contributed to the evolution of the Internet of Things, families of technologies that converge data from different sources and that are equipped with sensors or applications that track use and behaviors.[15,16] The Internet of Things is an open, comprehensive network of intelligent objects that have the capacity to auto-organize and share information, data and resources, reacting and acting in response to situations and changes in the environment.

What sensors offer MERL.

Data produced by sensors, including data integrated into the Internet of Things, includes some of the most interesting and challenging types of data for program decision-making. Sensors are embedded into commonly used technology, such as smartphones.[17] They are low-powered, and their cost has declined steadily over time so this can be an efficient and cost-effective technology to employ in MERL.[18]

Sensor data is easy to update in real time, making it possible to monitor unfolding events. For example, cookstove sensors can monitor the use of improved cookstoves[19] in lower-income households. In Sudan, a comparison of data collected by survey and by cookstove sensors found that participants were overreporting time spent in cooking each day.[20] In an evaluation in Mongolia, cookstove sensor data was compared with self-reports and used to overcome acquiescence bias in respondents who said they had followed instructions when sensors showed low levels of compliance.[21] This suggests that collecting data with sensors is a valid method that can be applied in MERL to evaluate the reliability or effects of a program.

Challenges and Constraints in Using Sensors

Technological. The number of these devices and amount of raw data retrieved can lead to problems in sustainable storage, analysis, and efficient evaluation.[22] Although most sensors are very durable, an additional issue is that they must be replaced if they stop working. This can challenge sustainable data collection.

[14] Charu Aggarwal (2013). Managing and Mining Uncertain Data (Springer Publishing Company, New York, NY).

[15] Malio Del Giudice (March 2016). "Discovering the Internet of Things: technology and business process management, inside and outside the innovative firms." Business Process Management Journal, 22, No. 2. https://www.emerald.com/insight/content/doi/10.1108/BPMJ-12-2015-0173/full/html

[16] Muhammad Umar Farooq et al. (March 2015). "A Review on Internet of Things," International Journal of Computer Applications, 113, No. 1: 1–7. https://research.ijcaonline.org/volume113/number1/pxc3901571.pdf

[17] Phillip Biggs et al. (2016). "Harnessing the Internet of Things for Global Development," International Telecommunication Union. Accessed October 30, 2019. https://www.itu.int/en/action/broadband/Documents/Harnessing-IoT-Global-Development.pdf

[18] Sharmila Subramaniam and Dimitrios Gunopulos. A Survey of Stream Processing Problems and Techniques in Sensor Networks in C. C. Aggarwal, ed. (2007). Data Streams. Advances in Database Systems. (Springer Publishing, Boston, Massachusetts). Vol. 31, 333–352. https://doi.org/10.1007/978-0-387-47534-9_15

[19] Laura G. Hooper, et al. "Traditional cooking practices and preferences for stove features among women in rural Senegal: Informing improved cookstove design and interventions" (November 2018). National Center for Biotechnology: PloS one, 13, No. 11. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0206822

[20] Biggs et al., op. cit.

[21] Leslie Greene, et al. (2014). "Impact Evaluation Results from the MCA Mongolia Energy and Environment Project," Energy Efficient Stove Subsidy Program, Social Impact for the Millennium Challenge Corporation. Accessed September 20, 2019. https://data.mcc.gov/evaluations/index.php/catalog/133/related_materials

[22] Aggarwal, op.cit.

Methodological and behavioral. Sensors collect large amounts of data over time, which can lead to challenges in accuracy and scalability. So much information is generated that compressed representations of the data are made that may not accurately represent the condition. Further aggregation of data over time can lead to approximation errors,[23] a potential problem in MERL, which requires as accurate an understanding as possible regarding a project and its impacts. Thus, the use of sensors may make it difficult to draw correct conclusions about a project's effectiveness. As with any approach that produces large volumes of data, organizations should carefully assess whether they have the resources to manage and analyze sensor data.

Socio-political, legal, and ethical. Sensors that collect data without users' explicit consent may be inappropriate to use in the MERL context. For example, data produced by sensors such as cameras that use facial recognition could be considered an invasion of privacy. Sensors that detect movement (for example, in a clinic to confirm workers' attendance and time of arrival) could improve program performance but might also be used punitively. Due to increasing concerns about privacy, and growing calls to ban facial recognition software and other types of automated sensing, it is critical that organizations carefully consider whether sensor deployment is an acceptable approach. Ideally this should be discussed with communities where these tools would be implemented.

