







A Practical Guide to Using Routine Data in Evaluation

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Data for Impact

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Overview

Health information systems (HIS) play a critical role in improving the health of populations. Timely health information is needed to track trends in health, including to detect disease outbreaks, monitor services provided, inform response, and plan for future health system events. In addition, international donors and development agencies often require health information to track progress toward meeting targets, such as those in the Sustainable Development Goals.¹

The HIS comprises 12 data sources ranging from individual records to population-based surveys.² Some of these data sources are part of what is referred to as a routine health information system (RHIS) which is data collected at regular intervals at public, private, and community-level health facilities and institutions. RHIS data sources and subsystems are presented in Table 1 and comprise individual record systems, service record systems, and resource systems. RHIS has long suffered from lack of coordination, training, and resources—all of which have meant that stakeholders have little confidence in the data produced.

Table 1: Types of RHIS data sources and subsystems.

Source: https://www.measureevaluation.org/resources/publications/fs-16-187

Individual record systems (facility- and community- based)	Service record systems	Resource record systems
Paper-based records of patient care	Facility-based health management information systems (HMIS)	Financial management information systems
Electronic medical records (EMR)	Public, private, and parastatal HMIS	Human resource information systems
	Laboratory and imaging information systems	Logistics management information systems
	Disease surveillance information systems	Infrastructure and equipment management information systems
	Routine supervisory information systems	Routine supervisory information systems

USAID and other donors have made significant investments to improve these systems through a wide range of interventions. For the US government, HIS has been an area of major investment since 2011.³ The U.S. President's Emergency Plan for AIDS Relief (PEPFAR) in particular has played a major role in scaling up HIS interventions and promoting the use of data for informed decision making.⁴ MEASURE Evaluation, funded by USAID, worked to improve HIS over the last 12 years with an evolving mandate to build capacity and improve decision making, to analyze how to improve health

¹ <u>https://sustainabledevelopment.un.org/?menu=1300</u>

² https://www.measureevaluation.org/resources/publications/tr-17-225/

³ United States Government (2011). The United States Government global health initiative strategy, 21 p,

http://www.pepfar.gov/documents/organization/136504.pdf

⁴ <u>https://www.cdc.gov/globalhivtb/who-we-are/resources/keyareafactsheets/health-informatives-data-management-and-statistics-</u> automating-pepfar-and-ministry-of-health-indicators.pdf

information systems, and to examine how to work in complex systems to improve health.⁵ A review of HIS interventions in 11 MEASURE Evaluation high-investment countries (i.e., where it worked for more than one year with investment of greater than \$1 million) between 2015–2020, revealed that the most common interventions were:⁶

- Supporting training (and training of trainers) on the use of information systems at the central level
- Conducting or supporting trainings for health care providers or data managers on data collection and reporting
- Contributing to a new or existing national technical working group (TWG) structure to coordinate planning for HIS strengthening and related activities
- Implementing or transitioning to DHIS2 as the data platform for HIS, and other integrated disease-specific systems
- Supporting information and communications (ICT) infrastructure development, such as providing and procuring computers, mobile technology, and internet access
- Developing HIS guidance, standards, and standard operating procedures

These interventions have contributed to improvements in data quality—such attributes as data timeliness, completeness, and accuracy. In addition, other tools were developed to assess data quality and overall HIS performance—examples include the Routine Data Quality Assessment (RDQA) tool, Data Quality Audits (DQAs), Data Quality Review (DQR), and an update of the Performance of Routine Information System Management (PRISM) assessment tool to better assess the performance of the HIS.

Data use remains a challenge for decision making, yet routine data can be and is being used for research and evaluation. Historically, routine data have been passed over by evaluators in favor of other options, such as stand-alone surveys tailored to meet evaluation objectives. But primary data collection can be expensive and time-intensive. Further, there is no guarantee the survey data will be captured as planned. Now more than ever, there are many reasons to consider routine data. The availability of this data, the perception of cost-efficiency of using routine data over other methods of data collection, and the complex nature of health interventions being implemented have led to the use of routine data. But routine data comes with its own set of challenges to consider and address. For example, RHIS was not set up with research in mind and so not all indicators, time periods, or facilities will be available.

Methods for the review

This document was prepared to provide guidance to future evaluators and researchers who are considering using routine data in their projects. We began by reviewing evaluations conducted under MEASURE Evaluation that used routine data. We also conducted a literature review to identify additional examples of studies that used routine data (Appendix A). We originally looked for evaluations addressing quality of care outcomes but decided to include other types of evaluations of health programs because all evaluations that used routine health data offer insights and lessons. We decided not to limit the search just to data collected by government facilities but also to include evaluations that used data routinely collected by the health program being evaluated. Programs sometimes establish robust data collection systems as part of their own monitoring, evaluation, and learning plans and these can be rich sources of data for evaluators and researchers. We then selected 18

⁵ https://www.measureevaluation.org/about/history

⁶ https://www.measureevaluation.org/his-strengthening-resource-center/his-interventions/common-his-strengthening-interventions

evaluations for further investigation, based on the type of evaluation design, the source of data, and the health area being evaluated. We then developed technical briefs that focused on:

- Rationale for using routine data
- Research questions answered with routine data
- Data description and management
- Assessment of the usability and quality of the data
- Data analysis methods
- What worked well and what limitations were found

The process was iterative and collaborative with the original authors. We drafted most of the technical briefs based on information available in the article or evaluation report. We shared our drafts with lead authors to fill in gaps and answer additional questions. In some cases, the lead author drafted the brief and revised it based on our internal review. We completed 13 of 18 possible briefs—we were unable to reach the remaining authors. We also consulted a brief prepared by MEASURE Evaluation outlining considerations on using routine data based on evaluations conducted by the project.⁷

This guidance document is a summary of the technical briefs, including topics such as why routine data was used, what worked well, the main challenges, and guidance based on what was learned.

Summary of briefs

All of the evaluations are from countries in Africa—with the exception of one example from the Ukraine—and covered a wide range of programs: two on tuberculosis (TB), one on prevention of mother-to-child transmission of HIV (PMTCT), two on anti-retroviral care and treatment (ART) for HIV, three on maternal and child health (MCH), one on family planning (FP), two on malaria control, and two on health service utilization. The evaluations often used mixed methods; however, the focus in this summary is on how routine data were used. Chief aspects of the research methods, data sources, successes, limitations and methods of addressing or preventing missing and inaccurate data are outlined in this document (Appendix B).

Routine data were used to determine disease counts and incidence, treatment cascades, program coverage levels, service utilization rates, and to assess cost effectiveness. These outcomes were assessed using various designs and analysis methods. Interrupted time series (ITS) was the most commonly used—in five briefs. Other designs were cluster-randomized control trials (cRCT), used in two briefs; descriptive analyses, used in three; before-and-after comparisons, used in one; and associations with programs and outcomes, used in one. The design chosen was largely dictated by the availability of data, as well as how the programs and interventions were delivered. One main consideration was the ability to randomize to treatment and control groups. This was possible in two instances, and in those instances a cRCT design was chosen. When randomization was not possible, ITS was often the method of choice.

The analyses in the ITS and cRCTs involved the development of regression models, frequently using generalized estimating equations (GEE) for unknown correlation structures. Designs employing ITS typically assessed the change in slope at intervention time points or during the intervention time period. Due to the lack of randomization, modeling in these studies involved important decisions around the inclusion of covariates. In the two cRCT designs examined, neither included other covariates in their models, relying on randomization to account for variation. However, they did consider clustering in their data and how to adjust precision estimates accordingly. Both examined programmatic effects by

⁷ https://www.measureevaluation.org/resources/publications/fs-20-418

comparing intervention groups to the control, and one (the Quality of Care evaluation in Mali and Senegal) was able to adjust for pre-intervention values.

Chi-Square and Fisher exact t-tests were used to examine associations in the Support Club for Children and Youth in Haiti. The main analysis examined the associations between outcome and level of involvement in the support club. Other analytic methods included the creation of treatment cascades. These were calculated in two HIV treatment studies in the Ukraine and Ghana. In Ghana, data collected on program costs enabled the evaluation to consider the costs per program for three types of recipients. The TB control evaluation in the Ukraine also completed survival analyses for TB/HIV coinfected patients.

The most common source of routine data was RHIS from the District Health Information Software, version 2 (DHIS2). Five of the evaluations reviewed used DHIS2 data. In some instances, the data used were captured in a legacy electronic system or from paper files that were later uploaded into DHIS2. Other sources of data were reviews of treatment records—that often had to be abstracted from paper files and entered electronically. This was a laborious process given the difficulties in archiving, accessing, and reading paper files.

Reasons to use routine data

The reasons cited for using routine data are that these data were the best source of data to answer evaluation questions, the availability of routine data, and improved data quality. It is also typically an inexpensive source of data. In some instances, these data may be the only source of quantitative data. Combining use of routine data with other methods, such as qualitative interviews, allows for a more complete understanding of the program and how it is functioning. Even some of the data flaws are indicative of program functionality and can point to needed improvements in essential program functioning.

The proliferation of DHIS2—now the national-scale information system deployed in 58 countries—has made it easier to access data. Data are now available faster in an electronic format and some dimensions of data quality are easier to assess. These improvements reduce the time required to abstract data from paper records and enter it into electronic databases. The other benefit to note is that DHIS2 is typically used at the national level to collect, manage, and analyze data from the district-level reporting unit on health service delivery, including some patient outcomes.⁸ Whether or not captured through DHIS2, a lot of routine information is available on geographic coverage and the time periods covered. Routine data also are collected at regular intervals, making them well suited for the ITS designs often employed by the evaluations presented here. RHIS may allow for retrospective (pre-intervention period) and prospective (after intervention) data to be used in the evaluation, depending on the evaluation design. Having pre-intervention data allowed for more rigorous evaluation designs. Finally, using routine data demonstrated its potential value and increased health workers' commitment to collecting quality data. In fact, in one of the evaluations reviewed, part of the stated goal was to improve the quality of program data.

Summary: what worked well

Several aspects of using routine data worked well in the evaluations. In some instances, access to the data was easier than anticipated. Two authors discussed the ease of access and collaboration with partners as an example of what worked well. In the evaluation of the Mali FP campaign, the

⁸ <u>https://www.dhis2.org/home</u>

evaluators were able to add a "standard form" to the government routine data collection system. This form helped them answer some of the evaluation questions and it required good collaboration and flexibility of the national partners on the study. Two studies specifically highlighted time and cost savings as another benefit. The representativeness of the national laboratory database was highlighted as a strength in the brief on performance of the national TB program in South Africa—this because all TB lab testing is conducted by the national lab and therefore fully represents the national situation, even if samples were taken in private facilities.

The ability to conduct a retrospective analysis was a benefit for some of the evaluations. A good example is the evaluation of the malaria control interventions in Zanzibar. The interventions were implemented uniformly and sequentially over several years. The routine data and its general completeness over time allowed for assessment of how each malaria control activity contributed to reducing malaria cases. The brief on the evaluation of the impact of free healthcare in the Democratic Republic of the Congo (DRC) showed that using very recent retrospective data could inform the impact of the policy in near-real time. Also, of note, both this study and the one in Zanzibar that is referenced above showed that the routine data were relatively complete without a lot of missing data—which is often not the case with routine, HMIS data. The evaluations that relied on routine data specifically set up for a program—as opposed to national-level RHIS—found these sources invaluable in tracking participants.

