EXAMINING THE POLICY AND PRACTICE DISCONNECT: THE IMPACT OF DATA-DRIVEN PERFORMANCE MONITORING ON DATA QUALITY IN INDIA'S PUBLIC HEALTH SECTOR

by
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Abstract

Health management and information systems (HMIS) provide valuable data for monitoring and evaluating health services, identifying unmet needs, establishing local priorities, and measuring the performance of health programs. Considerable investments have been made in implementing technical approaches to improve HMIS performance, however, growing evidence suggest that focusing on these approaches alone is insufficient.

A recent HMIS policy reform in Uttar Pradesh, India, implementing a series of technical approaches to improve the quality and use of HMIS data in decision-making, offered a unique opportunity to examine how organizational factors, including organizational culture, shape the implementation of formal policy guidelines and influence overall HMIS performance. The first paper qualitatively examines how organizational factors, for example, hierarchy and distribution of power, influence HMIS implementation processes, and in turn performance, from the perspectives of policy implementers. The second paper quantitatively examines how data quality varies among HMIS indicators that are used in performance metrics (like district rankings), that are associated with financial incentives and that are only collected for routine monitoring. The final paper describes the types of HMIS data manipulation observed in Uttar Pradesh (UP), and their underlying drivers.

Results demonstrate that issues of weak HMIS implementation are not merely a reflection of insufficient resources or lack of technical guidelines. We found challenges associated with working within a strict hierarchy. Performance pressures and punitive work culture resulted in weak enforcement of data quality mechanisms and created perverse incentives to manipulate district ranking indicators to show high achievement of performance metrics. The HMIS data quality analysis corroborated these assessments and presented evidence to show the potential overreporting

of HMIS indicators that are associated with performance measures like district rankings and financial incentives.

Looking ahead, stakeholder engagements would be critical for identifying context-appropriate strategies to: (i) align health actors on HMIS goals, so that the goal of high data quality is not at odds with the goal of achieving a high district ranking; (ii) strengthen the integrity of data-related processes at all levels; and (iii) to implement system-wide policies that make data manipulation an anomaly.

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Chapter 1. Introduction

1.1 Introduction to the study

Health management and information systems (HMIS) in low- and middle-income countries (LMICs) like India routinely collect data on public health services provided by the government. For example, HMIS provide information about the availability of drugs, equipment, and the utilization of health services within a geographic area (Boerma, 2013). These data can be valuable for monitoring and evaluating health services, identifying unmet needs, and benchmarking the performance of different health facilities (World Health Organization, 2009).

The importance of investing in strengthening the performance of HMIS has been codified in the World Health Organization's (WHO) Health Systems Framework, which identifies Health Information Systems as one of the six critical building blocks of a health system (World Health Organization, 2007). Sustainable Development Goal 17.18 similarly underscores the importance of improving "the availability of high-quality, timely and reliable data disaggregated by income, gender, age, race, ethnicity….and other characteristics relevant in national contexts" to support decision-making (United Nations, 2016).

In discussing the importance of strengthening HMIS performance, it is important to acknowledge a paradigm shift that has occurred in the last few decades. In the early 1990s, improving the performance of HMIS often relied on technical solutions. These approaches focused on ensuring the availability of resources and designing and implementing technical rules for HMIS data collection, processing, and analysis. The expectation was that if managers had sufficient resources and developed appropriates rules and processes, then HMIS data would be used for decision-making (Aqil *et al.*, 2009). Aligned with this thinking, global health partners and national governments created technical outputs like the data management standards, training manuals on conducting data quality audits, and tools to better analyze and use data for decision-making (Health Metrics Network, 2008; MEASURE Evaluation, 2019).

Implicit in these technical approaches was the assumption that a well-designed HMIS would deliver on its intended HMIS performance goals of producing good quality data that are used in decision-making. However, growing evidence from evaluations of HMIS in many LMICs show that these technical approaches have been simply insufficient in improving HMIS performance; thereby, questioning a linear causal relationship between HMIS inputs (e.g., resources), processes (e.g., good organizational rules), and outputs (e.g., use of good quality data in decision-making) (Chaulagai *et al.*, 2005; Aqil *et al.*, 2009).

Increasingly, practitioners and evaluators of HMIS have underscored the importance of non-technical determinants, like organizational factors (e.g., the culture of information use), and behavioral factors (e.g., the demand for good quality data) in improving HMIS performance (Aqil *et al.*, 2009), and have contributed to a paradigm shift which begs the question: If technical policies and guidelines are insufficient for improving HMIS performance, then what else explains HMIS performance, and how can HMIS performance be improved in a health system?

The Government of Uttar Pradesh (GOUP) in the state of Uttar Pradesh, India, sees HMIS as an important source of information for planning, monitoring and evaluating health programs that are implemented across its 28,250 health facilities, which serve roughly 230 million state residents (Census Population, 2020). To improve the performance of its HMIS, beginning in 2014, the GOUP implemented a series of technical policies driven by the assumption that improvements in data quality would promote data use, and this reinforcing positive feedback loop would lead to better

HMIS performance. This HMIS policy reform in Uttar Pradesh offered a unique opportunity to look beyond the technical determinants and unpack the underlying organizational determinants of HMIS performance in Uttar Pradesh, India.

1.2 Study objectives

This dissertation explores the non-technical determinants of HMIS performance, such as organizational factors that are critical for effective HMIS performance, yet often less examined in literature. A majority of HMIS performance initiatives continue to rely on technical approaches, which predominantly focus on strengthening the formal rules and processes for HMIS, and insufficiently examine how contextual, organizational, and behavioral factors influence everyday HMIS practices.

Leveraging both qualitative and quantitative methods (explained further in Chapters 2-4), this dissertation seeks to identify the barriers to HMIS performance, including the unintended consequences that result from a partial implementation of well-intentioned technical policy guidelines. Understanding factors that weaken or deter HMIS implementation is critical for informing strategies and mechanisms to remove such barriers and for supporting the institutionalization of processes that can ultimately lead to a stronger HMIS. This study contributes evidence on how non-technical factors, such as hierarchy, distribution of power and authority, discretion, and interpersonal power dynamics, influence the implementation of HMIS policies, and HMIS performance. In addition, this study examines one aspect of HMIS performance – data quality – and analyzes the underlying drivers of poor data quality, including factors that incentivize HMIS data manipulation.

Each of the three dissertation papers has a distinct aim. The first paper (Chapter 2), a policy implementation study, analyzes how organizational factors, including organizational culture shape the implementation of new HMIS policies in Uttar Pradesh from the perspectives of policy implementers, and further explains the observed gap between well-intentioned HMIS policies and their implementation. The second paper (Chapter 3) quantitatively examines how data quality varies among HMIS indicators that are used in performance metrics (like district rankings), associated with financial incentives or those that are only collected for routine monitoring. Finally, the third paper (Chapter 4) describes the types of HMIS data manipulation observed in Uttar Pradesh, with a focus on investigating the underlying drivers that create opportunities and the pressures to manipulate data and the rationalization of data manipulation by those involved.

1.3 Conceptual framework

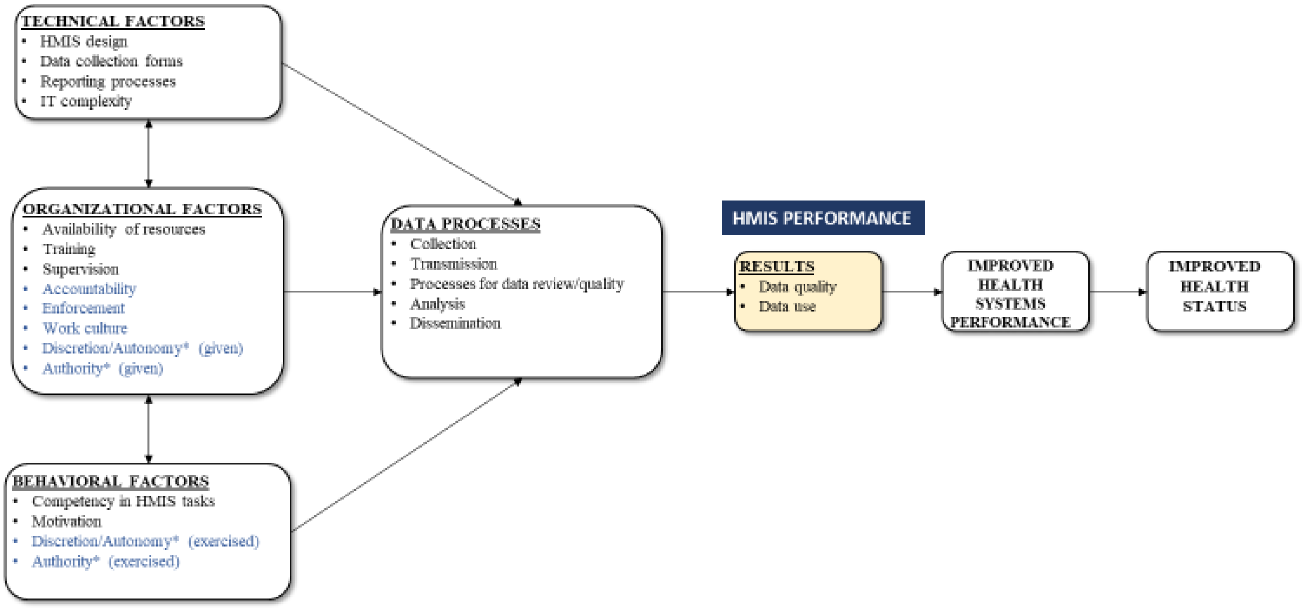
The conceptual frameworks and theoretical perspectives that were used to inform the research questions, data collection, analysis, and interpretation of findings, are presented in the chapters specific to each of the three aims. However, the overall dissertation and the literature review draws on the concepts presented in the Performance of Routine Information Systems (PRISM) framework (Aqil *et al.*, 2009), which emphasizes the role of underlying non-technical determinants like organizational and behavioral factors in influencing HMIS processes and ultimately, HMIS performance.

The PRISM framework promotes an integrated approach to analyzing HMIS performance. As shown in **Figure 1**, the framework recognizes that the collective interactions among technical factors, organizational factors, and behavioral factors can shape HMIS data processes, and in turn, influence overall HMIS performance (**Figure 1**). For example, technical factors, like HMIS design and the complexity of data collection forms can influence data processes, like data collection, which in turns affects HMIS performance. Similarly, the PRISM framework recognizes the importance of organizational factors (e.g., available resources, training and supervision), however among these, it does not explicitly recognize less tangible factors, like accountability, enforcement of HMIS rules, and work culture that may also influence HMIS data processes in critical ways. The PRISM framework below has been adapted to include these factors (reflected in blue). In addition, discretion, autonomy and authority have been added to the PRISM framework as both organizational and behavioral factors. While organizations may set, for example, the degree of authority one has in the workplace, we recognize that individuals also have the capacity to determine how to exercise that authority.