Drones and Drone Data

Also called unmanned aerial vehicles, drones are small, lightweight flying devices that collect live data through their sensors. Drones fly at lower altitudes than satellites, so they can collect visual data below cloud cover or in minute detail. Drone sensors may include multispectral, near infrared radiation, and light detection and ranging sensors that can be used to measure distances accurately.[24] Drones can map areas, detect heat, and measure forest density or water purity. They are often equipped with still or video cameras.

What drones offer MERL

Data collected by drones can use an aerial perspective to provide a broader picture of the current conditions of a project or area. This can help teams conduct monitoring across large areas and in terrains where it might be difficult to collect data manually. Drones can be particularly helpful in monitoring and evaluating large infrastructure, agricultural development, or protected area projects and can support reporting on humanitarian disasters in areas of flooding or collapsed buildings, for example.[25,26]

Using drones supports quick and efficient data collection, because spatial and temporal resolution is ensured during the MERL process.[37] Although practitioners remain at a distance, they can control where a drone flies, and the drone's sensors are advanced enough to monitor different phenomena. For example, drones with thermal cameras can take three-dimensional photos and videos of damages to wind turbines, whereas a worker would have to climb a turbine to inspect it for dents or holes.[28]

[23] Aggarwal, op.cit.

[24] Anita Simic Milas, Aurthur P. Cracknell, and Timothy A. Warner (2018). "Drones: the third generation source of remote sensing data." International Journal Of Remote Sensing 39, No. 21 (2018):7125–7137, https://doi.org/10.1080/01431161.2018.1523832

[25] The World Bank Group. "Tapping the Potential of Drones for Development" (2017). Accessed September 30, 2019. http://www.worldbank.org/en/topic/transport/brief/drones-for-development

[26] Swiss Foundation for Mine Action. "Rapid Damage Assessments of Tabarre and Surrounding Communities in Haiti following Hurricane Sandy" (2016) Accessed January 27, 2020. https://zoinet.org/wp-content/uploads/2018/01/6Case-Study-Haiti.14April2016.pdf

[27] Milas, op.cit.

[28] Mark Vincent Villaflor. "How to Use Drones in Development Projects," Development Asia (2017). Accessed September 30, 2019. https://development.asia/explainer/how-use-drones-development-projects

Challenges and Constraints in Using Drones

Technological. The cost of training and the drones themselves may be prohibitive for development and humanitarian organizations, although this may not be a constraint for long.[29] Understanding the specifications for different drone applications will remain a barrier in the development and humanitarian sectors until drones are more commonly used. Whether their use can be sustainable in many developing country contexts without donor support is not yet known. An additional challenge may be the systems within which drones are deployed. Ensuring there are clear guidelines for operating drones will be important considering that most countries have not yet developed legal frameworks to regulate drones.

Socio-political, legal, and ethical. Drones that carry improvised explosive devices (IEDs),[30] and their increasing use in military attacks, may limit use of this technology in many country contexts. Drones can deploy IEDs to specific locations quickly and accurately, which is an obvious concern for countries and their inhabitants due to the negative association of drones with violence.[31] The systems and technology needed to reduce risks from drones may be a higher hurdle in countries that lack applicable regulations or have banned drones altogether, as governments might take no action against deployment of drones are used in these ways. Other concerns include privacy, because drones can produce high-resolution images of people and property without their consent — informed or otherwise.

Other emerging technologies that can produce data for MERL include geospatial data or satellite imagery, biometrics, and dark data. These could be explored in future research.

[29] PwC and Agoria. "A Drone's Eye View" (2018). Accessed January 30, 2020. https://www.pwc.be/en/documents/20180518-drone-study.pdf

[30] Ben Hubbard, Palko Karasz, and Stanley Reed (September 9, 2014). "Two Major Saudi Oil Installations Hit by Drone Strike, and U.S. Blames Iran," The New York Times. Accessed September 30, 2019. https://www.nytimes.com/2019/09/14/world/middleeast/saudi-arabia-refineries-drone-attack.html

[31] Roger Davies (2017). "Drones and the IED threat," Action on Armed Violence. Accessed September 20, 2019. https://aoav.org.uk/2017/drones-ied-threat/

New Kinds of Data Storage and Organization

Below we discuss several new types of data storage and organization: distributed ledger technologies, the cloud, and the edge.