Finally, combining other data sources with routine data into one dataset was cited as a great benefit. The Maternal Mortality Quality Improvement Project in Ghana included programmatic data from other sources. Both the Free Health Care Policy evaluation in DRC and the Malaria Control Evaluation in Zanzibar married the routine data with census data to generate incidence estimates and rates of service use. The latter also included other data sources, notably climate data, to improve the predictive power of the models.

Limitations of working with routine data

The reviewed evaluations cite many benefits to working with routine data sources but, at the same time, the evaluators encountered some limitations that should be considered. An outline of the main issues that typically affect routine data and its validity are listed below.

Missing data

Missing data affects, in a number of ways, how they may be analyzed and how findings can be generalized. Data may be randomly and sporadically missing across a dataset, which is generally the least problematic. Data may also be missing from specific time periods, geographies, or points of data collection (e.g. facilities). Often this type of missing data is due to non-reporting. Sometimes no data are reported, and sometimes certain indicators or data points are not reported while others are reported. The latter instance may occur for many reasons, but those expressed in the evaluations presented here were: lack of diagnostic or testing capabilities (i.e., a facility did not have the ability to perform a test, therefore it was not performed and was not reported), missing diagnoses from records especially in emergency situations (providers prioritized treatment over documentation of treatment), missing data due to transfer of clients from one facility to another, or sporadic or inconsistent reporting at a facility, district, or larger area with no apparent reason given.

Missing data is one of the easiest issues to detect because value fields are left empty. In a typical electronic data format with individual cases listed as rows and indicators as columns, the blanks are easy to spot, creating what is often referred to as a *Swiss cheese* appearance. In other words, missing

data cannot "hide" as a plausible value or entry. Missing data is one of the most frequently cited issues of data quality. The one exception to note in these technical briefs was with ART treatment record data. Evaluators in the Ghana continuity of care project evaluation and in the brief on support clubs for children in Haiti could not distinguish whether the value was truly missing, or the test was not even performed.

Inaccurate data

Two main types of inaccuracies are typical generally in the evaluations reviewed. The first is implausible data. While not as easy to recognize as missing data, it is typically detectable through data logic checks. The classic example of implausible data is a "pregnant male." One of the two data points recorded has to be incorrect as the conditions of being "male" and "pregnant" are contradictory. Another example of implausible data highlighted in the evaluations we reviewed are dates of treatment that pre-date dates of enrollment in treatment.

Outlier inaccuracies are data points that are outside the normal range—usually rare, and often dealt with on a case-by-case basis. They are, however, important to consider as they may skew results, especially when reporting averages. A good example of an outlier might be a body a height measurement of 7 feet for a young adolescent. While it is possible, it is unlikely. Other outliers may not be plausible. For example, a blood pressure reading of 15/10 is clearly too low for a living person. While sometimes data values legitimately fall outside of normal ranges, such an instance makes a data point suspect and warrants examination. The evaluations reviewed did not provide specific details on the identification of outliers.

Finally, errant data are those that are neither implausible nor out of range, making detection quite difficult. These errors are usually found when checking data against patient records or through double data entry and data recording procedures. There was not much discussion in the evaluations reviewed about the detection of such data; however, authors did discuss measures to prevent using errant data, as prevention is the best defense.

Changes in indicators and data collection over time

Shifts in how data are collected over time affect routine sources of data, especially as the time frame and geographic coverage of the evaluation and dataset increase. Temporal changes often affect the indicators themselves—there are additions, changes, and fluctuations. For instance, many policy changes have required the addition of new indicators into routine systems to better manage and track outcomes. An example of this is the "FP Checklist" added to the HMIS data in the evaluation of the Mali FP campaign. Before the evaluation, the essential FP indicator data were not being collected. Now, the data are being collected and will be important for program monitoring moving forward, but not retrospectively. Analysis is possible from the point at which these data came into existence, but information before that time was not captured and cannot be assessed.

There may also be changes in how an indicator is defined or captured. This could be due to a conscious policy shift in how information is captured, which is often in response to improvements in diagnostic capabilities, changes in clinical definitions, or changes in international indicators. Changes in indicator definitions and capture also could be due to improvements in standardizing definitions, consistency of reporting, and procedures for reporting (e.g., electronic versus paper, or at the facility or district-levels). Specific case studies highlighting such issues were the Maternal and Child Quality Improvement Project in Ghana, the malaria control evaluation in Zanzibar, and the TB Control Program in the Ukraine.

Fluctuations in data collection may also be problematic. Fluctuations can result in missing data when contextual factors affect the ability to document and record the data. It may also affect data accuracy if an incorrect value was recorded. Examples of such situations from the technical briefs were the Free Health Care Policy evaluation in DRC and the PMTCT service delivery evaluation in Côte d'Ivoire, Kenya, and Mozambique. The purpose of free health care was to encourage use of services for early Ebola detection, but the Ebola outbreaks caused data collection to lapse during some periods. The PMTCT evaluation cited several contextual factors that affected the data, including outbreaks of violence in Kenya. They also highlighted the variations in data quality and therefore comparability across countries, an important consideration for multiple-country evaluations.

Lack of Electronic Data

One of the main reasons given for using routine data is that now much of it is captured in electronic form through DHIS2. This was not always the case. Some of the evaluations reviewed encountered some form of data capture through hand-written charts or forms that required manual abstraction and electronic entry. This was time consuming for several reasons. The first is that these charts and or files are not typically stored in a central location. Especially when dealing with treatment records, these medical files are stored where the patient receives care. This was an issue for the Continuum of Care evaluation in Ghana, the PMTCT Service Delivery evaluation in Kenya, Mozambique, and Côte d'Ivoire, the QUARITE evaluation in Mali, and the TB Control evaluation in Ukraine.

Best practices

This section addresses best practices identified from the technical briefs and from other experiences we've had working with routine data and using them in general and in evaluation and research. Each evaluation is unique, and all routine data are also unique, which makes it a challenge to be specific. MEASURE Evaluation published a brief (see footnote 7) on considerations for using routine data on evaluations that listed data quality, usability of the data, and access to data as key considerations.⁹ These considerations are pervasive throughout the evaluations reviewed and the best practices outlined here begin with becoming familiar with RHIS in general and then move to other practical considerations.

Understand the RHIS of the country or countries of interest

Many evaluators and researchers may never have worked with routine data, so the first step is to become familiar with RHIS in general and specifically for the country where the evaluation will take place. It is helpful to know how data is collected, transmitted, aggregated, and used. A good place to start is with MEASURE Evaluation's RHIS curriculum for a basic understanding of RHIS.¹⁰ This curriculum covers data generation, data management, data strengthening, and reform. Understanding data flow, for example, is important to understand how data is transmitted from one level of the health system to the next (Figure 1). Many countries are now using DHIS2 for data management and transmission but there is great variation on when data are entered into the system. In the example below, paper forms are used at the community and facility levels and these data are aggregated and entered into DHIS2 at the county level. But in some countries, electronic entry into DHIS2 is done at the facility level. Another good source for general RHIS knowledge is the Data Management Standards for RHIS.¹¹

⁹ https://www.measureevaluation.org/resources/publications/fs-20-418

¹⁰ https://www.measureevaluation.org/our-work/routine-health-information-systems/rhis-curriculum-modules

¹¹ https://www.measureevaluation.org/resources/publications/ms-15-99

Figure 1: Example of data flow.



Country-specific information is also available, although not always easily accessible. Common documentation sources to provide country-specific information include: the HIS strategic plan; HIS

policy; health sector or program performance reviews; annual health statistics reports; core health indicators reference sheets; RHIS guidelines and standards for data collection, reporting, and analysis; PRISM assessment results; and DQA and RDQA results. The PRISM and DQA or RDQA results provide a sense of problem areas and possible indicators that may be problematic along with the overall performance of different administrative units in the country. Having a good contact at the national ministry of health (MOH) is helpful in obtaining this information.

Another major issue is getting permission and access to the data. In our review, the evaluators or their organizations had long-standing relationships with MOH, or another arm of their organization was implementing an HIS intervention that could help facilitate access to the data. We have found huge variation across countries in getting access to data. Some countries are much more willing to share while others guard the data more closely.

Box 1: Understanding indicators

Understanding the timing of the reporting of indicators is important because not all indicators have the same reporting schedule, i.e. some are reported monthly, quarterly, annually. Indicator definitions and how they are collected can change over time.

Some indicator calculations need population data for denominators. Accurate denominators is another ongoing problem with RHIS. In one country, population estimates were only available at the district level and not the health facility level. In another, the regional government did not trust the national population estimates for their region and used their own conversion factors to estimate population.

To address this in maternal and child health, D4I conducted an analysis adjusting numerators and denominators in RHIS using a nationally representative survey and Census data in Uganda. It found that this method worked well for some indicators but not all (paper under review).

These challenges are illustrated by other MEASURE Evaluation and D4I activities not included in the technical briefs (Box 2).

Box 2: Challenges accessing data

- One MEASURE activity in Tanzania required access to the databases of several sectors and agencies, all which had their practices in datasharing. Permissions were easy for some of the data sources but not for others.
- In Zimbabwe, the MOH gave access to district level data but not health facility level data. The intervention was also rolled out at the ward level (which is below the district) but the MOH also did not give access to ward-level intervention data.
- In Côte d'Ivoire, a request to access the entire data base was denied by MOH who requested a list of data elements and time periods be submitted. Getting the correct data required a significant amount of back and forth between the evaluators and MOH which delayed the activity.

Guidance

- Familiarize yourself with RHIS in general
- Obtain as much information as you can for the country, either online or from an in-country contact. For example, look for the HIS policy or PRISM results. Some of this information can be found in the HIS country profiles¹² provided on the HIS Strengthening Resource Center.
- Determine how to get permission for access to the data.
 - One-way access has been addressed is by having a local coprincipal investigator (PI) but this also has its own difficulties.
 - Another option is to go through a World Health Organization country office to try to get access.

Understand the RHIS context

HIS across the world have evolved in unique ways despite similar interventions implemented. It is important to understand the history and context in which the data have been collected, particularly if the evaluation covers a long time period. In the evaluations reviewed, there were several instances of changes in how data was collected (paper-based to electronic), in the electronic systems, or in the forms that were used in health facilities. In some cases, indicator definitions changed. In another evaluation that used routine data in Tanzania, districts had been split up during the timeframe of the evaluation. All these factors can affect evaluation design, sampling strategy, and data collection. Some of this contextual information can be gleaned from the background materials mentioned above (i.e., RHIS guidelines) but if not available, it is important to find some source for context.

Other factors outside of the RHIS and the health system can also affect the quality of RHIS data. Anything that will disrupt the delivery of services—disease outbreaks like Ebola, natural disasters, labor disputes where data is withheld to extract concessions, or violent conflict—will impact data. Health facilities may shut down, become damaged, lose electricity, or people may be afraid to seek services. We expect the current COVID-19 pandemic will have serious impacts on other health services to an extent we can't yet envision.

Guidance

- Review background material for contextual information that may affect the quality of data or the health outcome of interest
- If not available, create a list of questions, such as:
 - During the evaluation period, have there been changes to the way the indicators of interest have been defined?
 - Have there been changes in the time period in the way data have been collected?

¹² <u>https://www.measureevaluation.org/his-strengthening-resource-center/country-profiles</u>

- Have there been any changes to administrative alignment during this time?
- Are there any expected changes to administrative alignment during the evaluation?
- Have there been any contextual disruptions that may have affected service delivery, stockout of required commodities (e.g., vaccines or therapeutics), or data entry?