Overall, the conceptual framework suggests that technical, organizational and behavioral factors can influence the implementation of data processes, which in turn drive HMIS performance, reflected in improved HMIS data quality and use of HMIS data in decision-making. Decisions made based on good quality data are expected to improve health systems performance and ultimately lead to better health status.

An examination of interactions between technical, organizational and behavioral factors presented in the PRISM framework, or even a subgroup of them, may help inform the development of different interventions to strengthen or reform HMIS.

Figure 1. Performance of Routine Information Systems framework



*Adaptations; Source (Aqil *et al.*, 2009)

1.4 Overview of health management information systems (HMIS)

Brief history of HMIS strengthening efforts

A well-functioning HMIS is a core component of a country's health system and is designed to generate timely, relevant, and accurate information to facilitate decision-making about managing, planning, and monitoring health programs. During the Millennium Development Goals (MDGs), the escalating demand for data to monitor and track the progress of health programs, build accountability and create transparency, drew global attention to the challenges of existing HMIS in many low- and middle-income countries (LMICs) (Chan *et al.*, 2010). In addition, as vertical donor-funded data collection efforts proliferated, the MDGs highlighted the missed opportunity of making better use of routinely generated HMIS data (Chan *et al.*, 2010).

To coordinate and align HMIS efforts on a global level and to strengthen the performance of HMIS in LMICs, the Health Metrics Network was established in 2005 (Vidaurre-Arenas *et al.*, 2005). The Health Metrics Network created universal standards and methodologies for data collection, analysis, synthesis and dissemination, and developed a technical framework outlining the components of a successful national health information system (Health Metrics Network, 2020). This framework highlighted the core technical components (including resources and data management policies) that would ultimately lead to good data quality and data use. Around the same time, in 2009, the International Health Partnership (IHP+) also organized themselves around a common monitoring and evaluation platform. Through a common evaluation framework, IHP+ aimed to align countries and partners to develop a national comprehensive monitoring and evaluation plan that would generate the data required for monitoring progress and performance of health programs without creating undue reporting burdens in accordance with the principles of the Paris Declaration of Aid Effectiveness (International Health Partnership+, 2009).

Health partners generated and implemented technical tools in LMICs to: (i) inform and assess the design of a well-performing HMIS, (ii) identify barriers to data quality and data use; (iii) determine appropriate stakeholders for data-related processes; and (iv) develop measures to monitor data quality and use. Varying levels of financial and technical investments were made to strengthen national-level capacity building efforts, for example, by developing HMIS training curricula and implementing trainings, designing HMIS monitoring tools and documenting best practices to support continuous HMIS improvement (Health Metrics Network, World Health Organization, 2012; MEASURE Evaluation, 2017, 2019).

In parallel to these strengthening efforts at the global and national levels, there was increasing evidence on factors affecting HMIS performance in LMICs. While technical guidelines and the implementation of technical processes were expected to improve data management, data quality and data use, some researchers acknowledged that they were not an end in themselves for assuring good data quality and data use (Garrib *et al.*, 2008; Karuri *et al.*, 2014). In fact, there was growing recognition of underlying non-technical determinants that may influence HMIS processes and overall performance. The Performance of Routine Information System Management (PRISM) developed by Aqil and colleagues (Aqil *et al.*, 2009) encapsulated some of these concerns and identified three interrelated determinants - technical, behavioral and organizational factors - that influence HMIS processes and performance, which is measured by good data quality and the use of those data in decision-making (Aqil *et al.*, 2009).

Factors affecting HMIS performance

Based on a review of literature, the underlying challenges and opportunities to strengthen HMIS performance are presented below according to the three determinants identified in the PRISM framework (Aqil *et al.*, 2009).

A. Technical factors

Technical factors have been defined as the "know how" for designing, implementing, and strengthening HMIS processes (Aqil *et al.*, 2009). These include the design of data collection forms, the reporting processes that govern data collection, analysis, and review, as well as the complexity of information communication and technology (ICT) services that support HMIS data collection and management processes. In many countries, technical barriers - reflected in the high burden of data collection and data entry, use of complex reporting forms, and lack of universal data reporting standards - have adversely affected data quality (Odhiambo-Otieno, 2005; Andargie, 2006; Foreit *et al.*, 2006; Aqil *et al.*, 2009; Djibuti *et al.*, 2009; Braa *et al.*, 2012; Boerma, 2013; Teklegiorgis *et al.*, 2014; Nah and Sæbø, 2017). Relatedly, challenges arise from the complexity and design of the data collection forms, for example, the collection of too much data (Braa *et al.*, 2012) or the absence of relevant data (Al Laham *et al.*, 2001).

The implementation of user-friendly computer software, and HMIS data rationalization activities have been found to address HMIS-related technical barriers. For example, countries that have implemented the District Health Information System (DHIS) platform have reportedly improved the timeliness of reporting, and increased the use of data for decision-making at local levels (Boerma, 2013). The implementation of user-friendly software systems have also been found to facilitate data analysis by automating the analytical capacity and thereby supporting data use (Mutale *et al.*, 2013). With respect to improving reporting forms and the use of collected data, a study in Zanzibar demonstrated how regular review of HMIS data through quarterly workshops contributed to a reduction in number of data elements collected, and the integration of many vertical data collection forms into a more streamlined HMIS form. In addition to successfully rationalize the HMIS indicators, these quarterly data use workshops were also found to strengthen technical capacity such as, data analysis and interpretation skills, as well as data presentation skills, which contributed towards the timeliness, completeness, and accuracy of HMIS data (Braa *et al.*, 2012).

B. Organizational factors

Organizational factors refer to the broader organizational context that influences HMIS performance through formal and informal rules, organizational values and norms, as well as the availability of financial and technical resources, such as the level of training and supervision of those involved in HMIS activities (Aqil *et al.*, 2009).

Inadequate availability of human resources both in number and technical skill, as well as, the absence of inputs necessary for data collection and analysis efforts, such as data collection forms/registers, pens and papers, and computers for data managers to perform their jobs have been found to impede all aspects of HMIS performance, including data collection, data entry, data analysis and review, as well as activities, like supportive supervision (Aqil *et al.*, 2009; Ndabarora *et al.*, 2014; Nah and Sæbø, 2017). In particular, in clinical settings with persistent health worker shortages, where health workers have to decide between attending to their patients' needs or entering data; the latter has consistently been deprioritized (Nah and Sæbø, 2017). Relatedly, in settings where HMIS reporting from peripheral health facilities to the district-level is paper-based, delays in transferring data from one level to the next have been attributed to transportation challenges; for example, in Cameroon, submission of paper-based HMIS reports at district-levels depended on when sub-district supervisors traveled to district offices for meetings (Nah and Sæbø, 2017).

Organizational rules, both formal and informal, have also been found to affect data quality and data use. Rules refer to the shared understanding among actors about "what actions are required, prohibited, or permitted"(Ostrom, 2011). Formal rules expressed in government orders, circulars, letters, and other guidelines govern what data are collected, at what frequency, and indicate when and how data should be reviewed for accuracy or used in decision-making. Such rules dictate how information or data systems are structured, managed, or may be accessed by a decision-maker. However, formal rules may also reinforce silos among data collection processes, limiting the ability to harmonize and integrate data across different sources, and hindering a more holistic understanding of health needs. For example, the centralized data management structure in Mexico was found to affect data use by limiting the flow of information to lower, operational levels where those data may be most relevant for decision-making (Trostle *et al.*, 1999).

While formal rules reflect the "written policies," they may not always be practiced as such. In practice, "working rules" are what are implemented and adhered to (Ostrom, 2011). Working rules may arise from a lack of clarity or specification in formal documents. However, working rules more commonly reflect the shared values among actors within an organization (Ostrom, 2011), which may reinforce normative behaviors around HMIS-related processes, and in turn may influence HMIS performance. For example, organizational cultures that were unsupportive of ‘data collection’ and ‘information’ made minimal investments in the development and capacity of their information systems (Kamadjeu *et al.*, 2005).

Organizational culture and governance processes were also found to stymie HMIS processes, affecting both data quality and data use. For example, in Orissa, despite guidelines for conducting supportive supervision visits, presiding norms condoned weak implementation of supervision and data quality checks at lower administrative tiers, which contributed to overall low quality of HMIS data (Bhojani *et al.*, 2010). A study in Pakistan demonstrated that the weak prioritization of data-related activities by the leadership resulted in incomplete reporting and exacerbating the data quality of the province (Qazi and Ali, 2009). Poor data quality has also been attributed to intentional data manipulation, for example, studies in India, and Pakistan found HMIS data were overreported by junior staff at the insistence of their superiors, who wanted to secure additional funds for their health facilities (Qazi and Ali, 2011; Husain *et al.*, 2012). Similarly, a study in Nigeria showed the underreporting of maternal deaths to meet hospital performance targets (Oni-Orisan, 2016).

Overall, these findings suggest that factors related to organizational culture, such as strict adherence to hierarchies within a health system, may lead staff to operate in ways that meet favor with their supervisors (perhaps through reporting inaccurate data) rather than enhancing data quality.
Though not explicitly stated in the PRISM framework, the ability to implement HMIS-related processes and use data for decision-making is also influenced by the level of power and autonomy given to HMIS data staff and data units within the health system (Mutemwa, 2006; Wickremasinghe

et al., 2016). For example, the low prioritization of national statistical agencies reflected in their small annual financial budgets has limited the functional authority necessary for strengthening HMIS performance in many LMICs (Sandefur and Glassman, 2015).

C. Behavioral factors

The behaviors of both data collectors and users, as well as underlying drivers influencing their work-related motivation, confidence, and competency may affect the prioritization and implementation of HMIS-related processes (Harrison and Nutley, 2010; Moreland *et al.*, 2010; Oliver *et al.*, 2014). For example, interpersonal relationships between supervisors and supervisees, and workplace culture, may influence the motivation to complete HMIS-related tasks and shape other behaviors that influence HMIS processes (Mutemwa, 2006; Aqil *et al.*, 2009; Qazi and Ali, 2009). In Syria, poor feedback given to doctors who were expected to report on notifiable diseases contributed to a perception that reporting these diseases was not important (Al Laham *et al.*, 2001). Similarly, weak implementation of data quality checks also resulted in data clerks developing "the habit for data falsification" according to a study conducted in Cameroon (Nah and Sæbø, 2017). The same study noted that though monthly reports were an impetus for data review, the actual use of these data to improve health program performance was absent. Together, these findings suggest that despite having formal organizational processes, existing norms and values shaped individual behaviors that in turn affected the effectiveness of HMIS processes (Aqil *et al.*, 2009; Ndabarora *et al.*, 2014).