Distributed Ledger Technologies

Distributed ledger technologies (DLTs)— commonly referred to as blockchain — provide a way to store information that is based on shared recordkeeping, multi-party consensus, independent validation of transactions, and methods to track tampering and promote tamper-resistance.[32] While distributing data across systems and servers was not entirely a new idea, and the computer industry has time-stamped digital documents to enable tracing of a document's version history for many years, DLTs may be useful for development because, as the name suggests, the data is distributed, potentially leading to increased transparency and accessibility.[33] Data transparency and accessibility remains an issue, especially in resource-constrained environments, and understanding what is the agreed or "final" version of data can sometimes be challenging. When using a DLT, data is no longer proprietary but rather a public good that can be accessed and understood without gatekeepers.

What DLTs offer MERL

Governments can easily reconstruct data stored on blockchain systems when a record (the ledger) is changed. It is easy to see what information was modified, where in the network the change originated, and who agreed to the change.[34] When governments have siloed data systems and many gatekeepers, improved access to data could be a boon. Data stored in a DLT is no longer siloed and controlled by individuals; it can be accessed across the network. For example, Truepic is a photo and video verification platform that stores photos on the blockchain with time, date, location, and exact pixilation data. Truepic has been used to verify information and disinformation campaigns in China, Jordan, Syria, Uganda, and Latin America.[35]

A key benefit of the DLT network is that it can be easily monetized through the use of cryptocurrency. This means small financial incentives can be provided for timely reporting, for example. Paying people to provide data could make MERL processes less extractive and more equalizing. A system like this could be used where MERL enumerators are paid to collect data based on their assignments, or respondents receive a credit of some type for sharing their data via sensors or manual inputs. For example, Fishcoin.co is attempting to incentivize reporting on the sources of fish entering the global supply chain. The organization developing a system through which buyers provide incentives for reporting on fish source.[36]

[32] Michel Rauchs, et. al. (2018). "Distributed ledger technology systems: a conceptual framework," Cambridge: Cambridge Centre or Alternative Finance, University of Cambridge. Accessed October 30, 2019. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3230013

[33] Accenture Labs (2017). "Blockchain for good: 4 guidelines for transforming social innovation organisations." Accessed October 30, 2019. www.accenture.com/t20180102T200432Z__w__/us-en/_acnmedia/PDF-68/Accenture-808045-BlockchainPOV-RGB

[34] Steve Cheng, Matthias Daub, et al. (2017). "Using blockchain to improve data management in the public sector," McKinsley Digital. Accessed September 30, 2019. https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/using-blockchain-to-improve-data-management-in-the-public-sector#

[35] Daven Maties (2018). "How a blockchain-based digital photo notary is fighting fraud and fake news," Digital Trends. Accessed March 2, 2020. https://www.digitaltrends.com/photography/truepic-blochain-image-verification/

[36] See fishcoin.co

Challenges and Constraints of Using DLTs

Technological. Training is required, and organizations need to understand DLT technology and whether it is appropriate for their data storage, reporting, or monitoring needs. A basic, defined skill set for blockchain for a MERL-type application does not yet exist. While some training on blockchain has focused the development and humanitarian sector,[37] it aims to orient practitioners to the overall technology rather than deploying it.

Methodological and behavioral. Nearly all applications of DLTs to date in the development and humanitarian sectors have been in program implementation (for example, increasing the transparency of cash transfers, enhancing financial access, or providing access to insurance) rather than MERL applications. More work is needed to develop a framework that can help MERL practitioners understand whether blockchain is right for their applications.

Socio-political, legal, and ethical. While DLTs may offer more protection against changes to data, it is not clear exactly how DLTs can improve data transparency if systems can still be set up within closed networks. Paying for data will likely have implications for data quality and affect bias.

Data Storage and Processing: the Cloud vs. the Edge

There is increasing discussion of the cloud versus the "edge."[38] Many MERL practitioners are familiar with cloud storage for program files, where cloud computing technology replaces traditional computing methods that store data on desktops or local servers in favor of decentralized software and data storage on remote servers, usually located in shared data centers.[39]

Edge computing is probably beyond the current use of most MERL practitioners but it could be our future as the Internet of Things becomes more pervasive. *Edge computing* refers to technologies that allow computation to be performed at the so-called edge of the network, without having to reach a data center or the cloud. For example, a smartphone functions on the edge between a user and the cloud, where data can be processed and stored on the phone without having to reach the cloud. Edge computing allows for much faster processing times.[40] Technically, the edge is not data storage but a way to process and use data between storage devices.