Understand the specific data source before designing the evaluation

RHIS comprises various data sources that present their own opportunities and challenges. We should be familiar with the peculiarities of the data source(s) intended to answer the evaluation questions. It is possible for one component of the RHIS to be more mature than another because the investment in data sources has not been uniform. You may find the routine service statistics systems is well developed or mature and well documented. However, an electronic health record (EHR) may be newer and less complete because of the shorter time of use or because of incomplete implementation across health facilities. Some health or disease programs still maintain program-specific, parallel reporting systems which would need to be accessed separately from the HMIS. Consider for each data source its usability for evaluation, levels of maturity for various sources, unique identifiers, and factors that would limit longitudinal research.

First and foremost, RHIS are set up to meet a country's information needs and not for research or evaluation. The evaluator has no ability to change how the data is collected or the indicators collected nor can the evaluator determine what kind of data each register collects, i.e., case-based or visit-based. For example, ANC case-based data would include information on individuals and track information for each patient. A visit-based register would track the number of visits regardless if they were unique or repeat service clients. These differences may limit or rule out that data's usefulness for evaluation.

The data may also not be extractable in a way that is easy to use. In one evaluation using EHR data for prenatal care services in southern Africa, the data could only be extracted from the system in a long format, where a single ANC visit for one patient could result in five or six rows for each service that was provided (for example, one row with background information and CD4 count, one row with background information and syphilis test results, etc., (see Figure 2). This format made it a challenge to reshape the data into a database that captured all the information in one row.

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Figure 2 Example of FHR data showing multiple records for one patient

	А	В	С	D	W	Х	Z	AA	AB	AC	AE	AF
		Date Of										
1	PatientNumber	Visit	WHOStage	CounselledOnEIMC	TBScreeni	TestName	Result	GenericName	Unit	Form	Route	Strength
2	308048787	7/17/2017	I	TRUE	Non-React	ALT	9	Co-Trimoxazole	mg	Tablet		800
3	308048787	7/17/2017	I	TRUE	Non-React	AST	21	Ferrous Sulphate Co	mg	Tablet	PO	200
4	308048787	7/17/2017	I.	TRUE	Non-React	AST	21	Folic Acid	mg	Tablet	PO	5
5	308048787	7/17/2017	I.	TRUE	Non-React	AST	21	Tenofovir,Lamivudine,Efavire	mg	Tablet	PO	300

In another activity, the routine data was provided in Excel but without commas. Instead, there were spaces where commas would be (see Table 2). An Excel formula was used to convert the blank spaces to a comma, but it was a tedious process to apply it to every cell. This was time-consuming but necessary in order to analyze the data.

District	Jan to Mar 2015	Apr to Jun 2015	Jul to Sep 2015	Oct to Dec 2015	Jan to Mar 2016
District 1	2 334	1 841	2 620	2 866	2 617
District 2	4 121	4 837	5 650	7 549	5 606
District 3	3 294	3 203	3 735	4 214	3 735

Table 2: Sample data received from DHIS2

Unique identifiers can also be an issue with various data sources. The increased use of EHRs in health facilities has opened opportunities to conduct research but can still be problematic, for example, if the unit of analysis is the individual and the study design is longitudinal. EHRs should minimize the duplication of individual records observed in paper-based forms and registers but there are still problems with unique identifiers or patient numbers that are used every time to identify an individual coming in for service. The evaluation may need to merge various data sources (e.g., HIV testing data, ANC registers, child registers) and the issue of unique identifiers may also be a problem depending on how the unique identifiers were created—for example, systems that use first and last names in combination with other identifiers, duplicate IDs are still possible—for instance when patients or clients don't remember their number or forgot their ID card bearing their number.

Different data systems also pose issues of interoperability. Given the different timing of when RHIS components have been established and implemented, systems were not developed to "talk" to each other. There may be a logistics information system that tracks commodities, another system that tracks the service statistics, and one that tracks human resources. We have also observed instances where an older system for HIV testing, for example, is not interoperable with a new system. There may have also been a switch from paper to electronic data management that will require different methods of data abstraction.

Guidance

- Find out how data can be extracted (electronic or paper-based) and get a sample of data to inspect
- If there have been changes in systems used to collect and transmit data, is there a way to link these data sources?
- If multiple RHIS data sources are used and need to be merged, ask:
 - Is there a way to extract the data that facilitates this?
 - Are there unique identifiers that can match patients, health facilities, districts, etc.?
 - How were the unique identifiers created?

Data quality protocols

Having a data quality protocol is a best practice for all evaluations. In this case, we are referring to both the data quality of the RHIS but also the quality of data that is abstracted from paper forms. A substantial amount of work has been made to improve the RHIS data quality, so a good first step is to look at the data quality principles for RHIS. For example, the DQR toolkit uses four dimensions of data quality.¹³

- Dimension 1: completeness and timeliness of reporting for districts and facilities, data element completeness, and the consistency of reporting completeness over time.
- Dimension 2: internal consistency of reported data; this covers presence of outliers, consistency over time, consistency between indicators, and the consistency between reported data and original records. (i.e. source documents).
- Dimension 3: external consistency—i.e., agreement with other sources of data such as surveys.
- Dimension 4: comparisons of population data (a review of denominator data used to calculate rates for performance indicators).

¹³ https://apps.who.int/iris/bitstream/handle/10665/259224/9789241512725-eng.pdf?sequence=1

An application available to install on DHIS2 can examine completeness and timeliness of reporting, completeness of data, consistency of data (over time and between related indicators) and look for outliers. Data timeliness and completeness may be a concern if the evaluation needs real-time data. Reporting often is late or lags, even with electronic systems like DHIS2. The WHO Data Quality Tool can be used as a first step in evaluating the quality of indicators and data elements selected for the evaluation. The DQR already mentioned has an Excel-based tool that does much the same thing.

It is important to determine what the typical reporting lag time is for the country of interest. Table 3 shows an example in which the completeness of data increases the further one gets from the reporting deadline (in other words, late reports are often more thorough—see the percentages in red in Table 3). In this example, only 24 percent of facilities had submitted reports for May by June 11, whereas 86 percent of facilities had reported by July 2. The lag may even be greater in countries using a hybrid method of paper and electronic systems.

Month/Year	HF	Denominator	Percent of HFs with value for cases received
Jan 2020	12,725	13,043	97.6%
Feb 2020	12,703	13,043	97.4%
Mar 2020	12,642	13,043	96.9%
Apr 2020	12,352	13,043	94.7%
May 2020			
as of June 11, 2020	3,234	13,403	24.8%
as of June 22, 2020	9,657	13,405	74.0%
as of July 2, 2020	11,216	13,046	86.0%

Table 3: Completeness reporting lag

Data completeness

The first step in dealing with missing data is to determine why it is missing. Are data missing randomly or systematically? If data are missing systematically, this could introduce a bias, and the bias will increase with the proportion of the data missing. If data are missing randomly, that fact may not lead to bias, but it can reduce power if missing data are simply excluded from analysis.

Data might be missing systematically if the data are not reported for a period of time, in a particular geography, or by a type of facility or about a type of patient. Data could appear to be missing at random, but then upon investigation one might find that cases in a dataset with certain characteristics are more likely to have missing data. This possibility was noted in the QUARITE evaluation in Senegal and Malawi where emergency cases were more likely to have poor documentation of patient diagnosis and outcome and were missing in the evaluation dataset more frequently. Emergency case outcomes are likely to differ from non-emergency cases, which would introduce a bias.

There are a number of approaches for addressing missing data. The best approach will depend on the extent to which data are missing and the likely cause for the missing data. The simplest approach is to ignore missing data. If a small number of cases are missing, there is no risk of bias and very little loss of precision by exclusion. Another time at which one might ignore missing data—even if the data are missing systematically and even if the volume is sizable—is when there is no reasonable way to estimate the data. Data missing for certain geographies known to be different than other parts of the country, for example, probably cannot be estimated with accuracy. Often evaluators will exclude any data from the region and report this as a limitation, with findings only applicable to the geographies contributing data. The Maternal and Child Health Outcomes evaluation in Kenya ignored all non-reporting facilities, the FP campaign evaluation in Mali ignored large percentages of missing data and

accepted that this made the evaluation less rigorous, and the Quality Improvement evaluation in Ghana decided that some indicators with large proportions of missing data simply were not usable in the evaluation analysis. Box 3 below details the cleaning procedures of RHIS data from the Democratic Republic of Congo for an ongoing D4I evaluation.

Box 3: Assessing data quality for DRC evaluation

One use of DHIS2 data is to evaluate changes to a time series for specific data elements collected through the RHIS. Depending on the context of the evaluation, a difference in analysis may be useful to discern the effects of specific policy changes or of an intervention with either immediate or downstream effects on health service utilization. The D4I project was tasked, in part, to evaluate efforts meant to influence rates of health service utilization in targeted provinces of the DRC. In the DRC, DHIS2 has been in use since 2016 and improvements to data completeness and quality have been observed over time. The D4I evaluation made use of DHIS2 data to identify control health facilities using propensity score matching for subsequent use in an event evaluation. The following points describe the process D4I used to prepare the time series pulled from DHIS2. This process may be adapted for use elsewhere.

- The project identified well-reported data elements from DHIS2 by visualizing monthly values for the number of health facilities reporting a specific data element, overlaid with the actual time series values for that data element. Additionally, an R package called "visdat" can be used to help visualize what is missing from the time series.
- 2) To establish the initial data set, well-reported data elements identified in the step above were pulled from DHIS2 at the health facility level, covering an 18-month pre-intervention period.
- 3) The DRC DHIS2 contains health facilities and structures that never report data and so were dropped from the data set.
- 4) The DRC DHIS2 also contains blank cells for facilities which may have reported values for other data elements in the same month. This is challenging to address as it is impossible to know if these are blank by accident or if they should actually be zero counts.
 - a. To fill in the blanks, the same month for all selected data elements was reviewed to see if there was at least one value reported. If even one data element had a reported value, then blank cells across all the other data elements for that month were replaced with a zero. The underlying assumption was that the facility had at least one value reported for the month in question, so it must have submitted a report and the blank cells should actually represent zero counts. Including "cases received" or its equivalent in this process is highly recommended.
 - b. If there were no values reported for any of the data elements for the month in question, it was assumed the facility truly did not submit a report for that month and blank cells were left blank.
- 5) Even though data from DHIS2 are count data and not—strictly speaking—continuous, apparent outliers were deleted if they were beyond +/- either 3 or 4 standard deviations from the mean. This process removed values that were likely data entry errors. There are a few R packages (e.g., "AnomalyDetection" or "anomalize") that may help with this process.
- 6) Individual data elements (all associated monthly columns) and facilities (records) that had low reporting rates within the times series were dropped from the data set if at least one-third of the data were missing. Each series of data elements was assessed for exclusion based first on completeness and then individual health facility records were assessed for exclusion.
- 7) After completing the data processing and cleaning steps described above, the D4I project had created a data set that included data elements with 6.5 percent missing data. These steps resulted in uniform "missingness" across each set of data elements.

In addition to these procedures outlined in Box 3, a DQA was conducted in 2019 during health facility baseline data collection on eight data elements (i.e., first and fourth antenatal care visit, new acceptors of family planning, insecticide-treated nets distributed at first ANC visit, cases of simple diarrhea in children under age five, malaria, pneumonia, and administered doses of Bacille Calmette-Guérin [BCG]). The analysis is ongoing and, thus far, there are no significant differences between the data on the registers and what is available in DHIS2. Reporting rates vary by service type, (e.g., ANC is always reported but other services like BCG vaccinations were reported at a much lower rate). Reporting rates

also varied by province within specific services. Conducting a DQA is not always possible to do but is helpful in predicting any bias in the data.