Specifically with respect to data use, studies have found that multiple factors, including: a decision-makers' perceptions about data; their technical ability to understand, analyze and/or use the data, their work-related motivation, their personal interests, as well as the vested interests of other actors may influence demand and use of HMIS data in decision-making (Harrison and Nutley, 2010; Moreland *et al.*, 2010; Oliver *et al.*, 2014). Due to their preconceived notions or perceptions about program operations and performance, decision-makers may have low appreciation for data, especially, if data contradict their own perceptions of success (Weiss and Bucuvalas, 1980). Relatedly, decision-makers may also discredit data for being of low quality, inaccurate or irrelevant to their decision-making needs (Mutemwa, 2006). For example, Aqil and colleagues noted that some decision-makers found household- and facility-level surveys more objective than HMIS data, and therefore preferred the former in decision-making (Aqil *et al.*, 2009). Such perceptions not only affect decisionmakers' demand for the data, but also influence how inclined they may be to take 'ownership' of the data. Those who are less likely to take ownership of these data, are also found to be less likely to invest in improving data quality and thereby reducing the usability of data in decision-making (Odhiambo-Otieno, 2005; Harrison and Nutley, 2010).

1.5 Study context and research site

The data for this study were collected from the district, division and state-levels in Uttar Pradesh, India. Data were collected from 16 different districts that span four different administrative divisions. At the state-level, data were collected from Directorates of Medical Health and Family Welfare, and the National Health Mission, which are in Lucknow, Uttar Pradesh.

To place the research site into a broader context, Uttar Pradesh is the most populous state in India and home to roughly 230 million people (Census Population, 2020). If it were a country, Uttar Pradesh would be the sixth most populous country in the world following China, India, United States, Indonesia, and Pakistan (US Census Bureau, 2020). However, when measured based on health outcomes, Uttar Pradesh continues to lag behind other Indian states in maternal and child health indicators as well as social development indicators, such as poverty and literacy rates (The DHS Program, 2016). To address these pressing challenges, the GOUP has prioritized improving the performance of its health system, particularly its HMIS (Government of Uttar Pradesh, 2013, 2015). As described in the next section, the GOUP expected that improvement in HMIS data quality would better inform health program planning and monitoring, which in turn, would improve service delivery and increase the impact of different health interventions and programs (Government of Uttar Pradesh, 2013, 2015).

HMIS system overview in Uttar Pradesh

Many of the challenges affecting HMIS performance (described in Section 1.4) have also been observed in Uttar Pradesh. In 2009, consistent with national-level Government of India (GOI) policy recommendations, the GOUP implemented the national-level HMIS platform (hereafter, HMIS)(Government of India, 2008). In 2014, five years following the implementation of HMIS in Uttar Pradesh, an assessment conducted by the GOUP with the support of the Uttar Pradesh Technical Support Unit (UP-TSU) revealed several technical and process-related challenges affecting HMIS performance.

On a technical level, several issues with the existing HMIS were noted (Meghani *et al.*, 2020). Firstly, HMIS data reporting forms were unavailable at different levels of the health system. Secondly, duplicative data were being collected between the HMIS reporting forms and vertical program specific paper-based reports. Thirdly, there was a mismatch between what data program managers at the district- and state- levels found useful (e.g., indicators capturing inputs and processes) versus what was actually being collected in the HMIS (e.g., indicators capturing outputs). In addition, managers at the block- and district- levels lacked digital access to the facility-level HMIS data for analysis. At the state-level, though program managers had access to these data, monthly reports from at least 28,000 health facilities had to be individually downloaded in order to conduct state-wide analysis, a process that could take up at least two weeks.

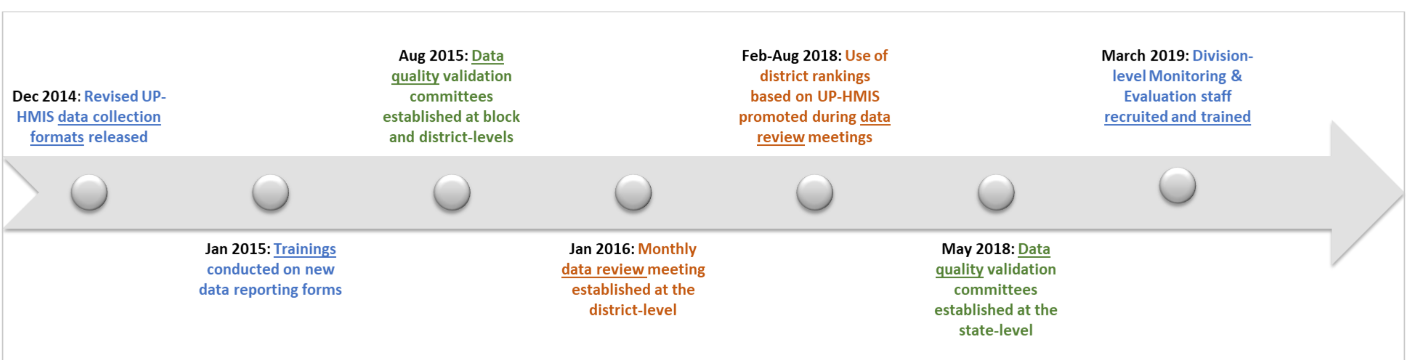
Weak reporting processes at the block- and district-levels were also found to contribute to untimely and incomplete reporting of data to the HMIS. In part, this was attributed to the varied implementation of reporting guidelines across the state. Because data were usually aggregated and analyzed before the monthly District Health Society meetings held by the District Magistrates, reporting periods varied from district to district based on when this meeting was scheduled. This resulted in districts forwarding data to the state at different time points resulting in unique monthly reporting periods by district (e.g., 16-15th, 26-25th, 1-30th) that diverged from the state's expected HMIS reporting guidelines.

The assessment also revealed that districts had inadequate mechanisms in place to validate HMIS data quality before they were entered into the HMIS at the district-level. This challenge was reflected in the incompleteness and inaccuracy of several data element reported in HMIS. Relatedly, the assessment also found that mechanisms to promote the use of HMIS data for decision-making were weak at the district-level. While two monthly district-level meetings chaired by district-level Chief Medical Officers and District Magistrates were held, these meetings tended to focus on resolving logistical issues rather than strategically reviewing data to inform decision-making about program improvement. In part, this was attributed to the lack of understanding about what data sources/portals should be reviewed during these meetings, and how those data should be analyzed and interpreted to identify performance gaps and inform decision-making.

The development of UP-HMIS and policy guidelines to strengthen its performance

To address these technical challenges associated with the HMIS, with the support of the UP-TSU, the GOUP created its own data platform known as the Uttar Pradesh HMIS (UP-HMIS) in 2015. The three primary objectives for developing UP-HMIS were: (1) to capture data elements that were absent in the HMIS but imperative to decision-making at the district- and state-levels; (2) to integrate data elements from government data portals and different health program paper-based reports into one centralized data source – the UP-HMIS; and (3) to provide decision-makers at different levels of the health system with relevant data to measure holistically the performance of health programs. Following the development and implementation of the new UP-HMIS, the GOUP with the support of the UP-TSU conducted state-wide trainings for sub-center, block, district, division and state staff on the new UP-HMIS data formats and the corresponding web-based UP-HMIS portal in 2017. These initial capacity building activities were followed by targeted efforts to strength the processes governing HMIS data quality and HMIS data use for decision-making, particularly at the district-levels. To this end, the GOUP developed and released a series of government orders, circulars, and memos. **Figure 2** presents a simplified timeline highlighting the major policy decisions that were implemented by the GOUP. These policy decisions are discussed further in Chapter 2, which examines UP-HMIS policy implementation at the district-level.

Figure 2. Simplified timeline of major GOUP policy decisions with respect to improve HMIS data quality and data use



The parent project and my role

This dissertation was nested in a health system strengthening project led by Johns Hopkins Bloomberg School of Public Health (JHSPH) in Uttar Pradesh, India under the direction of Dr. David Peters, the Principal Investigator from JHSPH. The overall project aimed to provide analytical support to the Uttar Pradesh, Technical Support Unit (UP-TSU), a technical unit to the Government of Uttar Pradesh (GOUP). One of the key priorities of the UP-TSU has been to improve the performance of the state's Health Management Information Systems (HMIS). In collaboration with the GOUP, the UP-TSU has played a critical role in designing and implementing the UP-HMIS described above, as well as, designing and scaling up initiatives to improve the quality and use of UP-HMIS data in decision-making at the block, district and state-levels.

As a research assistant and doctoral student on this project, I was closely involved with the project's Data Use workstream, which focused on understanding the performance of the UP-HMIS. I played a key role in designing, planning and implementing the primary data collection for the Data Use workstream; developing the study protocols and managing the submissions of the Institutional Review Board approvals; as well as preparing training materials, conducting trainings, pilot-testing data collection tools, and analyzing and drafting the results.

To oversee and implement these activities, I was based in Lucknow, the capital city of Uttar Pradesh, for roughly one year. This time allowed me to collaborate with our colleagues at the UP-TSU who informed the conceptualization and supported the implementation of this dissertation. At the outset of my dissertation, I spent several weeks trying to understand the UP-HMIS – for example, what led to its development and why; what are the new reporting mechanisms; and what are GOUP's processes to verify data quality, and what are their expectations for data use at different levels of the health system.

At the time, many of my conversations with UP-TSU colleagues focused on understanding how broader institutional mechanisms promoted or hindered the use of data for decision-making at the district-level, given the important administrative role districts play in the state's health system. In addition, we discussed how district-level decision-makers' perceptions about their own empowerment in the workplace might influence their use of data for decision-making. These discussions largely reflected my previous dissertation interests, which focused on understanding the relative role of individual- and organizational-factors in shaping the use of data in decision-making.

However, findings from my formative work, consisting of in-depth interviews and a few district-level meetings observations, which aimed to understand UP-HMIS policy implementation processes at the district-level (first aim), brought a fundamental question to the forefront: are HMIS data of high enough quality to be used for decision-making? Challenges associated with data quality dominated nearly every interview and for strong technical reasons, I revised my second and third aims to focus explicitly on issues affecting HMIS data quality as presented in Section 1.2.

During the revision process and during subsequent stages of data collection, I periodically discussed emerging themes and general observations with UP-TSU colleagues and sought their reactions. Currently, UP-TSU colleagues are reviewing the three papers presented in this dissertation (Chapters 2, 3, and 4) and I will be discussing the findings with them by Zoom in August 2020. Their written and oral feedback will be incorporated into the final drafts of the manuscripts before publication.
I would also like to note that this dissertation research is closely linked with other work products from the Data Use workstream. The Data Use workstream's two primary goals are to: (i) describe existing processes, including barriers and facilitators, for data quality and use; and (ii) examine and strengthen HMIS data quality in Uttar Pradesh, India. Findings from this dissertation will contribute

to both the goals by: (i) describing the factors affecting the implementation of data quality and data use policies at the district levels and identifying data-related processes and systems that may not be functioning as expected (Chapters 2 and 4), and (ii) examining the quality of HMIS data (Chapter 3). In addition, findings from this dissertation, which focuses largely on processes at the district-level, complements the objectives of a separate data use survey, which examines the capacity to demand and use HMIS data by division- and state-level officials. Overall, our hope is that the Data Use workstream is able to provide a comprehensive view of how HMIS data is being collected, analyzed, monitored and used in Uttar Pradesh, with the aim of helping GOUP build a culture of information use – one that aligns incentives and existing accountability mechanisms for data use and data quality activities across the state.