Challenges and Constraints in Using Cloud and Edge Computing

Technological. The main technological issue for cloud data storage is bandwidth, both to transmit data to the cloud and to access the data again when needed. While bandwidth is improving exponentially, storing and accessing data are challenging in some settings.

[37] See www.techchange.org

[38] Karthik Ramasamy, "The Data Center And Cloud Aren't The Leading Edge Of Innovation, Forbes. (October 18, 2019). Accessed 20 January 2020. https://www.forbes.com/sites/forbestechcouncil/2019/10/18/the-data-center-and-cloud-arent-the-leading-edge-of-innovation/#5b61e208db30

[39] Kenji E. Kushida, Jonathan Murray, and John Zysman (2011). "Diffusing the Fog: Cloud Computing and Implications for Public Policy BRIE Working Paper," Semantic Scholar. Accessed September 20, 2019. https://pdfs.semanticscholar.org/b6c6/34fabb7dbf9dd2ce521b1927b91dd97834df.pdf

[40] Weisong Shi, et al. (2016)."Edge Computing: Vision and Challenges," IEEE Internet of Things Journal, 3, No. 5, (2016):637–646. https://ieeexplore.ieee.org/abstract/document/7488250

Edge computing faces other challenges. If programs use many Internet of Things devices (sensors, cameras, devices that staff use to collect data), the amount of data they generate may exceed what we can process easily. Edge computing may speed data to use cycles by helping process the results more quickly. For example, a weather station that provides information to farmers can receive temperature, humidity, pressure, and other data; save it; analyze it; and generate new data based on the analysis. Thus, the weather station can generate forecasts for farmers' specific locations and send the data to the cloud. Again, bandwidth is required to share the data with the cloud and learn from other weather stations.

Socio-political, legal, and ethical. MERL practitioners may be familiar with host country concerns about data residing in the cloud. In many instances, countries request that sensitive data, especially citizens' health data, be stored on servers in the country. Many governments agree that their information assets should remain in national territory — not in the cloud —to avoid foreign sovereignty and access issues.[41]

With edge computing, the main concerns relate to the security of Internet of Things devices, which may be less secure than cloud-based systems. As Internet of Things devices are added to a MERL system, it will be essential to carefully consider data security and ensuring that the data on devices is encrypted.

[41] Kristina Irion (2013). "Government Cloud Computing and National Data Sovereignty." Policy & Internet 4, No. 3–4: 40–71. https://onlinelibrary.wiley.com/doi/abs/10.1002/poi3.10

New Kinds of Data Processing

Artificial intelligence makes it possible for machines to learn from experience, adjust to new inputs, and perform human-like tasks, making it possible to partially or fully automate decision-making.[42] Artificial intelligence often relies on machine learning, a branch of artificial intelligence that automates analytical model building[43] to enable computers to "recognize patterns in data and use these patterns for predictions."[44]

Data comes in two broad types: quantitative (structured) data, and qualitative (semi-structured or unstructured) data. While the human mind often struggles to process quantitative data and is prone to biases in interpretation,[45] computers are particularly good at processing, analyzing, and interpreting numbers. This advantage has become even more important with the massive increase in data, leading to important advances in data analytics, machine learning, and artificial intelligence.

Machine Learning and Artificial Intelligence for Text

Text analytics is a type of artificial intelligence and machine learning that automatically discovers previously unknown information in unstructured textual data or that extracts useful insights from text using different types of statistical algorithms.[46] Text analytics, text mining, and machine learning applied to text are, broadly speaking, similar concepts.

The advent of big data has quickly demonstrated the limits of the human mind in processing and understanding the volume of available unstructured information in text, sound, or video format. Text analytics studies the challenge of making machines as good as or even better than people in analyzing unstructured textual data.

Humans have an edge in processing, analyzing, and interpreting qualitative data, semi-structured and unstructured text — except extremely large textual data sets. Computers struggle to understand or resolve ambiguity in words, phrases (see text box), text, or documents.[47] Computers also have trouble interpreting inferred or implied information, synonyms, homonyms, metaphors, humor, and sarcasm. People are much better at these tasks as they can appreciate nuances in texts and communications.