Imputation to deal with missing data

In some instances, missing data may be determined from another source. It is an uncommon situation, but if there is a secondary source of information, it can and has been used to determine or estimate the missing information. For example, in the Maternal and Child Health Outcome evaluation in Kenya, the evaluators used Demographic and Health survey data to predict missing the values. Another approach is to impute the missing data, although this is not straightforward and can have heavy computational demands. The approaches for imputing include (1) inserting non-missing mean values for the missing values, (2) randomly or systematically selecting another value from a non-missing case (usually similar to the missing case in some way), (3) interpolation or extrapolation from other non-missing values, or (4) estimating from a regression equation formed from non-missing cases. Box 4 below provides some considerations when imputing. Imputation can be helpful but requires certain skills and computational power to accomplish.

Quality protocols for data collection and abstraction

It may be necessary to manually abstract data in cases where paper records are still being used. This was the case for a few of the evaluations reviewed. People collecting the data may be either hired research assistants or health facility staff that are paid a stipend to abstract the data from individual records, tally sheets, or registers. For example, the QUARITE evaluation hired nurses and midwifes to collect clinical data using a standard form to collect maternal characteristics, prenatal care, labor and delivery, diagnosed complications, and the vital status of both mother and child upon discharge from hospital for each patient giving birth in the health center.

Regardless of who collects the data, it is important to have a set procedure to abstract the data and assess quality of the data being collected. Use the existing resources like the DQR and PRISM assessment tools and reports to develop a protocol. There should also be a standard procedure to check the data once it is entered into an electronic database. Dumont provides details on how this was done for their study.¹⁴

Guidance

- Become familiar with standard metrics to assess RHIS data
- Identify what the reporting lag is for the data sources used in the evaluation
- Document all decisions made during the process of cleaning the data
- Consider imputing missing data if possible
- Calculate your own indicators if numerators and denominators are available
- If data abstraction from paper records is needed:
 - $\circ~$ Hire people familiar with the health system and the HIS. This can be clinicians who work in health facilities or M&E officers.
 - Review DQA/RDQA methodology to help draft data abstraction methods
 - Develop a clear method to abstract the data to train and monitor the data collection process.

¹⁴ See page 12, https://www.ceped.org/IMG/pdf/birth_day_prize.pdf

• Develop a protocol to assess the quality of the data being abstracted and entered into an electronic database.

Determine if other sources of data will be required to meet the evaluation's objectives

The majority of the evaluations reviewed used additional data sources, including primary data collection, to answer all of the evaluation questions although our review focused on the use of RHIS. Additional data may be of particular importance if the goal of the evaluation is to provide recommendations on how to improve a program. Such an evaluation often requires information from service delivery professionals, program implementers, or beneficiaries. Qualitative data (such as interviews and focus group discussions) can also help explain some of the patterns that are observed. Additional data collection has cost and time implications. Therefore, they should be considered but, in the end, may not be possible.

Other data sources may be needed if the analysis involves construction of regression models. Covariate data also may be important to control for seasonality in routine data and health outcomes, gaps in collection, and under-reporting. Covariate data may come from a variety of sources.

Guidance

- Determine if additional data is needed to answer all the research questions
- Seek out secondary data sources that may exist, for example climate data, population surveys, service provision assessment surveys, PRISM assessments, etc.

Box 4: Considerations for multiple imputation

After completing the steps described in Box 3, any remaining missing values may be addressed through a process called multiple imputation (MI). MI can be performed with most statistical packages including R. MI literature recommends rearranging data to a wide format for the imputation step.

 The default number of imputations conducted by the R "mice" package is set at five. Alternate guidance suggests using a number of imputations that match the percent of missing data across the data set to be imputed. So, for instance, if 20 percent of the data are missing, 20 imputed data sets would be desired.

2) If you do not parallelize the process across available core processors on your computer, the imputations will run one after another in series. This can be a lengthy process, depending on the specifications of your computer and the size of the data set to be imputed. The D4I project noted that one data set required about 15 hours to run a single imputation. However, parallelizing across n-1 available core processors resulted in multiple imputed data sets that finished simultaneously.

3) The number of iterations to run within each imputation should also be considered. Ultimately, the mean value from each imputation for each variable being imputed should converge around a single value (or fluctuate slightly around that value). Generally, more iterations result in better convergence; and trace plots can help assess whether or not convergence has been reached. The R "mice" package suggests 20–30 iterations, but there are time and computational demands to consider.

4) Estimates derived from multiply imputed data sets should follow "Rubin's rule" (i.e., pooled estimates should be taken when an analysis uses multiply imputed data sets).

Determine best method for analysis

The evaluations reviewed used a variety of methods to answer the research questions. Several of the authors indicated they had a method in mind when they first started looking at the data. The statistical methods included bivariate and multivariate analysis, all depending on the goals of the evaluation.

Guidance

- Review other examples of analysis methods used by other evaluators or researchers
- Assess whether your team has the necessary data analysis skills to conduct the analysis

Conclusion

Routine data can be a valuable source of information to assess the performance and impact of health programs on outcomes but are accompanied by many essential considerations. There is no perfect solution—each approach must be tailored to goals of the evaluation and the nature of the data. Evaluators may need to assess the data first and present a summary of it to donors who suggested the use of routine data so that all parties are aware of possible limitations.

Best practices highlighted in this document began with understanding the nature of RHIS in general. The RHIS does not function alone and extraneous factors and the health system structures can affect how and if data are collected. Unique details about each data source also need to be questioned and understood. Finally, evaluators need protocols to assess, clean, and prepare RHIS data for analysis. Fortunately, there are a growing number of examples that future researchers and evaluators can draw from when planning for evaluations.

Appendix 1: RHIS briefs

Name of study	Country	Type of program evaluated	Evaluation design/main analysis	Source of routine data	Main outcomes	Worked well	Main data limitations	Treatment/ prevention of missing data	Treatment/ prevention of inaccurate data	Other aspects of data quality and use
1. Strengthening the Continuum Care Project in Ghana: Midterm Assessment	Ghana	Comprehensive Care program to reach key populations. Three models were assessed.	- Mixed methods - Routine data were used to calculate treatment cascades and estimate cost per beneficiary	- Facility ART records -Program database set up to track participant outcomes	- KPs follow-up at 3 and 6 months, and their clinical profiles - Cost per beneficiary for each model	Collection of cost data The database set up for the program worked well to track enrollees	- Large chunks of missing data in ART files and some costing data - No way to verify ART data - No way to distinguish between a missing clinical outcome or loss to follow-up	arge chunks of missing Ita in ART files and some Isting data - Missing ART data was treated as null or service not occurring Missing salary data Vo way to verify ART data Vo way to verify ART data vo way to verify ART data vo way to distinguish tween a missing clinical trocome or loss to follow-up		ART data were not collected electronically, they were extracted from the 'paper' files stored at the clinics
2. Improving Maternal & Child Health Outcomes in Kenya: Impact of the Free Maternity Service Policy on Healthcare use and Lives Saved	Kenya	Free maternity services	- Interrupted time series -Used OLS regression with time- series specification to examine effects before/after policy introduced	- District level health facility data in Kenya through DHIS2	- Use of maternity services - Impact on maternal and neonatal outcomes. This involved using specific software to estimate the lives saved.	-Accessing data -Model estimation - Data for specific indicators missing - Data for specific indicators - Did not use i - Did not use i - For some an DHS data wer predict missin and some der data were ext		 Ignored non- reporting facilities Did not use indicators with lots of missing data For some analyses DHS data were used to predict missing values, and some denominator data were extrapolated 	- Detected outliers using box-plots. Replaced outliers with mean values (excluding outlier data) for the same indicator	Used software to estimate deaths averted, but much of the input data required were not in DHIS2. Estimated imperfectly from other sources.
3. Impact of a Systems Engineering Intervention on PMTCT Service Delivery in Côte d'Ivoire, Kenya, and Mozambique: A Cluster Randomized Trial	Côte d'Ivoire, Kenya, Mozambique	Five-step package to improve PMTCT	 Stated as a cluster- randomized trial, but unit of randomization and analysis are the same, and analysis did not control for clustering. Randomized facilities to one of two study arms stratified by country. 	- Facility registers - Denominator data to assess coverage levels at the facility level were estimated from other sources in Kenya.	- Difference between mean coverage levels of key indicators between intervention and control.	- Access to the data and collaboration among study partners facilitated the work.	 Lack of unique patient identifiers limited to a cross- sectional analysis. Various levels of data quality/control in each country - Various levels of data quality/control in each country 		- Same as for missing data	- Contextual factors affected data collection - ANC registers updated in Côte d'Ivoire
4. Can a Quality Improvement Project Impact Maternal and Child Health Outcomes at Scale in Northern Ghana?	Ghana	Evaluation of a QI intervention to improve maternal and child health	 Interrupted time series Multivariate analysis models were constructed with GEE (due to missing data and clustered data) Sensitivity analysis performed 	- Routine facility data entered into DHIS1/ DHIS2. - Programmatic information was collected at the facility level to include things like type of intervention, presence of a QI team, and its size.	- Examined intervention associations with ANC, skilled delivery, and underweight infant outcomes.	The inclusion of the program data added greatly to the richness of the analysis dataset. The quantity of missing data, esp. for child healt indicators (31-43%) mea they were unusable. The shift from DHIS1 to DHIS2 led to fewer facili reporting denominator data required to calcular maternal indicators. Assessment of death v limited to those occurrin within facilities.		 Data quality trainings and routine quality checks. GEE used in analysis to limit impact of missing data. 	- Same quality trainings and routine quality checks as for missing data. - Inaccurate/ implausible data were not discussed as main issues.	- Shift in how data were collected between DHIS1 and DHIS2 affected the data quality. -Because of this, some maternal indicators could only be calculated for DHIS2 reporting period.
5. Assessment of the 2017 National Campaign for the Promotion of Family Planning Mali	Mali	National FP campaign	- Mixed methods - Routine data used descriptively	-DHIS2 health statistic data; standard form was added for 2017 evaluation to ensure FP indicators captured	- Number of FP acceptors, and by method for age and sex. Number counseled in FP by age and sex. - Tallied days of stock-outs - Source of information about the campaign	- Adding the standard form to ensure capture of FP information - Evaluation seemed to engender commitment to improve routine data collection systems.	 Only 39% of facilities reported. Of those reporting, incomplete data and late submissions were a problem Non-uniformity in facility- level data collection 	- There were a lot of missing data, biasing results. Missing data were excluded from analysis	- The accuracy of the data was not assessed - It is suspect, as standard definitions of indicators varied. Also, some reporting of community events may be incorrect due to lack of first-hand knowledge of these events.	- The data in this evaluation were very poor, but were deemed the only cost-effective source.