Positionality

It is important to reflect on my positionality as a researcher given my roots and strong family connections in Uttar Pradesh. First and foremost, I found being able to speak Hindi with native fluency, and using my middle name - formerly my maiden name (a common surname in Uttar Pradesh) to introduce myself during interviews - immediately created a sense of familiarity, which helped me build a stronger rapport with my respondents. Often, my interviews began and ended with questions about myself and my family, including, which part of Uttar Pradesh I belong to and where my family lives. I found these conversations created a sense of kinship, which I think was critical for rapport building, and helped create a comfortable interview space.

During district-level interviews, and particularly when discussing issues around hierarchy, a punitive work culture, and data manipulation, I deemphasized the “foreign” aspects of my identity, like my international institutional affiliation, which could be viewed as prestige marker, and could lead respondents to perceive me as being more powerful relative to them. In addition, especially for sensitive issues, like data manipulation, I found my myself switching between being informed and uninformed, or even at times, being naïve in order to encourage respondents to provide greater details, which otherwise they would have been assumed to be commonly understood.

When speaking with a few senior health and administrative officials at the district and state levels, I found that drawing on my international institutional affiliation actually made it easier for me to schedule interviews with them. Similarly, for some interviews at the division- and state-levels, being introduced by UP-TSU colleagues was critical for gaining access to potential respondents. To access district-level respondents generally, I found approaching contractual data staff and scheduling interviews with them first, enabled subsequent access to the remaining district-level respondents during my visit.

Across all the interviews, I found that having a strong foundational understanding of the UP-HMIS was critical for gaining access to their more intimate insights and opinions about implementation processes and challenges. In two occasions, I found being conversant in the content and details of UP-HMIS government orders was imperative for being given time to conduct interviews with two district-level health officials.

Nearly all my study respondents at the district-level, and most of my respondents at the division- and state-level were men. Often being the only woman or one of the only women was especially obvious when I conducted district-level meeting observations. Overall, I did not see being a woman factored into the quality of my interviews because I found my strong ties to Uttar Pradesh and being a native Hindi speaker was most critical for developing a strong rapport with all of my respondents, and gaining access to intimate insights, which I think otherwise would have been quite difficult. In one notable occurrence, I did find that my caste played a role. After my interview ended, one district-level respondent personally introduced me to a senior district health official because of our common caste (which is identifiable based on my maiden name). This was an exception. The issue of caste did not emerge during my interview with this district health official, nor did it come up again in the interview process.

I think coming to the interview space as an “outsider” also had its advantages. Because I did not have any preconceived notions, I was able to open myself up to new perspectives. For example, while the problem of data manipulation is well-known among actors within the GOUP health system, I was surprised by how frequently respondents spoke about it with a blithe lack of concern. I was also equally surprised to see how infrequently data manipulation was explicitly discussed in HMIS literature.

In this respect, being able to draw upon attributes of being an “insider” and an “outsider,” provided me with a unique advantage that fueled my motivation and interest to study data manipulation in greater depth without having to worry about standing out.

1.6 Organization of the dissertation

The subsequent three chapters – 2, 3, and 4 – pertain to my three aims. Chapter 2, a policy implementation analysis, examines how organizational factors, including organizational culture, shaped the implementation of new HMIS policies in Uttar Pradesh, India from the perspectives of policy implementers. Chapter 3 quantitatively examines how data quality varies among HMIS indicators that are used in performance metrics (like district rankings), associated with financial incentives or those that are only collected for routine monitoring. Chapter 4 qualitatively explores the construct of data manipulation. It first describes the types of data manipulation observed in HMIS, and then explains the driving factors that have allowed data manipulation practices to persist. Reflecting on the findings of this dissertation, Chapter 5 offers concluding remarks on strengthening HMIS performance, including considerations for addressing the problem of data manipulation and potential areas for future research.

Chapter 2. The disconnect between policy intentions and implementation practices: How organizational factors influence health management information systems in Uttar Pradesh, India

2.1 Introduction

Timely, accurate and relevant health data are fundamental for the effective implementation, monitoring, and management of health programs (Aqil *et al.*, 2009). For example, data gathered in health management information systems (HMIS) are critical for informing public health decision-making (World Health Organization, 2019). Among other data sources, HMIS data routinely provide national and local decision-makers with information about the changing disease burden of their populations, and the range and number of health services delivered to them. These data further enable decision-makers to establish and plan local health priorities, allocate resources, evaluate health services, and identify areas of unmet health needs.

The Millennium Development Goals (MDGs) underscored the importance of strengthening data systems as a "global public good" (Chan *et al.*, 2010). The increased demands for data, including HMIS data, during the MDGs were largely fueled by global donors who used results-based mechanisms to track performance, enhance accountability, and evaluate their own investments in low- and middle-income countries (LMICs) (Chan *et al.*, 2010). However, these demands for data also revealed the weaknesses of HMIS in LMICs (Boerma and Stansfield, 2007) including challenges exacerbated by the fragmented disease-specific data collection efforts, and high reporting burdens associated with donor-sponsored programs (AbouZahr *et al.*, 2007; Chan *et al.*, 2010).

Over the past 15 years, there has been a renewed focus on strengthening HMIS in LMICs (MA4Health, 2015). However, persistent barriers to HMIS performance remain (Akhlaq *et al.*, 2016;

Macfarlane *et al.*, 2019). HMIS performance, reflected in the quality and use of HMIS data in decision-making, has been influenced by three interrelated determinants: technical, behavioral and organizational factors (Aqil *et al.*, 2009). Technical factors, like complex reporting forms and insufficient human resources, have been found to weaken HMIS data collection, entry and analyses (Andargie, 2006; Foreit *et al.*, 2006; Aqil *et al.*, 2009; Djibuti *et al.*, 2009; Teklegiorgis *et al.*, 2014). Relatedly, the behaviors of both data collectors and users, including their levels of work-related motivation, confidence, and competency to perform their work, influence the prioritization and implementation of HMIS-related processes (Harrison and Nutley, 2010; Moreland *et al.*, 2010; Oliver *et al.*, 2014). Organizational factors, such as interpersonal relationships between supervisors and supervisees and workplace culture, may also influence the motivation to complete HMIS-related tasks (Mutemwa, 2006; Aqil *et al.*, 2009; Qazi and Ali, 2009). Similarly, existing norms and values around data use within organizations may directly influence HMIS performance (Aqil *et al.*, 2009; Ndabarora *et al.*, 2014).

Evidence suggests that technical tools have only been partially effective in improving HMIS performance (Belay *et al.*, 2013; Welay *et al.*, 2017; Wandera *et al.*, 2019). In fact, non-technical factors, such as social and political influence in decision-making have been found to contribute to low HMIS data use (Wickremasinghe *et al.*, 2016) and poor HMIS data quality (Qazi and Ali, 2011). Chauglagai et al. corroborated this point, in their reflection of Malawi's HMIS implementation, and concluded: "no matter how good the design of an information system, it will not be effective unless there is internal desire, dedication and commitment of leadership to have an effective and efficient health service management system" (Chaulagai *et al.*, 2005). So far, few studies on HMIS have moved beyond technical assessments (Mutemwa, 2006; Qazi and Ali, 2009, 2011; Maluka *et al.*, 2010), and a fundamental question remains unanswered: why have HMIS strengthening objectives not been met despite significant financial, technical and capacity building investments?

To address this question, it is critical to understand how the "software" components of HMIS (e.g., organizational cultural factors including hierarchy, distribution of power and authority, discretion, and interpersonal power dynamics) interact with their "hardware" counterparts (e.g., formal rules and processes) (Sheikh *et al.*, 2011). Thus, we analyze how organizational factors, including organizational culture, shape the implementation of new HMIS policies in Uttar Pradesh (UP), India from the perspectives of policy implementers. In addition, we attempt to explain the observed gap between well-intentioned HMIS policy guidelines and their actual implementation, which has contributed to the partial achievement of the HMIS policy objectives; and finally, we conclude with considerations for strengthening HMIS.

Study context

This section provides an overview of the new HMIS policies implemented in UP, and summarizes the roles of key government workers, who are involved in policy implementation.

A. The design of the Uttar Pradesh - Health Management Information System (UP-HMIS)

In 2015, the Government of Uttar Pradesh (GOUP) with the support of the Uttar Pradesh, Technical Support Unit (UP-TSU), an entity established in partnership between the Bill and Melinda Gates Foundation and the GOUP, implemented new policy guidelines (hereafter referred to as policies) to strengthen the state's HMIS performance. These policies aimed to address existing barriers with HMIS performance, for example, the complexity and duplication of reporting formats, and weak processes resulting in the lack of timeliness and completeness of reporting across block- and district-levels (Meghani *et al.*, 2020).

First, the GOUP designed and implemented its own data platform, the Uttar Pradesh HMIS (UP-HMIS), to include data elements that state program managers felt were absent in the national HMIS but relevant for decision-making. Second, the GOUP developed policies to improve the UP-HMIS data quality and use. **Table 1** presents these policy details and their current implementation status.

1. Data quality policies

To improve data quality, the GOUP targeted two points in the UP-HMIS data flow (**Appendix 1**): (i) the block-level, where data from public and private health facilities are collated before being forwarded to districts; and (ii) the district-level, where data from blocks and additional private health facilities are collated before being forwarded to the state-level.

Data quality policies targeted strengthening UP-HMIS reporting and monitoring and evaluation (M&E) processes. First, all paper-based health facility reports which were collated at the block-level were directly entered into web-based portals, thereby discontinuing paper-based reporting from block- to the district- and state- levels. Second, blocks and districts were required to establish data validation committees to ensure UP-HMIS data quality were vetted before being forwarded to subsequent administrative levels (from block to district, and district to state) (**Appendix 2**). To complement these initiatives, a state-level data validation committee and data quality audit teams were subsequently established.