[42] Amy Paul, Craig Jolley, and Aubra Anthony (2018). "Reflecting the Past, Shaping the Future: Making AI Work for International Development." Washington DC: USAID Center for Digital Development (Washington, D.C.). https://www.usaid.gov/sites/default/files/documents/15396/AI-ML-in-Development.pdf

[43] Machine Learning: What it is and why it matters (2019). Accessed March 2, 2020 https://www.sas.com/en_us/whitepapers/machine-learning-primer-108796.html

[44] Paul, op.cit.

[45] Daniel Kahneman (2011). Thinking, Fast and Slow. (Farrar, Straus and Giroux, New York, NY). Retrieved from http://www.worldcat.org/isbn/9780374275631

[46] Charu C. Aggarwal (2018). "Machine Learning for Text: An Introduction," in Machine Learning For Text, ed. Aggarwal (Springer Publishing Company, New York, NY). 1–16, https://doi.org/10.1007/978-3-319-73531-3_1

[47] David Madigan (2019). "Text Mining, an Overview," (Columbia University, New York, NY). 1–83. Retrieved from http://www.stat.columbia.edu/~madigan/W2025/notes/IntroTextMining.pdf

Too Ambiguous for a Machine

"I made her duck" may mean:
- I cooked waterfowl for her.
- I cooked waterfowl belonging to her.
- I created the (artificial) duck she owns.
- I caused her to quickly lower her head.

See Daniel Jurafsky and James H. Martin (1999). Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition (Second ed.). https://b-ok.cc/book/2927623/125ad3

What Text Analytics Offers MERL

Text analytics is becoming important for MERL because it has the potential to tap into unused information available in unstructured data. Thus, text analytics can support information retrieval and knowledge management within an organization and can facilitate understanding and analysis in an environment where information increases constantly. Above all, text analytics contributes to efficiency and productivity.

As shown in the table below, text analytics includes a sub-set of solutions, in various stages of development, that could be useful for MERL practitioners.

State of Development of Text Analytics with Potential Applications for MERL Practitioners

Ready for Use in MERL	Making Good Progress	Still Difficult
Named entity recognition	Text classification	Paraphrasing
Sentiment analysis	Topic modelling	Abstractive summarization
	Machine translation	Qualitative coding
	Automatic transcription	Question answering

On the following page, we describe how some types of text analytics — sentiment analysis, text classification, topic modelling, and abstractive summarization — could be applied for MERL.

[42] Amy Paul, Craig Jolley, and Aubra Anthony (2018). "Reflecting the Past, Shaping the Future: Making AI Work for International Development." Washington DC: USAID Center for Digital Development (Washington, D.C.). https://www.usaid.gov/sites/default/files/documents/15396/AI-ML-in-Development.pdf
[43] Machine Learning: What it is and why it matters (2019). Accessed March 2, 2020 https://www.sas.com/en_us/whitepapers/machine-learning-primer-108796.html
[44] Paul, op.cit.
[45] Kahneman, op. cit.

Sentiment analysis uses supervised machine learning or rule-based approaches to extract an author's opinion or sentiment from a document or defined sub-entity. Sentiment analysis uses lexicons (lists of words with general or content-specific positive or negative sentiments) or machine learning approaches to develop classification algorithms.

Text classification uses supervised machine learning techniques to extract topics or themes from large qualitative data sets. Text classification categorizes documents, paragraphs, or sentences into user-defined categories. (See text box for an example developed by Devex.)[48] Effective text classification requires some knowledge of the topics or themes in the data so supervised learning algorithms can be used to tag documents. A classic example is spam detection, which trains an algorithm with tagged email messages. The algorithm is then applied to new emails.

Content Creation

Devex developed a text classification algorithm to partially automate the manual review of up to 3,000 items per week for its website's news section. The classifier that Devex developed screens potential content and selects about 33 percent for manual review, keeping the process efficient.

Topic modeling is a classification approach that is more suitable for large volumes of documents when the topics are unknown or only partially known. This process supports automatic theme discovery in a document or a group of documents by identifying the main topics in a set of documents (reports, emails, Twitter feeds, social media content, or others), groups the documents according to their main topics, and then predicts the mix of topics the document covers (see text box for an example of topic modeling[49]).