Name of study	Country	Type of program evaluated	Evaluation design/main analysis	Source of routine data	Main outcomes	Worked well	Main data limitations	Treatment/ prevention of missing data	Treatment/ prevention of inaccurate data	Other aspects of data quality and use
6. Quality of Care, Risk Management, and Technology-based Maternal Mortality in Senegal and Mali (QUARITE): A Cluster Randomized Trial	Senegal and Mali	Quality of care, risk management and technology in obstetrics to reduce maternal mortality	- Stratified, cluster- randomized design -Pre/post data with control and intervention groups - ORs reported on individual-level outcomes, assessed through multivariate regression models and using the GEE link to account for clustering in the data	 Hospital records Patient medical records Other non- routine data (from survey questionnaires and in-depth interviews) also collected 	 Assessed on 38 indicators in hospital and medical records Main outcome was maternal mortality 	- Consistency in monitoring data quality and standardized procedures for assessing quality and correcting errant data.	 Initially accessing information from records was extremely challenging due to poor archiving practices Incomplete documentation of patient diagnosis and outcomes, esp. in emergency situations. No inferences may be drawn outside of the hospital system 	- Data were extracted directly from hospital and patient records by study staff and transferred to national coordinating center for double-entry into electronic format. Regular quality control and verification through 3-stage process that also allowed for data oddities to be corrected by facility staff	- Same as for missing data	
7. Evaluating the Impact of Interventions in Zanzibar, 2000–2015: Report Prepared for US President's Malaria Initiative	Zanzibar, Tanzania	Malaria control program	- Interrupted time series - District-level monthly incidence compared by intervention period, including pre- interventions - Modeled district- level lab-confirmed case count using a random effects, negative binomial model that accounted for several covariates - Cases averted were also estimated	- HMIS data reported by health facilities, now captured in DHIS2 - This was combined with census data to generate incidence rates and climate data to improve model predictions of malaria incidence.	- Lab-confirmed malaria incidence rate ratio to assess changes in the trend at the various 'break-points' as well as the trend itself.	- Overall levels of reporting were quite high with 98.3% of the district months reported - Estimating cases averted was not the main outcome, but this outcome helped quantify the human impact	 Used data over a very lengthy time period (15 years), and changes to data collection over time limited usability Some variations in reporting over time. Data regarding intervention uptake was not available at the facility level, preventing a dose response assessment 	 Missing data were problematic in several ways. In 2011, in some places, 62% of the number of tests performed were missing. While this was not the main outcome, it was a covariate. Laboratory-confirmed testing was mostly absent for early years, potentially underestimating true burden of disease. 	- Facilities came into and out of existence over the 15-year assessment period. This could bias findings due to shifts in data collection and reporting methods, but we found no evidence of that being the case.	Note: Absence of laboratory testing in early years would bias towards the null
8. Impact of a Free Health Care Policy in the Democratic Republic of the Congo during an Ebola outbreak: An interrupted time- series analysis	DRC	Free health care policy to encourage use of health services for early detection of Ebola	 Mixed methods Routine data were used in an interrupted time series analysis Data were compared over 3 intervention periods Analyzed each outcome separately Modeled with a two- level mixed-effects negative bionomial regression, adjusted for clustering. 	-DHIS2 facility- level data from both Ebola- affected zones and those adjacent - Count data from DHIS2 were combined with census data to generate rates of services	-Level and slope over the time periods for each outcome {rate of total clinic visits, use of maternal health services, institutional deliveries, postnatal care, vaccination, and use of infectious diseases services}	 Able to assess in near real-time how policy changes affected use of services While some indicators were missing too much data to be included, most of the health service delivery data were complete 	- Limited by availability of data; constrained to indicators that were relatively complete - Data quality affected by outbreak as missing data increased for two indicators in particular - Data were only available for one facility type and excluded private service delivery	 Several efforts were implemented to improve data quality—these included incentives for report completion and submission. Missing data were generally excluded from analysis 	- Same for missing data, though unclear how errant data were detected or handled	

Name of study	Country	Type of program evaluated	Evaluation design/main analysis	Source of routine data	Main outcomes	Worked well	Main data limitations	Treatment/ prevention of missing data	Treatment/ prevention of inaccurate data	Other aspects of data quality and use
9. Support Clubs for Children and Youth in Haiti Living with HIV: Technical Brief on a Case Study	Haiti	Support clubs for HIV-positive children to encourage contact with health services and adherence to medications	 Mixed methods Routine data were used to evaluate the association between exposure level/ involvement in Kids Club with behavioral and clinical outcomes. Strength of associations were examined with fisher exact t-tests and chi- square tests. 	- The project monitoring database with data on all program enrollees - Clinic treatment records	Enrolment by year, club type, and level of club, and in relation to participant characteristics - Three main clinical outcomes - Self-reported full adherence to ART doses and viral load suppression— in relation to level of club participation	 Cost effective approach for substantiating findings from other methods used in this evaluation. Program managers gained a great appreciation of the importance of the data they had been collecting 	 Obtaining access to the data was difficult at first due to recent changes in data protection Large quantity of missing data, and no ability to distinguish between missing clinical outcome or loss to follow-up. No control data 	- Lots of missing ART records per child (68% had at least one of the six forms expected). - Incomplete data on available records (40% were missing disease status classification). - Some of these issues were due to ART transfers and re- assignments of new patient IDs.	 Little information on data quality checks of data entered into the clinic records and project monitoring database. Data range checks, key field verification. Very few inconsistencies or implausible values. 	-Creating the analysis dataset, which linked project monitoring data and that from clinic records, was a fairly intensive process. -The clinic records created non- standard text fields that had to be hand-coded
10. Initial Evidence of Reduction of Malaria Cases and Deaths in Rwanda and Ethiopia Due to Rapid Scale-Up of Malaria Prevention and Treatment	Rwanda and Ethiopia	Evaluating the effects of malaria control efforts in two countries	-Routine data used measure the effect of control programs on malaria disease burden. -Pre-intervention data were used to model expected malaria burden without intervention. Greater than expected differences in outcomes between actual and predicted were attributed to the intervention. - Other outcomes relied also on data from MICS and DHS surveys.	- Outpatient and inpatient records	- Change in malaria cases (including death) in children <5 years of age	- Time and cost savings using routine data	 Only public-sector facility data available, excluding examining the burden of disease outside the public health sector Analysis methods limit ability to attribute reductions in malaria cases and deaths to malaria control efforts 	- Facilities were excluded if they did not have complete data for the study period. In Rwanda, only 1 facility was excluded; in Ethiopia, seven of 20 facilities were excluded.	- Inaccurate data were not discussed	
11. Assessing Healthcare Quality Using Routine Data: Evaluating the Performance of the National Tuberculosis Program in South Africa	South Africa	TB Quality of care evaluation	Trend study Second specimen, monitoring tests and DST (drug sensitivity testing) analyzed at varying time windows. Correlations were measured using Pearson's paired correlation coefficient and the differences in testing rates were determined using OLS regression	- Retrospective national laboratory data on TB test results before PCR available	-Proportion where diagnosis based on two patient specimens, proportion adhered to treatment monitoring guidelines, and completion of drug sensitivity testing among those not responding to treatment	- Collaboration with the National Health Laboratory Service	 All TB lab testing is conducted by the national lab even if treated in a private facility, so is nationally representative. Database does not include full measures such as patient demographics, socio-economic factors and comorbidities Poor patient record linking, leading to the underestimation of the testing rate 	- Facility IDs were often missing and data were dropped from the analysis	- Inaccurate data was not discussed	

Name of study	Country	Type of program evaluated	Evaluation design/main analysis	Source of routine data	Main outcomes	Worked well	Main data limitations	Treatment/ prevention of missing data	Treatment/ prevention of inaccurate data	Other aspects of data quality and use
12. Impact of a District-Wide Health Center Strengthening Intervention on Healthcare Utilization in Rural Rwanda: Use of Interrupted Time Series Analysis	Rwanda	Evaluation of program to improve utilization of rural health care services	 Interrupted time series Routine data was used to analyze the impact of the intervention on maternal health, outpatient visits, and childcare. Propensity score used to account for differences in health center characteristics Generalized least squares (GLS) models used to assess each outcome 	- Rwanda health management information system (RHMIS) – Merging of a SQL-server database and DHIS2	- Facility delivery rates, outpatient visits rates, and referral rates for high risk pregnancies	- Propensity score matching and use of five years of monthly time series HMIS data addressed some of the data challenges	- The merging of the database resulted in missing data (not all outcomes and potential confounders could be merged)	- Control facilities with more than four missing HMIS reports were not included	- Inaccurate data was not discussed	- During the study period, the data management system was upgraded from a legacy SQL database to DHIS2 in 2011. The databases were merged.
13. Strengthening Tuberculosis Control in Ukraine: Evaluation of the Impact of the TB-HIV Integration Strategy on Treatment Outcomes	Ukraine	Integrated TB/ HIV treatment approach	 Mixed methods Routine data used to calculate treatment cascades Cox proportional hazard analysis used to examine complete survival of HIV- coinfected patients and TB-coinfected patients separately 	- Medical charts and electronic registers from TB and HIV facilities	TB treatment adherence (treatment default, treatment success and treatment failure, death, and transfer)	- Most of the data were readily available at the facilities - Data challenges were expected ahead of time and adequate resourcing in place to handle them.	 Indicators from routine service delivery not well suited for survival analysis Missing CD4 count and disease classification precluded their use in the survival models Extremely labor intensive to abstract hand-written medical records often stored in more than one location for a single patient. 	- Both TB and HIV clinics documented treatment data from the other service, but data were often missing and used different classifications - Disproportionate data missing from baseline; lots of data missing on important clinical indicators - Rules for imputing or handling missing data were developed and followed	 Data in TB registers entered by encounter, creating duplicate data on unit of analysis (patient). HIV registers had data on all HIV treatment, not just those at their clinic. Excess data were removed. Inconsistencies in data collection tools and indicator codes. Reconciled by reviewing patient files Implatible and suspicious data were noted; imputation and decision rules were referenced but not specified 	- Patients in both TB and HIV treatment registries could not be identified as one individual across both registries

Appendix 2: Authors of technical briefs on the use of RHIS in evaluation

Brief Title	Writer	Affiliation
Assessing Healthcare Quality Using Routine Data: Evaluating the Performance of the National Tuberculosis Program in South Africa	David Boone, PhD	John Snow International
Impact of a District-Wide Health Center Strengthening Intervention on Healthcare Utilization in Rural Rwanda: Use of Interrupted Time Series Analysis	David Boone, PhD	John Snow International
Evaluating the Impact of Malaria Interventions in Zanzibar, 2000–2015: Report Prepared for the U.S. President's Malaria Initiative	Gwyneth Vance, MPH	Consultant
Brief on Strengthening Tuberculosis Control in Ukraine: Evaluation of the Impact of the TB-HIV Integration Strategy on Treatment Outcomes	Zola Allen, PhD	Palladium
Quality of Care, Risk Management, and Technology in Obstetrics to Reduce Hospital-based Maternal Mortality in Senegal and Mali (QUARITE): A Cluster Randomized Trial	Francine Wood, MPH	Tulane University
Assessment of the 2017 National Campaign for the Promotion of Family Planning in Mali	Gwyneth Vance, MPH	Consultant
Improving Maternal and Child Health Outcomes in Kenya: Impact of the Free Maternity Service Policy on Healthcare Use and Lives Saved	Lyubov Teplitskaya, MS	Palladium
Can a Quality Improvement Project Impact Maternal and Child Health Outcomes at Scale in Northern Ghana?	Francine Wood, MPH	Tulane University
Impact of a Free Health Care Policy in the Democratic Republic of the Congo during an Ebola outbreak: An interrupted time-series analysis	Francine Wood, MPH	Tulane University
Impact of a Systems Engineering Intervention on PMTCT Service Delivery in Côte d'Ivoire, Kenya, Mozambique: A Cluster Randomized Trial	Francine Wood, MPH	Tulane University
Strengthening the Care Continuum Project in Ghana: Midterm Assessment	Gwyneth Vance, MPH	consultant
Initial Evidence of Reduction of Malaria Cases and Deaths in Rwanda and Ethiopia Due to Rapid Scale- Up of Malaria Prevention and Treatment	David Boone, PhD	John Snow International
Support Clubs for Children and Youth in Haiti Living with HIV: Technical Brief on a Case Study	Susan Settergren, PhD	Palladium

Appendix 3: Using Routine Data in Evaluation: Review of Studies Seeking to Improve Quality of Care

Part 1: Data for Impact Literature Review

Objective

Data for Impact (D4I) envisioned this activity as a review of published literature (peer-reviewed articles, program reports, and grey literature) to identify evaluations or studies in which routine health data—routine health information systems (RHIS)—were used as an important source of data. We placed particular emphasis on evaluations that focused on improving quality of care but also considered other outcomes.