Table 1. Overview of key Government of Uttar Pradesh (GOUP) policy guidelines to improve data quality and use

		Policy topic (description)	District policy status [4]	Situation post policy implementation	Implications
Data quality					
Reporting	**January 2015**	Timeliness and periodicity of reporting by blocks (Paper-based health facility reports[1] are entered into digital portals at the block-level during a specific timeframe)	Partial implementation	Overburdened data entry operators are unable to enter data from health facilities during the allocated time	(1) Data on digital portals are incomplete, missing or inaccurate, especially those data elements that are not used to calculate district rankings; (2) Due to incomplete data some district and state officials rely on paper-based or other forms of reporting resulting in multiple sources of data
	June 2015	Reporting from private health facilities and medical colleges in Uttar Pradesh to the UP-HMIS digital portal (Private sector services are captured on paper-based forms and entered to digital portals at the block- and district-levels)	Low implementation	Private facilities rely on paper-based reporting; reporting has been infrequent despite the state- and district-level directives urging compliance	(1) Limited data on utilization of services in the private sector
	May 2017	Discontinuation of paper-based reporting[1] in favor of reporting via digital portal (Only digital reports are to be used at all levels of the GOUP health system so that decisions are made using a single source of data)	Partial implementation	Paper-based reports are being used to cross-check the data reported in the UP-HMIS digital portal at the district-level	(1) Validation of data quality between paper-based reports and digital portal data has replaced recommended data quality checks like supportive supervision visits; (2) When discrepancies exist, paper-based reports are viewed as the "gold standard" because they are signed off by block health officials

Monitoring	January 2015	Data quality supportive supervision visits by block officials (Block officials are expected to check data accuracy by comparing digital data with source data reported in health registers using supportive supervision checklists)	Low implementation	Irregularly implemented based on assessment of district program and data staff Block staff are viewed as lacking the technical know-how to conduct data quality checks	(1) Frequent detection of data quality errors at the district-level, particularly during the district data validation committee meetings
	August- September 2015 [2]	Establishment of block and district level data validation committees (Data validation committee meetings are expected to review the accuracy of digital portal data before they are reviewed by the next administrative level)	Block: Partial implementation District: High implementation	Meetings held irregularly held at the block-level Meetings held regularly at the district-level	(1) Frequent detection of data quality errors at the district-level, particularly during the district data validation committee meetings
Data use					
Monitoring & feedback	January 2016	Guidelines outline: (1) the review of UP-Health Dashboard, specifically the district rankings, to inform decision-making during monthly district-level meetings; (2) the analyses that should be conducted to identify gaps in health services based on district ranking indicators; and (3) the development of an action plan to address identified gaps	Partial implementation	District rankings are reviewed, however the preparation and review of action plan during meetings is variable across districts. Meetings focus on addressing logistical issues rather than using data to inform strategic planning decisions	(1) Focus on district ranking indicators reduces focus on other program indicators that are excluded from the monthly district ranking; (2) Greater emphasis is on using district ranking data to manage performance rather than giving equal consideration issues of data quality; (3) Limited focus on developing action plans to improve performance of low performing health indicators

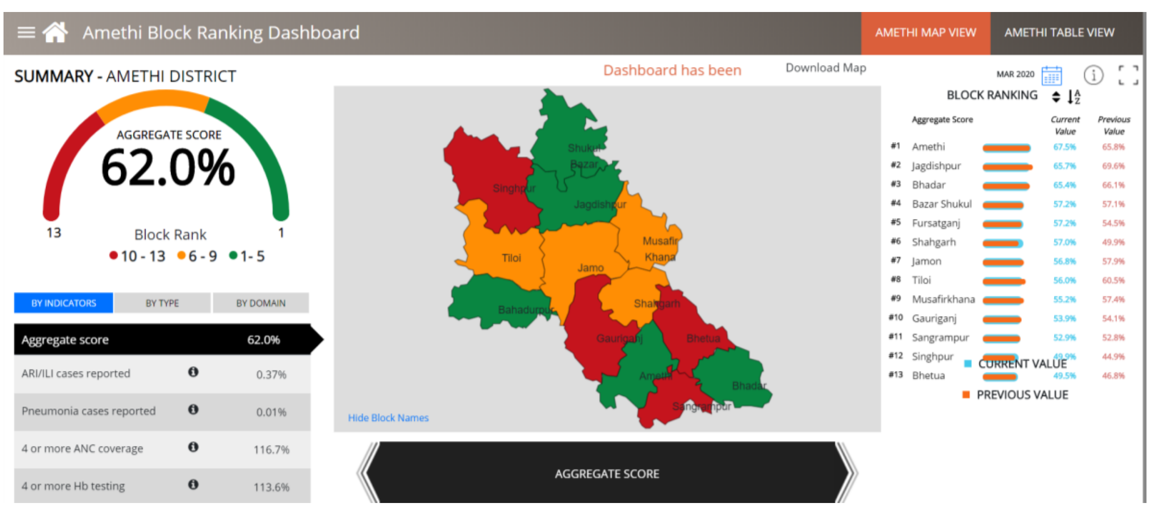
	February / August 2018	Use of rankings & UP Health Dashboard during monthly Executive Committee/program review meetings[3] Promote the review of key indicators in the district rankings, available on the UP-Health Dashboard to ensure progress on the state's priority health programs	High implementation	District rankings and the indicators used to achieve those rankings are regularly reviewed during executive committee meetings, in addition to the district health society meeting chaired by the District Magistrate	
Resources to support policy implementation					
Cross-cutting	July / Sept 2017	Training on UP-HMIS Orders released to ensure full participation of in health trainings at the primary health center, block, district, division and state levels and the availability of required logistics to implement trainings	High implementation	Results suggest 88% of targeted actors participated in the UP-HMIS trainings across all levels of the health system,[6] however the quality of trainings is unclear	(1) Limited technical knowledge and understanding of issues of data quality, particularly, at the block level (from the perspective of district-level staff/officials); (2) High demand for refresher UP-HMIS trainings for field staff and block-level data entry operators
	Annual[5]	Release of annual funds to support the printing of UP-HMIS formats and financial support to hire data entry operators at the block level	Unable to assess	Unable to assess	(1) Indication that block data entry operators are insufficient; (2) Unclear whether larger budgets for hiring are required or existing budgets are not being allocated for the intended purpose

[1]Blocks are the first administrative level where paper-based reports are digitized by being entered into the UP-HMIS web-based portal; [2]A separate government order in September 2015 required the inclusion of members from district hospitals in the district data validation committees; [3]Executive committee meetings are also referred to as program review meetings or monthly medical-officer-in-charge (MOIC) meetings; [4]This analysis is based on our in-depth interviews from a purposive selection of high, middle and low performing districts across Uttar Pradesh; [5]To support policy implementation, these guidelines are released every annum; [6]Assessments based on Meghani *et al.*, 2020

2. Data use policies

To promote UP-HMIS data use at the district-level, the GOUP implemented two policies. The first, focused on improving the periodicity and quality of monthly district-level Executive Committee meetings, which convene all block and district health staff, and are chaired by the district's chief medical officer. The second, required the review of the UP-Health Dashboard during Executive Committee meetings, and the high-level Governing Body meetings of the District Health Society (hereafter, District Health Society), chaired by the District Magistrate and attended by block and district health staff and health partners (**Appendix 2**). The UP-Health Dashboard (**Figure 3**) was viewed as an important data use tool for these meetings because it presents the monthly ranking of each district (relative to the other 74 districts in the state) using a set of UP-HMIS indicators. Based on the monthly performance in the district rankings, districts are expected to prepare an action plan for improving poorly performing health indicators and facilities.

Figure 3. District-level performance data available on the Uttar Pradesh Health Dashboard



Note: this Figure presents an example of Amethi district

3. The role of key staff/officials in UP-HMIS implementation

Five main types of government workers involved in UP-HMIS policy implementation are:

(i) Permanent employees of the Directorate of Medical Health and Family Welfare (DOMHFW), who receive full benefits and paid time off;

(ii) Contractual employees of the Uttar Pradesh National Health Mission (NHM), who receive fewer benefits than permanent employees and have less job security;

(iii) Temporary contractual staff, who are hired by external agencies, like data entry operators;

(iv) M&E specialists, contractual data staff of the UP-TSU, who are posted in 25 high priority districts out of the 75 districts in UP; and

(v) District administrative officials (e.g. district magistrates), who are members of the prestigious Indian Administrative Services, govern the district and play a peripheral role in UP-HMIS policy implementation.

With respect to data quality policies, permanent data staff in blocks and districts lead data quality processes, including data validation committee meetings, with the support of contractual data staff at each level.

With respect to data use policies at the district-level, contractual data staff are responsible for analyzing the district performance data and presenting those data (including district rankings) during the two district-level data use meetings. They are also expected to conduct gap analyses and develop action plans with support of district program staff, who are permanent employees and manage health programs in the district. **Appendix 3** provides additional details about the roles and responsibilities of staff by administrative level.

Conceptual framework

We investigated policy implementation from the lens of district-level respondents, the primary implementers of the UP-HMIS data policies. To understand their experiences, we drew from Lipsky's street level bureaucracy theory (Lipsky, 2010), which challenges the key assumption that if policy objectives are neatly laid out, then implementation will follow suit. Instead, the theory focuses "on what organizations actually did [do] in the name of policy" by examining the perspectives of the policy implementers on the frontlines - the street level bureaucrats (SLBs) - and understanding how their realities shape policy implementation (Brodkin, 2012). Often, it is their interpretation of policies, based on their worldviews, which creates a gap between "policies as written" versus "policies as practiced" (Brodkin, 2012).

SLBs exercise varying levels of discretion and autonomy that shape how, when and where policies are implemented. SLBs often face high performance pressures and are expected to deliver on them despite limited time and resources. Under these circumstances, SLBs develop "coping mechanisms." Some SLBs use their discretion to comply with policy directives, while others bend policies to meet broader organizational objectives. Therefore, the discretion exercised by SLBs reflects the powers they have negotiated within their organizational and work environment, which Lipsky argues influences SLB practices. In line with street-level bureaucracy theory, we investigated how the discretion, autonomy, and authority of district officials/staff in Uttar Pradesh influenced UP-HMIS policy implementation. We examined how their behaviors and implementation practices were shaped by organizational factors, like performance pressures.

We also drew on organizational culture literature to study how the behaviors of the SLBs were influenced by their broader environment. We understand organizational culture as "the beliefs, norms, values, and behaviors of organization members relative to the characteristic way in which work is approached and conducted" (Shortell *et al.*, 2000). Within organizational culture, we examined two specific dimensions given their importance in the UP bureaucracy and how SLBs operate namely: (i) organizational hierarchy, focusing on reporting relationships among actors, formal rules, processes and regulations; and (ii) performance management culture, including approaches to enforcing accountability, participation, and coordination among different team members.

2.2 Methods

Our study draws on a pragmatist epistemology (Strübing, 2007) and follows an emergent research design (Creswell, 2013). For this research inquiry, we drew from three primary data sources: (i) document review; (ii) in-depth interviews; and (iii) meeting observations. The document review was conducted first, followed by in-depth interviews and meeting observations, which were conducted concurrently.