Topic modeling offers a solution to three challenges in qualitative research: 1) it can process large datasets, well beyond the capacity of manual qualitative data analysis using computer-assisted qualitative data analysis software, 2) it brings reproducibility and objectivity to qualitative research because researchers can share their analysis and code similar to quantitative research processes, 3) and it can identify trends over time or differences in geographies or entities.

Topic Modeling on Qualitative Research Data

The Malawi Journals project was a qualitative component of longitudinal HIV/AIDS household surveys between 1999 and 2012. Local participant observers wrote more than 1,000 journals, each averaging 7,500 words. Because manual coding was too labor-intensive, researchers used topic modeling to identify key topics and then documented changes in trends over time and geography. The project demonstrated that text analytics adds value to and complements traditional qualitative data analysis.

Abstractive summarization technologies can provide extractive summaries by selecting key sentences in a document and presenting them sequentially. Extractive summaries can at best give an idea of what a text is about, but they are not robust enough for MERL work. Abstractive summarization, in which system fully understands a text and composes a summary in new sentences, is still under development.

[48] MonkeyLearn. "How Devex used MonkeyLearn to scale its content curation process." Accessed January 29, 2020, https://monkeylearn.com/customers/devex/

[49] Parijat Chakrabarti and Margaret Frye (2017). "A mixed-methods framework for analyzing text data: Integrating computational techniques with qualitative methods in demography," Demographic Research, 37, No. 42:1351–1382, https://www.jstor.org/stable/pdf/26332229.pdf

Challenges and Constraints of Using Text Analytics

Technological. Text analytics is a new field with great potential to complement traditional qualitative data analysis and to automate content selection, content curation, data management and retrieval, and knowledge management. Initial investment is required to learn and understand the methodologies and set up an analysis approach. Practitioners and organizations should weigh this investment against potential advantages over time, compared to traditional or manual qualitative analysis.

Methodological and behavioral. MERL practitioners need to understand both qualitative research and machine learning and artificial intelligence techniques. In other words, text analytics should combine the skill sets of MERL practitioners and data scientists, who use different theoretical frameworks and practical approaches.

Socio-political, legal, and ethical. Just as humans bring bias to their interpretation of data, use of machines to interpret data can be biased, depending on the method used. With supervised machine learning, for example, the user who tags the initial data and trains the machine can introduce bias. With unsupervised machine learning, many artificial intelligence algorithms are "black boxes" that make it difficult to know where or how biases are introduced.[50] Bias is an important concern that requires careful assessment.

[50] Brian Wahl, et al. (2018). "Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings?" BMJ Global Health 3, No. 4: https://gh.bmj.com/content/3/4/e000798

Key Challenges with Emerging Approaches

There is great potential in these new data sources and technologies for storing, organizing and processing data — as well as key risks, biases, and ethical issues inherent in the use of these new approaches for MERL practice. Some main challenges that will need to be addressed include:

1. ***Defining the problem.*** All too often, technology solutions are looking for a problem. Clearly defining a specific problem and the MERL need is critical to selecting and deploying a technology system that can provide the correct support. Ensuring people and organizations understand what to ask for in the system, and any tradeoffs, is essential.

2. ***Selection bias.*** Selection bias occurs when data is selected for analysis in a way that makes it less likely to give equal consideration to all items being selected or evaluated. If sampling is not representative, the data produced also will not be representative. MERL data currently includes many non-text files that need further processing to avoid exclusion — which could cause selection bias. Paying enumerators for reporting (for example, through blockchain) may also affect data quality in unintended ways.

In the machine learning realm, it is unclear whether sufficient data is currently available to train systems in development settings. Data are often siloed and thus unavailable to improve training algorithms. The less training data available, the more likely bias may occur. While Google suggests having at least 1,000 cases, other systems have been trained with far less data. Further investigation is needed to determine the amount of data that development practitioners will need to ensure a well-trained system. It is also not clear whether data used for training in one domain or geographical context can be used for other domains or contexts.

3. ***Reduced levels of researcher control.*** With Internet of Things and machine learning systems, it can be difficult to describe exactly how information is derived. Evaluators may feel they have less control over the research process and that it lacks transparency. These perceptions could diminish trust in the findings, especially if results are not replicable or explainable.

4. ***Change management.*** A switch to emerging technologies has the potential to increase the use of large volumes of inert secondary data, but would require changes in data management and practice. Political will for such change is a major requirement for the endeavor to be successful. It will be essential to gain early buy-in from those who will need to change.