Methods

In this exercise, routine health data was defined as data collected at regular intervals (daily, monthly, etc.) at public, private, and community-level health facilities, and institutions. These data included vital registration, sentinel reporting, community-based services statistics, health facility services statistics, and program reporting systems.

Search terms

Search terms included "routine health data," RHIS, "routine health information systems," "routine data," "routine health management information systems," and "electronic health records." Additional terms were "evaluation," "assessing," "assessment," "impact," or "evaluate."

During September 2019 to December 2019, we conducted a search for peer-reviewed articles in English using Google Scholar, CINAHL, PubMed, Academic Search Complete, EBSCO, and PsycINFO. After this initial search, we reviewed articles identified by another researcher at MEASURE Evaluation on the use of existing data in evaluations. Lastly, we cross-checked the reference sections of relevant peer-reviewed articles to identify additional articles or reports.

The inclusion criteria were:

- a) The study must collect routine data and the analysis must use routine data
- b) Some aspect of the study or intervention must focus on improving quality of patient care
 - We considered quality of care to include interventions that sought to improve care by training health providers, by improving services, or by improving the equipment used by the health facility.

Articles and reports were excluded that did not focus on quality of care, that were not written in English, and that were conducted in developed or in upper- or middle-income countries (e.g., the United States, Canada, Europe, China, etc.). Additionally, articles and reports were excluded if the study collected routine data but did not use it in the analysis.

Results

The titles of 310 articles and reports on evaluations that used routine health data were identified and screened. One hundred and seventy-four articles were excluded because the evaluations were either conducted in developed or upper- and middle-income countries, did not specify that routine data were used, or did not use the collected routine data in the analysis. Eighty-six articles that did not have a quality of care component were initially excluded but later reviewed to augment the findings from the review. Out of the 310 articles and reports, 50 focused on quality of care. Studies were published between 1997 and 2019. Seven articles or reports were published prior to 2000, 16 were published between 2000 and 2010, and the remaining 28 were published between 2011 and 2019. Most of these studies were single-country evaluations, four studies investigated two countries (Dumont, et al., 2013; Otten, et al., 2009; Pirkle, Dumont, Traoré, & Zunzunegui, 2013; Zongo, et al., 2015), and one was conducted in three countries (Rustagi, et al., 2016).

These studies focused on various aspects of maternal and child health. Fifteen articles focused mainly on obstetric care; nine on maternal, neonatal, and child health; 12 on HIV; and five on malaria. The remaining literature focused on neonatal mortality (3 articles), maternal mortality (3 articles), tuberculosis (TB) (3 articles), immunization (1 article), and health service utilization (1 article).

Study design and method

The majority of the studies used a pre- and post-study (before and after) design; five were randomized control trials; four were quasi-experimental studies; three were cross-sectional studies; and one was an observational study. These studies used varying ranges of methods to analyze the routine data used. Overall, most of the studies analyzed their routine data using only descriptive statistics (including proportions, percentages, or means) and based their conclusions on this method of analysis. Nine studies went further to include inferential test statistics or a test of significance (t-test, chi square test, etc.) in the analysis of the routine data collected. Only 16 of the 43 articles or reports used a form of multivariate analysis or adjusted for potential confounders.

Type of data source

Data sources used in each evaluation varied depending on the outcome and the health information system used in the study country. During the time of the review, there were many changes made to routine data collection—from almost exclusively paper-based systems to the rapid adoption of electronic systems. Most used health facility or patient records, although the type of record depended on the study outcome of interest. For example, Ediau, et al., (2013) used data from Ministry of Health facility registers (antenatal, delivery, and birth registers) and health information management systems (HIMS) reports. A study in public health clinics in rural Liberia collected routine data from TB patient registers (Wickett, et al., 2018). A few studies used more than one routine data source in their analysis. Singh, et al., (2013) collected data from health facility registers, program records (for program and facility-level information), and census data. Some studies used non-routine data sources like census data while others collected primary qualitative (focus groups, in-depth interviews, observations) and quantitative data (surveys).

Data availability was a factor for the inclusion criteria for several studies. Many studies excluded health facility data during the analysis stage due to incomplete reporting over the course of the study or issues of missing data. For example, a study in Rwanda (Iyer, et al., 2017) excluded health centers in the control group due to incomplete reporting over the study period, thus reducing the sample size for analysis. Data availability also factored into the number of outcomes that could be analyzed. Djan (1997) excluded data from the analysis because the record-keeping system was in such a poor state that the data were not meaningful. Singh excluded neonatal and infant mortality from the analysis because of data quality concerns stemming from changes in health reporting systems.

Limitations identified

Frequently mentioned or inferred limitations of routine data included:

- Issues of missing data and poor data quality (specifically, data completeness)
- Absence of health facility data when women delivered at home or in the community or sought healthcare in more traditional settings; likewise, deaths at home
- Lack of a comparison group, or means of adjusting for confounding factors

- A short study period for assessing trends (applicable to studies using time series analysis)
- Failure to control for similar interventions
- Different data quality across health facilities or countries (applicable to studies occurring in multiple countries or facilities)
- Lack of detail on the data source used—in some cases, the authors indicating that health facility records were used without naming the specific record
- Missing patient data in some routine data records, thus affecting the analysis method that could be used

Other articles or reports not focused on quality of care

Although this review focused primarily on quality of care, other articles without this focus were reviewed to increase our understanding of how routine data has been used in various settings.

Most of the 86 articles or reports with a focus outside quality of care had collected routine data from health facility records or from national systems such as the District Health Information Software, version 2 (DHIS2). As was seen in the articles on quality of care, the outcomes of interest, analysis methods, and data sources varied. Most of these were reporting on trends in health outcomes over time; increased access or utilization of health services, products, and facilities after the implementation of an intervention; descriptions of data quality, data use, and access to health information management systems (HMIS); or on improvements in the same.

References

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Part 2: Summary of Articles/Reports

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Agarwal R, Agarwal K, Acharya U, Christina P, Sreenivas V, Seetaraman, S	Impact of simple interventions on neonatal mortality in a low- resource teaching hospital in India	2007	To evaluate the impact of simple interventions on neonatal mortality in a low-resource teaching hospital	Neonatal mortality	Pre- and post- study	No	India	medical records	None	Descriptive Analysis
Ande B, Chiwuzie J, Akpala W, Oronsaye A, Okojie O, Okolocha C, Omorogbe S, Onoguwe B, Oikeh E	Improving obstetric care at the district hospital, Ekpoma, Nigeria	1997	To assess the impact of an intervention (designed to improve emergency obstetric care) on preventing maternal deaths, with a focus on deaths caused by hemorrhage	Obstetric	Pre- and post- study	No	Nigeria	hospital records (admissions and delivery, operating room, and death registers); patient case notes; lab technician record books	focus group discussion transcripts, existing literature	Descriptive Analysis (time series analysis)
Broughton E, Saley Z, Boucar M, Alagane D, Hill K, Marafa A, Asma Y, Sani K	Cost-effectiveness of a quality improvement collaborative for obstetric and newborn care in Niger	2013	To (1) describe a quality improvement collaborative aimed to improve maternal and newbom care outcomes by increasing compliance with high-impact, evidence- based care standards and (2) examine intervention costs and cost-effectiveness and potential scale-up costs to additional sites.	MNH	Quasi- experiment al study	Yes	Niger	monitoring data from participating facilities	None	Descriptive Analysis
Bukirwa H, Yau V, Kigozi R, Filler S, Quick L, Lugemwa M, Dissanayake G, Kamya M, Wabwire-Mangen F, Dorsey G.	Assessing the impact of indoor residual spraying on malaria morbidity using a sentinel site surveillance system in Western Uganda.	2009	To evaluate the impact of the indoor residual spraying intervention	Malaria	Pre- and post- study	No	Uganda	surveillance data	None	Descriptive Analysis (time series analysis)
Carlo W, McClure E, Chomba E, Chakraborty H, Hartwell T, Harris H, Lincetto O, Wright L	Newborn care training of midwives and neonatal and perinatal mortality rates in a developing country	2010	To assess the impact of an Essential Newborn Care (ENC) and neonatal resuscitation program training program on 7-day neonatal mortality rates for low-risk institutional deliveries	Neonatal mortality	Pre- and post- study	No	Zambia	screening logs, clinic logs	None	Descriptive Analysis Test of Significance Multivariate analysis (no adjustment of confounders)
Cannon M, Charyeva Z, Nascimento N, Namisango E, Ddumba- Nyanzi I	Uganda's SCORE Program for Vulnerable Children and Their Families: Mixed- Methods Performance Evaluation	2017	To assess the effects of the Sustainable Comprehensive Responses for Vulnerable Children (SCORE) project on its beneficiaries and to assess the strengths and challenges of the SCORE program approach	Maternal and Child Health	Pre- and post study- (retrospecti ve)	No	Uganda	program data (service-delivery data)	Vulnerability Assessment Tool data	Descriptive Analysis Test of Significance Multivariate analysis
Cannon A, Treves- Kagan S, Cuthereil M, Fehringer J, Apps H, Ramaphane P, Bloom S	Botswana's Gender-Based Violence Referral System Project: Operations Research End Line Report	2018	To explore and evaluate the short-term effects of the Gender-Based Violence Referral System Project (GBVRSP) across comparison and interventions sites over time to facilitate system corrections, and to provide feedback for potential scale-up and future gender-based violence (GBV) interventions	Gender-Based Violence	Quasi- experiment al study	Yes	Botswana	referral information system and program monitoring data	focus group transcripts and interview transcripts	Descriptive Analysis
Charyeva Z, Curtis S, Mullen S	Strengthening Tuberculosis Control in Ukraine: Evaluation of the Impact of a Social Support Strategy on Treatment Outcomes.	2018	To assess the impact of the social support strategy on the TB treatment adherence	ТВ	Quasi- experiment al study	Yes	Ukraine	Patient medical records (TB diagnosis, treatment and outcomes data); program data (surveys with facility lead doctors and administrators; interviews with patients, nurses and program staff	Descriptive Analysis Test of Significance Multivariate analysis
Chomba E, McClure E, Wright L, Carlo W, Chakraborty H, Harris H	Effect of WHO newborn care training on neonatal mortality by education	2008	To determine the effect of the ENC training of health workers on all-cause 7-day (early) neonatal mortality among women accessing delivery services (also determine if this was moderated by the educational level of the mother)	Neonatal mortality	Pre- and post- study	No	Zambia	screening logs, health facility files	None	Descriptive Analysis; Comparative Tests