Study Design

A. Document Review

We conducted a document review to describe the new UP-HMIS policies on data quality and use; examine their implementation status; and inform the development of a semi-structured in-depth interview guide. Review of GOUP government orders, circulars and memos helped: (i) define the new data collection, data quality and use processes at the district-level; (ii) describe proposed meeting platforms for data quality and data review/use; and (iii) distinguish the roles and responsibilities of district officials/staff in UP-HMIS policy implementation.

The UP-TSU and district level participants shared documents, such as, the agendas, presentations, and meeting minutes for data quality and data review meetings, and examples of reports from supervision visits, which enabled us to ascertain policy implementation status.

We analyzed 49 Hindi and English documents according to steps outlined by O'Leary (O'Leary, 2004), focusing on who produced the document, when, and for what purpose. Results were summarized in English in an Excel sheet.

B. In-depth interviews

The district-level in-depth interview guide consisted of questions on the: (i) actual roles and responsibilities of district-level staff/officials in UP-HMIS policy implementation; (ii) status of data quality/use policy implementation in the district; (iii) barriers and facilitators influencing implementation; (iv) district-level interactions with block and state officials/staff relating to data quality and use; and (v) general perspectives on how to strengthen policy implementation. The division and state-level interview guide focused on understanding current practices for data use in decision-making, and potential challenges and opportunities to improve data use in UP.

We conducted 87 in-depth interviews with district-, division- and state-level staff/officials, who were involved in compiling, analyzing, or reviewing routinely collected GOUP health data, like the UP-HMIS, or were knowledgeable about UP-HMIS policies (**Table 2**). Interviews were conducted by AM primarily in Hindi, the official language of GOUP, in three rounds: (i) December 2018; (ii) February-March 2019; and (iii) August-October 2019. Except for 12 phone interviews, in-person interviews were largely conducted in GOUP administrative offices.

Table 2. Number of respondents interviewed by administrative level and employment type

Level	Staff type	Number of interviews
State	Program managers	26
	Data managers	5
Division	Data staff	7
District	District administrative & health officials	3
	Permanent - Program staff	10
	Permanent - Data staff	10
	Contractual - Data staff	26
	Total	**87**

Seeking maximum variation, district selection was based on two factors: (i) the district's performance based on its ranking in the UP-Health Dashboard during the interview month; and (ii) the district's designation as a high priority or non-high priority district. We found these two factors important given their potential to influence the level of UP-HMIS policy implementation at the district-level. First, this approach enabled us to examine whether high ranking districts had better implementation of UP-HMIS policies compared to lower ranking districts. Second, we were able to examine the potential influence of UP-TSU's contractual data staff in high priority districts on UP-HMIS policy implementation.

In sum, we conducted interviews in 5 top ranked districts (ranked 1-25), 6 middle-ranked districts (ranked 26-50) and 5 bottom-ranked districts (ranked 51-75); with each tier, having 2 high priority districts. In each district, we aimed to interview four respondent-types: (i) contractual data staff (e.g., district program managers or district data managers); (ii) permanent data staff (e.g., assistant research officers); (iii) permanent program staff (e.g., assistant chief medical officers); and (iv) district health officials (e.g., chief medical officers) or district administrative officials (e.g., district magistrates). We selected these groups to understand the relative roles of both permanent and contractual data and program staff in UP-HMIS policy implementation.

We interviewed M&E officers at the division-level, who are responsible for monitoring district-level data quality processes through supportive supervision and data audits. State-level respondents included program managers from the NHM, and directors or joint directors from the DOMHFW. To capture the diversity of experiences at the state-level, we purposively interviewed state-level respondents responsible for national health programs, state health programs, and involved in data-related activities.

We sought written informed consent before each interview. If permission was granted, interviews were audio-recorded; otherwise, hand-written notes were taken. Interviews ranged from 25 to 90 minutes. A qualified transcription service translated audio-recorded interviews to English; transcripts were reviewed for quality by AM.

Following interviews, AM wrote memos to record emerging themes/sub-themes, detail existing themes/sub-themes or identify areas of further inquiry for upcoming interviews. Constant comparison of emerging findings (Boeije, 2002) between interview rounds through memo writing, and discussions among team members informed the revision of the interview guide, and triangulation of findings by respondent-type. This iterative approach to data collection and analysis facilitated the achievement of data saturation (Morse, 2015).

C. Meeting observations

We observed 15 district and state level meetings, and notes were taken on the adherence to new UP-HMIS policy implementation guidelines, the nature of interactions among district officials/staff (SLBs), and between SLBs and their superiors, as well as the tone and the level of participation of meeting participants (**Table 3**). The observations helped contextualize and triangulate findings from the document review and in-depth interviews.

Table 3. Meetings observations conducted in Uttar Pradesh

Level	Number of observations
District[1]	
Data validation committee meetings	6
Executive Committee	5
District Health Society	3
State	
Data validation committee meeting	1
Total	15

[1]Meetings were observed in 8 districts, where interviews were also conducted.

Data analysis

The framework method was used to thematically analyze the in-depth interviews (Gale *et al.*, 2013). First, AM read through all the interviews, and performed line-by-line inductive coding on the first 20 transcripts. Following open coding and iterative discussions with study team members, an analytical framework was developed based on the identified inductive codes and the conceptual theories described above. The analytical framework identified five major categories: (i) policy environments at the national and state levels; (ii) UP-HMIS policy implementation observed in practice; (iii) organizational factors influencing policy implementation; (iv) SLBs' roles in policy implementation;

and (v) perceptions about barriers and opportunities to strengthen policy implementation. Each category was further divided into codes and sub-codes described in **Appendix 4**.

This analytical framework was applied to all the interview data and meeting observation notes, and relevant data were extracted into an excel sheet. For each category, memos were written to capture the following: definition of each category; codes and sub-codes within the category; summary of findings; deviant cases; and points for further consideration when comparing and contrasting findings across respondent type. The documentation summary excel sheet was also reviewed and relevant information was incorporated into the memos written for each category. After the analysis, a meeting was conducted with a couple of respondents as a way of member checking.

Authors' positionality

We are a team of researchers and public health practitioners, who combine perspectives of insiders and outsiders. Our research team includes UP-TSU members who were deeply involved with the design of UP-HMIS and initial implementation efforts, and JHU members, who were not associated with UP-HMIS policy reforms. Two authors (AM, SB) conceptualized and designed this study with input from other co-authors. UP-TSU colleagues additionally imparted important contextual understanding to inform this study.

2.3 Ethical Considerations

Johns Hopkins Bloomberg School of Public Health deemed this research as IRB exempt (00009106). The study was approved for ethical research by the Institutional Review Board of SIGMA Research and Consulting in New Delhi, India (10047/IRB/D/18-19).

2.4 Results

Overall, we found no meaningful differences in implementation experiences across high, middle, and low ranked districts. As district rankings fluctuate for many districts in UP, including those where we conducted interviews, this may not be a meaningful categorization reflecting larger underlying issues. Therefore, we do not present our results by these stratifications.

With respect to policy implementation, we found annual budgetary policies for printing UP-HMIS forms and hiring data entry operators were fully implemented. In contrast, process-oriented policies – which formed the crux of the GOUP data quality and data use policies – were partially implemented (**Table 1**). District-level staff/officials (SLBs) identified: (1) inadequate organizational inputs for policy implementation, such as, inadequate human resource capacity and technical skill; but also (2) deeply embedded organizational cultural issues, like seniority and hierarchy, which significantly influenced how staff/officials implemented UP-HMIS policies.

The first part of the results describes the role of organizational factors on UP-HMIS implementation practices, followed by a deeper investigation of the influence of organizational cultural factors in the subsequent section.

Organizational factors influencing policy implementation

A. Human resource capacity

Inadequacies in human resource capacity – both in number and skill – were universally acknowledged by respondents at all levels; as one succinctly stated, *"Where there is more manpower, there is better data"* (I-78, state-level respondent). District-, division- and state-level respondents also agreed that the shortage of block-level data entry operators was the greatest challenge facing UP-HMIS implementation. On average, each block data entry operator played a critical role of entering paper-based reports from each of its 26 to 31 health facilities (depending on block size) to up to 16 digital health portals every month.

District-level respondents acknowledged that the high data entry workload contributed to incomplete and inaccurate data, limiting their use at the state-level due to empty data fields and mistrust in some of the reported data. As a result, many state respondents described making separate data requests from districts, and at times, reverting to paper-based reports, despite the new policies discouraging their use.

Human resource constraints were also observed at the district-level. Such constraints arose from delays in recruitment or having disproportionately higher "less active" or low-performing district staff. To cope with these challenges, district health officials (namely, chief medical officers) were found to assign or transfer program responsibilities to "more active" health staff, who they perceived could "get the job done" (I-35, contractual data staff, district-level).

While this informal reallocation of responsibilities across existing staff allowed district health officials to manage work expectations by ensuring "no posts are [were] vacant because someone is [was] made-in-charge" (I-1, contractual data staff, district-level), many district staff felt the additional workload distracted them from performing their data-related responsibilities. Overburdened with program responsibilities, district-level program staff were unable to fulfill their data-related responsibilities, such as conducting supportive supervision visits at the block-levels or participating in district-level data quality meetings.

Many district staff also acknowledged that the reallocation of responsibilities resulted in performing duties that went beyond their terms of reference and training. While some reconciled this strategy as a form of coping with human resource constraints, others found the divergence between actual and assigned responsibilities demotivating:

> *"People see the difference between their TOR [Terms of Reference] of when they joined and what it is presently. They begin thinking 'what was the purpose of joining here when this is now the work that we are doing'"* (I-5, contractual data staff, district-level).

B. Technical skills & trainings

Though trainings on new UP-HMIS policies were conducted at all levels as a part of the initial policy implementation processes, district-level staff felt the lack of technical knowledge about UP-HMIS data elements among field and block staff was the root cause of poor data quality. Often limited knowledge about UP-HMIS data resulted in basic data entry errors, like the reporting of institutional deliveries in male hospitals. District respondents further explained that data entry problems increased when: (i) Hindi-literate field staff were expected to populate English-based data collection forms; and (ii) data collection forms were frequently revised or new ones were introduced. Reflecting on these technical barriers, one state respondent recommended:

> *"If any new indicator is getting included, permission should be taken from everyone… Recommendations like 'At least for six months, none of the indicators should be included or deleted from portal' should be suggested. Guidelines should also not change often."* (I-85, State-level respondent)

According to some district staff, poor data quality was expected given the high workload of data entry operators, and low pay. After paying their staffing agency, district staff shared that most data entry operators made low salaries of 5000-7000 rupees (US$66-93) per month; many worked second jobs for additional income.

District respondents observed that a second technical barrier among block staff/officials was their inadequate knowledge about the latest health program guidelines. District staff felt this knowledge-gap resulted in data discrepancies between financial and service data reported in UP-HMIS, and data validation errors between indicators one would expect to correlate. These barriers were also evident in district-level meeting observations.