5. ***Platform change.*** Investing in a single emerging technology system is unlikely to yield dividends due to the rapid pace of change in this field. Systems must be nimble and able to be updated or improved as platforms and the ability to process data change.

6. ***Greater appreciation of systems.*** Systems thinking has permeated social science discussions but has not yet fully influenced intervention design and evaluation. Interventions (programs, projects, activities) remain largely linear, tightly bounded, and prescriptive — inflexible, in fact — based on poorly articulated assumptions. Potential risks often remain unclear. In short, we do not design and evaluate very well. High levels of complexity and resulting uncertainty compound these challenges. No technology will save us from poor design and weak evaluation.

A Way Forward

It is likely that machines and humans will complement each other for the foreseeable future. Whereas machines are better at sifting through large quantities of text, humans are better at interpreting and contextualizing information. Developing a strategy that ensures MERL practitioners understand the technology well enough to act as critical interlocutors is important. MERL practitioners and decision-makers can consider investment in critical areas such as those discussed below.

Capacity Strengthening

Keeping abreast of new technology is a challenge for MERL practitioners, especially those who are not based in headquarters offices. Moreover, many technology-related trainings focus on information communications technology for development approaches rather than MERL. Many face-to-face trainings take place in the northern hemisphere. For the past two years, MERL Tech has offered pre-conference workshops on topics such as blockchain, big data, and, more recently, text analytics for evaluators. The American Evaluation Association, University of Oxford, and TechChange[51] offer classes and workshops (including some online) on a range of technology topics and MERL, information communications technologies for development, blockchain for social impact and others, although not all are MERL-specific.[52] The Development Café, a think tank based in Nairobi and Jakarta, offers online courses on emerging tools in evaluation, including blockchain, artificial intelligence, big data, and drones.[53] These courses are primarily offered in English, which may restrict access. And some online courses provide training in text mining and data science but are not generally merged with social science training programs in university systems. While capacity building may help increase understanding of a technology, it does not necessarily address the appropriateness of the use of technologies designed for the northern hemisphere in the southern hemisphere, or the lack of technologies specifically designed by and for those living and working in the southern hemisphere.

[51] TechChange. "Technology Changing for the Future." Accessed February 20, 2020. https://www.techchange.org/

[52] University of Oxford Said Business School. Oxford Blockchain Strategy Programme. Accessed February 20, 2020. https://www.sbs.ox.ac.uk/programmes/oxford-blockchain-strategy-programme

[53] E-Dev. "Professional Development for Development Professionals." Accessed February 20, 2020, https://e-dev.org

Collaboration

Technologists and social scientists must begin to share the data they currently silo. Technology does not drive social outcomes; it mirrors the realities of those who design and develop it. Often, these individuals or groups may not clearly understand the structural inequities in the regions where their technologies will be used (or abused). In the fields of machine learning and artificial intelligence for example, partnerships should focus on developing algorithms that are accurate and just for a social purpose rather than a commercial one.

Ethics and Privacy

MERL practitioners should stay abreast of developments in the sector so they can use new and emerging technology and data appropriately to improve the practice. It is critical that practitioners take part in discussions on ethics and privacy issues related to use of emerging technology. If MERL practitioners do not understand these new approaches, they will not be able to apply such important principles of evaluation practice as respect, informed consent, transparency, benevolence, and non-maleficence to MERL activities. MERL practitioners should be at the forefront of developing mechanisms to ensure that people can give meaningful consent to use of their data in its various formats based on a common understanding of the risks and benefits involved. In the absence of truly informed consent, the community should explore ways to assume a duty of care through mechanisms outside the traditional informed consent pathway.

Documentation

MERL practitioners may not be motivated to document and publish learning on the use of technology, but examples and documentation are just what the MERL Tech community needs. USAID has effectively incentivized documentation of this kind through calls for examples for its mHealth compendium and through Digi Awards. Catholic Relief Services has increased documentation through its annual Information Communication Technologies for Development conference. Could a donor or other development partner further incentivize documentation on emerging technology and its use for MERL?

This paper addresses some of the emerging technologies and how they are being used in MERL practice in international development. This is a rapidly evolving field and the authors recommend that practitioners continue to read, assess, and study new technologies with a critical eye. Looking at technological, methodological, behavioral, socio-political, legal, and ethical issues related to emerging technology can help practitioners to make educated choices to improve their programs.