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Cibulskis R, Posonai E, Karel S	Initial experience of using a knowledge-based system for monitoring immunization services in Papua New Guinea	1995	To determine whether a knowledge-based system is useful/effective as a management tool	Immunization	Post-test only	No	Papua New Guinea	performance indicators in immunization and other programs	semi- structured interviews, monthly evaluation forms, automatic log files of KBS system	Descriptive Analysis
Delva W, Yard E, Luchters S, Chersich M, Muigai E, Oyier V, Temmerman M.	A safe motherhood project in Kenya: assessment of antenatal attendance, service provision and implications for prevention of mother-to-child transmission of HIV (PMTCT).	2010	To investigate uptake and provision of antenatal care (ANC) services in the Uzazi Bora project: a demonstration-intervention project for safe motherhood and PMTCT in Kenya.	PMTCT	Cross- sectional study	No	Kenya	records from antenatal clinic, lab and maternity ward registers	None	Descriptive Analysis
Djan J, Kyei-Faried S, Twum S, Odanquah J, Ofori M, & Browne E	Upgrading obstetric care at the health center level, Juaben, Ghana	1997	To assess the impact of the intervention on the following: obstetric admissions, deliveries, complications, obstetric surgical procedures, obstetric referrals, and maternal deaths	Obstetric	Pre- and post- study	No	Ghana	delivery books, theater registers, admission and record books, and patient case notes; summaries	None	Descriptive Analysis (time series analysis)
Doherty T, Chopra M, Nsibande D, Mngoma D	Improving the coverage of the <u>PMTCT program through a</u> <u>participatory quality</u> <u>improvement intervention in</u> <u>South Africa</u>	2009	To report the findings of a participatory intervention to improve an integrated PMTCT program in a rural district (KwaZulu-Natal province, Amajuba) in South Africa	PMTCT	Pre- and post- study	No	South Africa	routine PMTCT data from DHIS	structured interviews with facility managers and lay counsellors, facility observations	Descriptive Analysis (time series analysis)
Dumont A, Fournier P, Abrahamowicz M, Traoré M, Haddad S, Fraser WD; QUARITE research group	Quality of care, risk management, and technology in obstetrics to reduce hospital-based maternal mortality in Senegal and Mali (QUARITE): a cluster- randomized trial	2013	To assess the effect of a multifaceted intervention to promote maternity death reviews and onsite training in emergency obstetric care in referral hospitals with high maternal mortality rates in Senegal and Mali.	Maternal mortality	Cluster- randomize d controlled trial	Yes	Mali Senegal	hospital registers (admissions, hospitalizations, operating room and morgue); available medical records	surveys collected info on activities	Descriptive Analysis Test of Significance Multivariate analysis
Ediau M, Wanyenze R, Machingaidze S, Otim G, Olwedo A, Iriso R, Tumwesigye N	Trends in antenatal care attendance and health facility delivery following community and health facility systems strengthening interventions in Northern Uganda	2013	To assess the impact of the program intervention and to document trends in key ANC and delivery indicators following implementation of program interventions	MNH	Pre- and post- study	No	Uganda	HMIS; Ministry of Health (MOH) registers (ANC register, delivery and birth register), annual HMIS report	None	Descriptive Analysis Test of Significance Multivariate analysis
Ellard D, Simkiss D, Quenby S, Davies D, Kandala N, Kamwendo F, Mhango C, O'Hare J	The impact of training non- physician clinicians in Malawi on maternal and perinatal mortality: a cluster randomized controlled evaluation of the enhancing training and appropriate technologies for mothers and babies in Africa (ETATMBA) project	2012	To evaluate the impact of the intervention on maternal and perinatal morbidity and mortality, to assess the acceptability of the intervention for stakeholders, and the fidelity of implementation	MNH	Cluster- randomize d controlled trial	Yes	Malawi	health facility records	semi- structured interviews, observation checklist	Descriptive Analysis (time series analysis)
Foreit K, Varela V, Agala C, Li M, Albert L	HIV Testing and Pregnancy Delay among Adolescent Girls and Young Women Enrolled in the DREAMS Initiative in Northern Uganda: Quantitative Report	2019	To assess the impact of the Determined, Resilient, Empowered, AIDS-free, Mentored, and Safe (DREAMS) initiative, specifically: (1) assess the influence of the family planning (FP) component of DREAMS on delay of subsequent pregnancies and contraceptive uptake among beneficiaries and (2) quantify the coverage of HIV testing and retesting and compare HIV retesting among beneficiaries who were reported to have received FP services with those who were not reported to have received FP	HIV and Pregnancy	Pre-and post-study (retrospecti ve)	No	Uganda	program data (Uganda DREAMS Tracking System), DHIS2	Demographic and health survey (DHS)	Descriptive Analysis

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Fournier P, Dumont A, Tourigny C, Dunkley G, Dramé S.	Improved access to comprehensive emergency obstetric care and its effect on institutional maternal mortality in rural Mali	2009	To evaluate the effect of a national referral system that aims to reduce maternal mortality rates through improving access to and the quality of emergency obstetric care in rural Mali	Obstetric	Pre- and post- study	No	Mali	referral system documentation	None	Descriptive Analysis Test of Significance Multivariate analysis (adjusted for confounders)
lfenne D, Essien E, Golji N, Sabitu K, Alti-Mu'azu M, Musa A, Adidu V, Mukaddas M	Improving the quality of obstetric care at the teaching hospital, Zaria, Nigeria	1997	To assess the effects of the Prevention of Maternal Mortality team's interventions on the utilization and quality of emergency obstetric care (EmOC) at the Ahmadu Bello University Teaching Hospital	Obstetric	Pre- and post- study	No	Nigeria	ward registers of daily admissions of women into the delivery suite and maternity and gynecological wards	None	Descriptive Analysis (time series analysis)
Iyer H, Hirschhorn L, Nisingizwe M, Kamanzi E, Drobac P, Rwabukwisi F, Law M, Muhire A, Rusanganwa V, Basinga P	Impact of a district-wide health center strendthening intervention on healthcare utilization in rural Rwanda; Use of interrupted time series analysis	2017	To evaluate the impact of a district-level health system strengthening (HSS) intervention implemented by the Rwanda Population Health Implementation and Training (PHIT) partnership in rural Rwanda on district-level health service utilization	Service use	Pre- and post- study	No	Rwanda	health center-level monthly time series data	Rainfall data	Descriptive Analysis Test of Significance Multivariate analysis (adjusted for confounders)
Kayongo M, Butera J, Mboninyibuka D, Nyiransabimana B, Ntezimana A, Mukangamuje V	Improving availability of EmOC services in Rwanda CARE's experiences and lessons learned at Kabqavi Referral Hospital.	2006	To describe project interventions and results with specific focus on the largest of the three facilities, Kabgayi referral hospital	Obstetric	Pre- and post- study (retrospecti ve)	No	Rwanda	case notes and facility registers	None	Descriptive Analysis (time series analysis)
Kayongo M, Esquiche E, Luna M, Frias G, Vega-Centeno L, Bailey P	Strengthening emergency obstetric care in Avacucho, Peru.	2006	To describe project interventions and their impact on service utilization intervention: comprehensive package of interventions designed to improve capacity to provide quality EmOC services	Obstetric	Pre- and post- study	No	Peru	patient registers (designed for the study)	None	Descriptive Analysis (time series analysis)
Kongnyuy E, Leigh B, van den Broek N	Effect of audit and feedback on the availability, utilization, and quality of emergency obstetric care in three districts in Malawi	2008	To assess whether audit and feedback can improve the availability, utilization, and quality of emergency obstetric care	Obstetric	Observatio nal study	No	Malawi	maternity registers	None	Descriptive Analysis Comparative Tests
Leigh B, Kandeh H, Kanu M, Kuteh M, Palmer I, Daoh K, Moseray F	Improving emergency obstetric care at a district hospital. Makeni, Sierra Leone. The Freetown/Makeni PMM Team	1997	To describe the project intervention and evaluate the impact of the intervention activities aimed to improve the quality of care at the government Hospital in Makeni.	Obstetric	Pre- and post- study	No	Sierra Leone	health facility records including outpatient records, operating theater registers, blood transfusion book, admissions and delivery book	interviews with staff and patients	Descriptive Analysis (time series analysis)
McLaren Z, Sharp A, Zhou J, Wasserman S, Nanoo A	Assessing healthcare quality using routine data: evaluating the performance of the national TB program in South Africa.	2017	To assess the overall facility quality of public health using process performance measures (indicators based on guidelines for clinical care of TB)	ТВ	Pre- and post- study	No	South Africa	health facility records, South African National Health Laboratory Service (NHLS) database	None	Descriptive Analysis Test of Significance Multivariate analysis
Mekbib T, Kassaye E, Getachew A, Tadesse T, Debebe A	The FIGO Save the Mothers Initiative: the Ethiopia_ Sweden collaboration	2003	To describe the Save the Mothers Project in Ethiopia and assess its impact on EmOC services, mortality from pregnancy and childbirth	Obstetric	Pre- and post- study	No	Ethiopia	health facility records	None	Descriptive Analysis (time series analysis)
MEASURE Evaluation	Evaluation of the Partnership for HIV-Free Survival (PHFS): Uganda	2018	To evaluate the activities related to the partnership for HIV-free survival (PHFS)	HIV	Pre- and post- study	No	Uganda	health facility records	interviews and surveys	Unknown
MEASURE Evaluation, National Malaria Elimination Programme (NMEP), and the U.S. President's Malaria Initiative (PMI/Nigeria)	Assessment of Malaria Interventions in Four Nigerian States: Final Report	2017	To document progress in malaria control interventions	Malaria	Pre- and post- study	No	Nigeria	PHC registers and monthly summary forms, referral hospital records	client exit interview questionnaire, observations, key informant interviews, household surveys	Descriptive Analysis