District respondents felt these technical weaknesses would be mitigated at the block-level if existing permanent block-level data staff, who were more experienced than their contractual counterparts, took ownership of UP-HMIS data quality processes, like data validation committee meetings, and if vacant data-related posts were filled. The lack of technical ownership to review data quality at the block-level was found to increase dependency on districts:

> *"MOICs [Medical Officers-in-charge; block health officials] do not have requisite knowledge and skills to use data. BPMs [block program managers] are also not that skilled to analyze and use data. Hence, they are dependent on the district. Whatever we brief them at the district, they blindly follow and implement the same but next time they again depend on us"* (I-1, contractual data staff, district-level).

In contrast, we observed higher levels of technical skills among district data staff (both permanent and contractual) based on district-level respondents' own assessments, as well as our meeting observations. During meetings, district data staff were critical in identifying data discrepancies in block-level reports, as well as informing block staff on how to review and analyze their data for quality.

Technical skills observed among district data staff, however, did not equate to computer literacy. Though commonly viewed as the data expert at the district-level, some permanent data staff, who had less experience using computers, were found to rely on others to access, download, or view the UP-HMIS data, limiting them from carrying out data-related activities independently:

> *"Most of them [permanent data staff] don't know how to use a computer. So, they won't be able to download the data. They feel comfortable in manual [paper-based] reports verification and if there are any errors then sit with the operator and get them rectified"* (I-49, contractual data staff, district-level).

Our state respondents, who had formerly held district-level data positions, corroborated this assessment, and described working in dyads for data entry.

Organizational cultural factors influencing policy implementation

A. Organizational hierarchy

Observance of strict hierarchical rules resulted in a significant power imbalance at the district-level. We observed that an individual's status within the health system hierarchy was usually determined by: (i) their formal position (e.g., decision-making authority); and (ii) their employment status (permanent or contractual staff), with permanent staff being more highly regarded. These factors influenced who had discretion, authority, and power, which at times, shaped how UP-HMIS policies were implemented. **Figure 4** depicts the hierarchical gradient we observed.

Figure 4. Hierarchical gradient described by district-level respondents

INCREASING POWER

1. District Magistrate
2. Permanent officers[1] – District
3. Permanent (data) staff - District
4. Permanent officers[2] – Block
5. Permanent (data) staff - Block
6. Contractual data staff – District
7. Contractual data staff – Block
8. Permanent Field staff – Primary health center/community levels

[1]Chief medical officers, assistant chief medical officers (program staff); [2]Block level medical officers in charge

B. Seniority-oriented organizational culture

District data staff explained that the disadvantages of a hierarchical organizational culture was felt most by field staff, who sat at the base of the organizational pyramid. Their perceived lack of authority contributed to the incomplete reporting as many private health facilities sent field staff away or directed them *"to come another day"* when they went to gather UP-HMIS reports (I-15, district-level permanent data staff).

The consolidation of power and authority among senior health officials, the medical officers-in-charges in blocks and chief medical officers (CMOs) in districts, resulted in an abuse of power. District-level staff/officials shared several examples of block-level health officials redirecting data entry operators to prioritize their personal errands over formal data entry duties:

> *“"Whatever work, like if the MOIC [medical officer-in-charge] needs a train reservation, he asks the MCTS [data entry] operator. The other work like typing up a letter is also assigned to him. So, there is problem in his priority. "* (I-11, contractual data staff, district-level).

This reallocation of priorities of data entry operators at the behest of block health officials exacerbated the extant problems of incomplete and inaccurate data, which were also attributed to the severe shortage of data entry operators. Despite the release of a state-level GOUP memo, reprimanding block health officials for this practice, district staff reported that little had changed.

District data staff also found themselves overburdened. Attending to the immediate priorities of their district-level superiors or managing urgent ad-hoc data requests from the state-level, left district data staff with little time for their own work. District data staff found state-level requests particularly distracting because state officials/staff had access to the same web-based data portals as they did:

> *"It [Ad-hoc requests] spoils our personal planning. Like 10 General Managers sit there [at the state level] and if they have called and asked for the report then they all want their report first. So, we cannot fix our priorities as we are bounded by them. If 9 get the report out of 10 then that one person will be upset"* (I-5, contractual data staff, district-level).

State respondents explained that data requests arose when data were missing, incomplete, appeared inaccurate or when additional data, not routinely collected, were needed for high-level meetings. However, state respondents also acknowledged increasing the frequency of data requests during national health campaigns or priority programs because they wanted data in real-time, whereas the portals only provided them access to monthly data.

To cope with these requests, district data staff often prioritized the reporting of closely monitored data, which they explained contributed to incomplete reporting of other data elements reported in UP-HMIS. Furthermore, district data staff felt the steep power differential precluded them from sharing feedback about their work-related challenges with their superiors at the district- or state-levels. Relatedly, they also acknowledged that their lack of power and authority at the district- and block-levels often resulted in escalation of data-related issues:

> *"Basically, in Data Cell, we do not have administrative powers, we cannot punish anyone, we can only request our boss and say this is the situation we are facing… I will give this letter to our senior, CMO [Chief Medical Officer] Sir, and he is the authority to take further action"* (I-18, permanent data staff, district-level).

As a result, minor issues were tabled to the monthly data use meetings chaired by district health and administrative officials, who helped to bring greater accountability to data-related processes at the block and district-levels:

> *"DM or the CDO [district magistrate and chief development officers; district administrative officials] ask questions directly to the MOICs [medical officers-in-charge; block health officials] about their performance. If the DPM [contractual data staff] asks it doesn't make much of a difference, even with the CMO [chief medical officers; district health official] you may not get the effects you'd see with the DM or CDO. There is a distance maintained so they take the feedback of these IAS [Indian Administrative Services; cadre of district administrative officials] more carefully"* (I-5, contractual data staff, district-level).

Escalation, however, came at a high cost. Only occasionally did the monthly data use meetings achieve their intended policy objectives of making strategic decisions (e.g., identifying drivers of poor performance) based on UP-HMIS district ranking indicators. Meetings we observed predominantly focused on coordinating logistics across teams, reflecting deep working silos among and between block and district staff.

Unequal distribution of power and authority between permanent and contractual staff

District contractual data staff universally noted one major exception to the strict observance of seniority in organizational culture: the distinction between permanent and contractual staff, with the former benefitting from power and authority not available to contractual staff.

Some district contractual data staff reported an inability to directly question or provide feedback to block-level permanent data staff or senior block health officials about data quality issues they were identifying. All feedback about data quality errors had to be directed to block-level contractual data staff. District-level contractual data staff recognized that the power gradient was steeper for block-level contractual staff who were incapable of mandating the implementation of data quality validation committees or data quality supportive supervision visits without support from their block-level permanent health officials.

In districts where paper-based reports were still used, district-level data staff (both contractual and permanent) noted how the distinction between permanent versus contractual staff influenced how block-level data were regarded at the district-level. If differences in data were observed between paper-based reports and those entered in UP-HMIS, preference was given to paper-based reports because they were signed off by permanent staff. In comparison, the UP-HMIS portal data was given less priority because it was managed by contractual data staff. Even in instances when district data or program staff questioned the integrity of these paper-based reports, the presiding norms around hierarchy was cited as a primary reason that compelled them to prioritize data from paper-based reports.

A. Punitive performance management

1. Overemphasis on performance data

Within the context of UP-HMIS implementation, district data staff noted a dichotomy: district rankings ended up generating accountability for performance data, but not for data quality. Particularly district-level data staff felt that GOUP's primary policy intention of using district rankings to actively encourage UP-HMIS data use to guide program improvement was overlooked by the district health (i.e., CMOs) and administrative officials (e.g., district magistrates).

Many district staff felt their district health and administrative officials were fixated with becoming the top-ranking district in their administrative division, if not across the state, as they saw the rankings as a reflection of their own performance. While some of this pressure was associated with improving actual performance on health indicators, many district staff felt the pressure of achieving high district rankings "at all cost" was passed on to them and block-level staff. If the district's monthly ranking was low, district staff described being verbally reprimanded during monthly district-level meetings or receiving warning letters from district officials demanding a justification for their low performance. One permanent program staff equated working in the GOUP health system to *"being in a pressure cooker, with the pressure coming in from all levels of the health system"* (I-42, permanent program staff, district-level).

Many district data staff acknowledged that rankings were misleading district officials. Because districts were ranked relative to others in the state, they were not absolute measures of performance:

> *"Competition should not be there in terms of ranking; it should be in terms of data entry improvement and improvements of indicators. We should focus on the percentage of improvement... If there is only 2-3% improvement, we should see what conditions led to that*

improvement, and then we need to work on them. We should change our thinking...” (I-33, Contractual data staff, district-level).

However, when some district data staff aimed to redirect attention to absolute achievement of targets as opposed to rankings, many felt unsupported by their senior district health officials because of their need to be a top ranked district, as one district data staff recounted:

> *" The CMO [district health official] said, “Bring me everything on one page. Tell me which block is poor. The rest I will take care of.” If I start telling the CMO which block are poor, letters will be sent against them. Then the blocks will send back letters with reasons achievement did not happen. Letters will keep getting exchanged from here [district] to there [block]...the meetings will get diluted"* (I-61, Contractual data staff, district-level).

2. Differential approaches to enforcing individual vs team-based accountability

Though district rankings measured the overall district performance on priority health programs, the prevailing norms around accountability targeted individuals rather than teams. District staff often felt district health and administrative officials targeted and blamed staff for wrongdoing, rather than suggesting corrective action. While district health officials and permanent district staff felt the burden of poor performance, contractual data staff felt they unfairly faced the greatest repercussions of poor performance: termination of their contractual status or warning letters by district administrative officials holding them accountable for the district’s poor ranking. In comparison, transferring or even firing permanent employees, which involves complex government processes (Legal Service India, 2018) was not pursued and reserved for high-profile misdemeanors (e.g., preventable deaths due to stock-outs)(First Post Staff, 2017).

Contractual data staff felt this differential approach to accountability was evident in a new accountability mechanism introduced specifically for contractual data staff that ranks district program managers on health and process indicators (UP NHM, 2019). While these indicators measured district-wide performance (e.g., percent of women accepting a birth-spacing method), a single individual was being held accountable in the ranking.

Examples of strengthening implementation of UP-HMIS policies

Leadership that valued good quality data for decision-making was critical in promoting adherence to UP-HMIS policies. This was evident during meeting observations, where we observed district health and administrative officials reiterating the importance of "real data," "not hiding neonatal deaths," and encouraging district staff to communicate the significance of data accuracy with their field staff. In another meeting, we also observed a district administrative official motivating district health officials to use data to uncover the root causes of low performing programs by commissioning them to complete analyses and present findings during the next monthly meeting. According to district staff, review of supportive supervision reports and surprise visits by district health and administrative officials created stronger accountability for data quality measures, which were otherwise ignored.