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Ministry of Health	The Partnership for HIV-Free Survival in Uganda: Experience and Lessons Learned	2018	To describe the experience and lessons learned from the activities related to PHFS	HIV	Pre- and post- study	No	Uganda	health facility records		Descriptive Analysis
Mushi D, Mpembeni R, Jahn A	Effectiveness of community- based safe motherhood promoters in improving the utilization of obstetric care. The case of Mtwara Rural District in Tanzania	2010	To describe a community-based safe motherhood in Mtwara rural district of Tanzania and assess the intervention's impact on service utilization, acceptability, and community perception.	Obstetric	Pre- and post- study	No	Tanzania	program data (on all deliveries) and health facility records	qualitative interview data, process evaluation data	Descriptive Analysis Comparative Tests
Nyarango P, Gebremeskel T, Mebrahu G, Mufunda J, Abdulmumini U, Ogbamariam A, Kosia A, Gebremichael A, Gunawardena D, Ghebrat Y, Okbaldet Y	A steep decline of malaria morbidity and mortality trends in Erritrea between 2000 and 2004: the effect of a combination of control methods	2006	To examine the impact of Eritrea's Roll Back Malaria Programme: 2000–2004, specifically: (1) assess trends in malaria morbidity and mortality rates in the country and (2) the effectiveness of the malaria control program	Malaria	Cross- sectional survey (retrospecti ve study)	No	Eritrea	HMIS data of the MOH, quarterly and annual reports of the National Malaria Control Programme (NMCP) and reports of the annual assessment workshops by NMCP	published reports of the midterm evaluation of the Roll Back Malaria program carried out in 2001, monthly rainfall data, interviews on program design and implementation process, health facility survey, community survey, household survey	Time series model
Olukoya A, Ogunyemi M, Akitoye C, Abudu O, Tijani M, Epoyun A, Ahabue C, Shaba O	Upgrading obstetric care at a secondary referral hospital, Ogun State, Nigeria, The Lagos PMM Team	1997	To assess the impact of the efforts to improve the health care received by pregnant women with complications at the project area hospital, state hospital, Ota.	Obstetric	Pre- and post- study	No	Nigeria	monthly data summaries from the registers of the maternity and gynecology wards	time motion data	Descriptive Analysis (time series analysis)
Otchere S, Binh H	Strengthening emergency obstetric care in Thanh Hoa and Quang Tri provinces in <u>Vietnam</u>	2007	To assess the impact of an intervention (Jan 2001 to Dec 2004) aimed at improving the availability of, access to, quality, and utilization of EmOC services at district and provincial hospitals in two provinces in Vietnam	Obstetric	Pre- and post- study	No	Vietnam	service data from health facilities	None	Descriptive Analysis
Otten M, Aregawi M, Were W, Karema C, Medin A, Bekele W, Jima D, Gausi K, Komatsu R, Korenromp E, Low-Beer D, Grabowsky M	Initial evidence of reduction of malaria cases and deaths in Rwanda and Ethiopia due to rapid scale-up of malaria prevention and treatment	2009	To assess the impact of malaria control on health facility burden in selected areas of Rwanda and Ethiopia	Malaria	Pre- and post- study - (retrospecti ve)	No	Rwanda Ethiopia	monthly surveillance data, patient registers	None	Descriptive Analysis (proportions, percentages, means, etc.)
Oyesola R, Shehu D, Ikeh A, Maru I	Improving emergency obstetric care at a state referral hospital, Kebbi State, Nigeria. The Sokoto PMM Team,	1997	To describe the intervention and to determine the impact of the intervention on service utilization	Obstetric	Pre- and post- study	No	Nigeria	patient registers and records	inventory of equipment, drugs, and supplies required for maternal care	Descriptive Analysis (time series analysis)
Pfeiffer J, Napúa M, Wagenaar B, Chale F, Hoek R, Micek M, Manuel J, Michel C, Cowan J, Cowan J, Gimbel S, Sherr K, Gloyd S, Chapman R	Stepped-Wedge Cluster Randomized Controlled Trial to Promote Option B+ Retention in Central Mozambique	2017	To describe the development and pilot of the intervention; and evaluate the impact of the health-facility intervention. The study sought to improve early Option B+ retention in large public clinics in a high- prevalence region of Mozambique	HIV	Randomize d control trial with a stepped- wedge design	Yes	Mozambique	routine health facility registries and forms, patient files	focus group discussion transcripts, observations	Descriptive Analysis Test of Significance Multivariate analysis
Pirkle C, Dumont A, Traoré M, Zunzunegui M & QUARITE group	Effect of a facility-based multifaceted intervention on the quality of obstetrical care: a cluster randomized controlled trial in Mali and Senegal	2012	To assess whether an intervention, based on maternal death reviews, could improve obstetric quality of care.	Obstetric	Cluster- randomize d controlled trial	Yes	Mali Senegal	hospital registers (admissions, hospitalizations, operating room and morgue); available medical records	surveys collected info on activities	Descriptive Analysis (proportions, percentages, means, etc.); Comparative tests (T-test, etc.); Multivariate analysis
Rustagi A, Gimbel S, Nduati R, Cuembelo Mde F, Wasserheit J, Farquhar C, Gloyd S, Sherr K; with input from the SAIA Study Team	Impact of a systems engineering intervention on PMTCT service delivery in Cote d'Ivoire, Kenya, Mozambique: a cluster randomized trial	2016	To quantify the effectiveness of a package of systems engineering tools, including QI, to improve PMTCT services in sub- Saharan Africa	PMTCT	Cluster- randomize d control trial	Yes	Cote d'Ivoire Kenya Mozambique	monthly facility registers	None	Descriptive Analysis Comparative Tests

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Santelli A, Ribeiro I, Daher A, Boulos M, Marchesini P, dos Santos R, Lucena M, Magalhães I, Leon AP, Junger W, Ladislau J	Effect of artesunate- mefloauine fixed-dose combination in malaria transmission in Amazon basin communities	2012	To assess the suitability of replacing quinine sulphate and doxycycline as a national first-line treatment policy for children and adults with uncomplicated P. falciparum malaria in Latin America	Malaria	Pre- and post- study	No	Brazil	national surveillance system, SIVEP-malaria	rainfall data	Descriptive Analysis Test of Significance Multivariate analysis (adjusted for confounders)
Santos C, Diante D Jr, Baptista A, Matediane E, Bique C, Bailey P	Improving emergency obstetric care in Mozambique; The story of Sofala	2006	To describe and assess the impact of the Averting Matemal Death and Disability (AMDD) project (occurred between January 2000 to December 2005) on the access, quality and utilization of EmOC in rural hospitals and health centers.	Obstetric	Pre- and post- study	No	Mozambique	monthly summary reports from health facilities, health facility registries	None	Descriptive Analysis
Singh K, Brodish P, Speizer I, Barker P, Amenga-Etego I, Dasoberi I, Kanyoke E, Boadu E, Yabang E, Sodzi-Tettey S	Can a quality improvement project impact maternal and child health outcomes at scale in northern Ghana?	2016	To present a methodology of using facility- based routine health data for a large-scale impact evaluation and to determine whether "Project Fives Alivel" influenced maternal and child health outcomes at scale	MNH	Pre- and post- study	No	Ghana	District Health Information Management System (DHIMS), facility and program records	None	Descriptive Analysis (time series analysis controlled for confounders) Comparative tests
Singh K, Speizer I, Handa S, Boadu R, Atinbire S, Barker P, Twum-Danso N	Impact evaluation of a quality improvement intervention on maternal and child health outcomes in Northem Ghana: early assessment of a national scale-up project	2013	To evaluate the influence of the early phase of Project Fives Alivel, a national child survival improvement project, on key maternal and child health outcomes (July 2008 to December 2009)	MNH	Pre- and post- study	No	Ghana	health facility registers, program and facility-level information	Census data	Descriptive Analysis Test of Significance Multivariate analysis
Spector J, Agrawal P, Kodkany B, Lipsitz S, Lashoher A, Dziekan G, Bahl R, Merialdi M, Mathai M, Lemer C, Gawande A	Improving Quality of Care for Matemal and Newborn Health: Prospective Pilot Study of the WHO Safe Childbirth Checklist Program	2012	To assess the impact of the WHO Safe Childbirth Checklist program (29 items) on the rate of delivery of essential childbirth practices linked with improved matemal, fetal, and neonatal health outcomes in a low-income setting.	MNH	Pre- and post- study	No	India	checklists attached to patient files, patient files	None	Descriptive Analysis Comparative Tests
Spitzer R, Steele S, Caloia D, Thome J, Bocking A, Christoffersen-Deb A, Yarmoshuk A, Maina L, Sitters J, Chemwolo B, Omenge E	One-year evaluation of the impact of an emergency obstetric and neonatal care training program in Western Kenya	2014	To determine the impact of introducing an EmOC training program on maternal and perinatal morbidity and mortality at Moi Teaching and Referral Hospital, Eldoret, Kenya.	MNH	Pre- and post- study	No	Kenya	patient registers and records		Descriptive Analysis Comparative Tests
Sutherland E, Cannon A, Day S, Nonvignon J, Foley S, Iskarpatyoti V, Torpey K	USAID Ghana's Strengthening the Care Continuum Project: Midterm Assessment	2019	To evaluate the midterm performance of the Care Continuum Project (aimed at providing and scaling up accessible, high- quality HIV services to Ghana's key populations (KPs)—men who have sex with men, female sex workers, and transgender people—and promote transition of service provision to the Government of Ghana)	HIV	Cross- sectional study	No	Ghana	program data, client clinical records (date of initiation of HIV treatment, viral load results, and the date of the most recent visit)	client and provider surveys, focus group discussions and key informant interviews, cost data	Descriptive Analysis
van den Akker T, van Rhenen J, Mwagomba B, Lommerse K, Vinkhumbo S, van Roosmalen J	Reduction of Severe Acute Maternal Morbidity and Maternal Mortality in Thyolo District, Malawi: The Impact of Obstetric Audit	2011	To evaluate the effect of audit at district level in Thyolo, Malawi, we assessed the incidence of facility-based severe maternal complications (severe acute maternal morbidity [SAMM] and maternal mortality) during two years of audit and feedback.	Maternal Mortality	Pre- and post- study	No	Malawi	medical records	None	Descriptive Analysis Comparative Tests Bivariate analysis (linear regression)
Waiswa P, Pariyo G, Kallander K, Akuze J, Namazzi G, Ekirapa- Kiracho E, Kerber K, Sengendo H, Aliganyira P, Lawn J, Peterson S & Uganda Newbom Study Team	Effect of the Uganda Newborn Study on care-seeking and care practices: a cluster- randomized controlled trial	2015	To assess the effect of the Uganda Newborn Study (UNEST) [a home visit strategy combined with health facility strengthening] on uptake of care-seeking, practices and services for newborns, and to link the results to national policy and scale-up in Uganda.	MNH	Cluster- randomize d control trial	Yes	Uganda	routine birth and death reports, data on pregnancy and outcomes collected from the Health and Demographic Surveillance Site (HDSS)	cross-sectional pregnancy history study	Descriptive Analysis Test of Significance Multivariate analysis

Author(s)	Title	Year	Objective	Outcome of Interest	Study Design	Comparison group?	Country	Data Sources	Other non-routine	Analysis Method (routine data)
Webster P, Sibanyoni M, Malekutu D, Mate KS, Venter W, Barker P, Moleko W	Using quality improvement to accelerate highly active antiretroviral treatment (HAART) coverage in South Africa	2011	To report on a health system strengthening intervention that used QI methods at the subdistrict level to accelerate HAART initiation for those requiring treatment.	HIV	Pre- and post- study	No	South Africa	clinic-based HIV/TB registers	None	Descriptive Analysis (time series analysis) Comparative tests
Were M, Shen C, Tierney W, Mamlin J, Biondich P, Li X, Kimaiyo S, Mamlin B	Evaluation of computer- generated reminders to improve CD4 laboratory monitoring in sub-Saharan Africa: a prospective comparative study	2011	To assess whether clinical summaries with computer-generated reminders could improve clinicians' compliance with CD4 testing guidelines in the resource-limited setting of sub-Saharan Africa.	HIV	Quasi experiment al study	Yes	Kenya	program data (patient encounter forms) and patient records	None	Descriptive Analysis Test of Significance Multivariate analysis (no adjustment of confounders)
Wickett E, Peralta- Santos A, Beste J, Micikas M, Toe F, Rogers J, Jabateh L, Wagenaar B	Treatment outcomes of TB- infected individuals attending public sector primary care clinics in rural Liberia from 2015 to 2017: a retrospective cohort study	2018	To evaluate the performance of routine clinical TB care and the effects of the community health worker program in the wake of the Ebola crisis	ТВ	Pre- and post- study	No	Liberia	TB patient registers	None	Descriptive Analysis Test of Significance Multivariate analysis
Zongo A, Dumont A, Fournier P, Traore M, Kouanda S, Sondo B	Effect of maternal death reviews and training on maternal mortality among cesarean delivery: post-hoc analysis of a cluster- randomized controlled trial	2015	To explore the differential effect of a multifaceted intervention on hospital-based maternal mortality between patients with cesarean and vaginal delivery in low- resource settings.	Maternal Mortality	Cluster- randomize d controlled trial	Yes	Mali Senegal	hospital registers (admissions, hospitalizations, operating room and morgue); available medical records	surveys, collected info on activities	Descriptive Analysis Test of Significance Multivariate analysis

ANC – antenatal; DHS – demographic and health survey; DHIS – District Health Information System ; DHIMS – District Health Information Management System; HIV – human immunodeficiency virus; MNH – maternal and neonatal health; PMTCT – prevention of mother to child transmission; TB – tuberculosis

Data for Impact

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Using routine data in evaluation