In high priority districts, the presence of UP-TSU M&E contractual data staff helped ensure the regularity of district-level data validation committee meetings, and the implementation of UP-HMIS supportive supervision visits. However, the enforcement of accountability for data quality by district leadership was still viewed as a critical factor in institutionalizing the new UP-HMIS policies.

To close the technical gaps in UP-HMIS data comprehension at field- and block levels, data staff in one district described implementing quarterly trainings. A majority of the data-related staff we interviewed across high priority and non-high priority districts also described using existing district-level data validation meetings to review data quality concepts and indicator definitions, which we also observed in practice during our district- and state- data validation committee meetings observations.

On a broader scale, many respondents acknowledged that widespread corruption affected the implementation of UP-HMIS processes, such as, the quality of supportive supervision visits, and UP-HMIS data quality. However, corrupt practices did not go unnoticed by district administrators. Some district administrative officials described resorting to independent monitoring to keep corruption in check, as one district administrative official shared:

> *"Most of the CMOs [Chief Medical Officers] are more into other things than their own jobs. By other things, I mean there is corruption…I believe that corruption is a culture that flows from top to bottom, and it would be worse at the bottom compared to top, because it is flowing down. That is a big reason for the poor performance of our district, but we do so much monitoring of it that we do not let it spoil a lot. Our project director is deputed for regular inspection…."* (I-26, district administrative official).

2.5 Discussion

Technical approaches to strengthening HMIS have been extensively examined in health systems literature. However, this paper explicitly examines the role of organizational cultural factors in shaping the behaviors of policy implementers in the context of new HMIS policies, an area which has been relatively understudied.

Consistent with other studies, we found that human resource constraints – the number and level of technical skill in light of the high reporting burden weakened the implementation of HMIS policies for supportive supervision and data validation meetings, and reduced data availability, completeness and accuracy (Odhiambo-Otieno, 2005; Garrib *et al.*, 2008; Qazi and Ali, 2009, 2011). While hiring more data staff and providing skills-based training may address these technical challenges, our evidence suggests that they would be unlikely to resolve the underlying organizational cultural barriers, which are critical for effective HMIS policy implementation at local levels. For example, studies examining the effects of training on HMIS implementation in South Africa and Zanzibar reported mixed findings: while trainings helped build analytical skills among district staff, they did not remove the feeling of "powerlessness" associated with low discretion to act on the data (Østmo, 2007).

The bottom-up perspectives of district-level respondents, namely, the street-level bureaucrats provided overwhelming evidence for the influence of organizational cultural factors on UP-HMIS implementation. Though the UP-HMIS policy guidelines were driven by a rational theory – that improved data quality (via stronger data validation processes) would drive data use (use of district rankings data to improve district performance) and this positive feedback loop would drive HMIS performance – our analysis points to several implementation gaps.

First, operating within UP's strong command-and-control hierarchy presented challenges for district-level data staff, who were responsible for UP-HMIS implementation. Holding relatively lowly positions in the hierarchy, district data staff had little discretion, autonomy, or authority to make decisions. They were expected to follow superiors' directives – even if that meant ignoring UP-HMIS policy objectives (e.g., using paper-based reports). Exacerbating these challenges was the inability of district-level data staff to share grievances with an independent entity, like a functional data unit at the state-level. Other studies have similarly reported on how challenges associated with strict hierarchies between supervisors and subordinates influenced the functioning of HMIS at different levels of the health system (Mumtaz *et al.*, 2003; Qazi and Ali, 2009), with one study reporting on data entry operators in their HMIS units being “forced” to complete non-work-related tasks per their superiors’ directives (Qazi and Ali, 2009).

Second, unequal distribution of authority between permanent and contractual staff complicated UP-HMIS accountability processes. Though district-level data contractual staff were held accountable for managing UP-HMIS across the district, they were unable in turn to hold others accountable for poor adherence to UP-HMIS guidelines because of their contractual status. The state envisioned creating accountability for UP-HMIS through contractual staff in a way they were unable to do so with permanent staff who hold more secure positions. Yet, power dynamics between contractual and permanent staff resulted in dysfunctional reporting relationships and minor issues being escalated to monthly meetings chaired by senior district officials. This escalation came at another cost: high-level data meetings became fora for troubleshooting trivial issues instead of being a platform for strategic discussions as outlined in the UP-HMIS policies. This discordance between contractual and permanent staff has also resulted in state-wide protests demanding “equal pay for equal work” (Tribune News Service, 2020).

Third, the overemphasis on the monthly district rankings - one component of the data use HMIS policies - also had unintended effects. So long as high district rankings were achieved, district leadership was found to condone low prioritization of data quality in the HMIS. To cope with performance pressures, district data staff , who saw themselves as having little power, routinized behaviors (e.g., prioritizing review of ranking indicators rather than those of other health programs) that allowed them to meet their superiors’ expectations while working with limited technical capacity and an overburdened staff. Such types of “task trade-offs,” i.e., “focusing on actions that receive rewards to the detriment of other tasks” (Renmans *et al.*, 2016) have been observed for health services associated with higher financial incentives (Basinga *et al.*, 2011; Chimhutu *et al.*, 2014).

Conceivably, such behaviors may also incentivize data manipulation to facilitate achievements of targets.

Finally, we found that policy implementation was also based on the SLBs' own values (e.g., how much district leadership valued good data quality); their commitment and motivation towards their work (e.g., initiating informal UP-HMIS trainings); and their own interpretations of outlined policies (e.g., seeing district rankings as assessments of their own performance).

A few limitations of our study must be noted. First, our respondent sample was weighted towards district-level staff because we unable to extensively capture the views of senior district health and administrative officials (e.g., chief medical officers and district magistrates) who had busy schedules, but whose insights would have valuably shaped our narrative. Second, while our goal was to conduct interviews in a quiet environment, we found this to be often challenging in district-level administrative offices. In some cases, our interviews were interrupted, which may have affected our rapport building with the respondent. Lastly, we recognize our findings may not be transferable to every district in UP, and that interviews in additional districts may further enhance our findings.

2.6 Conclusion

In order to achieve the UP-HMIS policy objectives, this study demonstrates the importance of incorporating the perspectives of policy implementers (the street-level bureaucrats), and recognizing the actual levels of discretion, autonomy and power they have in implementation processes. In the near term, policymakers may consider increasing trainings and hiring more data staff. However, addressing underlying organizational cultural barriers will require a comprehensive approach to help institutionalize socially acceptable, new norms that empower implementers to implement and promote data-related policies. Strategies may include building integrity into data-related processes through an independent monitoring unit, empowering data staff to enforce accountability, and increasing the prioritization of data quality processes in tandem with data use.

Chapter 3. Does the quality of data vary when indicators are associated with financial incentives or performance assessments? An examination of administrative health data in Uttar Pradesh, India.

3.1 Introduction

Performance-based financing schemes (Fritsche *et al.*, 2018) and performance metrics, like district rankings or league tables (Business Standard News, 2016; Kirunga Tashobya *et al.*, 2018), have commonly been used by governments, and development partners to increase the impact of their health programs. Performance-based financing schemes are designed to financially reward health providers for achieving outlined targets or for performing specific activities (WHO, 2020). For example, the Janani Suraksha Yojana program in India provides a financial incentive to frontline community health workers for encouraging pregnant women to give birth in health facilities and a separate financial incentive to women immediately after their health facility delivery (National Health Mission, 2020). Similarly, performance measures, like district league tables (KirungaTashobya *et al.*, 2018) and state-level or country rankings have also been widely used to benchmark the progress of health services in different geographic regions (Tandon *et al.*, 2016; Niti Aayog, The World Bank, Ministry of Health & Family Welfare, 2019). For example, India's national planning commission, the Niti Aayog, has developed a health index that annually ranks states and union territories to spark "positive competition" and learning within the country (Niti Aayog, The World Bank, Ministry of Health & Family Welfare, 2019).

Timely, reliable, and accurate data are fundamental to both these strategies. Monthly health facility-level data reported to the country's national health management information system (HMIS) often serves as the primary, routine data source for monitoring and evaluating the performance of health programs. Thus, appraising the completeness, reliability, and accuracy of HMIS data is critical for ensuring that high-quality data are available to government program managers and their partners for decision-making.

While performance-based financing schemes and performance metrics attempt to encourage better performance of health programs, studies have identified weaknesses in program design that inadvertently create perverse incentives that compromise data quality. Several studies have observed the overreporting of indicators associated with financial incentives; for example, one study examining data discrepancies between HMIS and survey data, found an overreporting bias of 5% in HMIS coverage data for the third dose of diphtheria-tetanus-pertussis (DPT-3) across 41 African countries when compared to survey-based DPT-3 coverage (Sandefur and Glassman, 2015). The authors explained that the overreporting bias may be attributed to a Global Alliance for Vaccines and Immunization (GAVI) policy which paid eligible African countries for each additional child vaccinated with DPT-3. Another study in India examining the agreement between HMIS indicators on maternal health services with an externally conducted survey similarly observed an overreporting of maternal health indicators that were associated with financial incentives (Phillips *et al.*, 2019). Challenges with data quality of indicators used in performance metrics have similarly been noted in qualitative studies that have described the pressures from supervisors to overreport data as a means of hiding low provision and utilization of health services and to secure additional funds for health facilities (Qazi and Ali, 2011; Husain *et al.*, 2012),.

Poor data quality has far-reaching consequences. Incomplete and inaccurate data may lead to inequitable distribution of limited resources, contribute to misinformed health priorities, and undermine the primary objective of a well-performing HMIS, which is to use good quality data to make better decisions that improve population health (Aqil and Lippeveld, 2009). To help governments and health partners improve overall HMIS data quality, the World Health Organization

(WHO) has developed a data quality toolkit that lay outs quantitative metrics for evaluating the quality of HMIS data within a geographic setting (World Health Organization, 2017). In a context like Uttar Pradesh (UP), India – where HMIS data are routinely used to disburse funds for performance-based financing schemes, and to inform performance metrics, like the district rankings that guide district-level and state-level health program strategies – a continuous assessment of HMIS data quality is essential (Uttar Pradesh Technical Support Unit, 2018).

Considering previously published literature that questions the data quality of HMIS indicators that are associated with financial incentives or used in performance metrics, a direct comparison of data quality across indicators with different characteristics, (e.g., ranked, incentivized, unranked and unincentivized) may illuminate data quality issues that are critical to address. To the best of our knowledge, the variation in data quality among HMIS indicators that: (i) are associated with financial incentives (hereafter, incentivized indicators); (ii) are used in performance measures, like district rankings (hereafter, ranked indicators); and (iii) are neither ranked nor incentivized (hereafter, unranked and unincentivized indicators) has not been examined. We aim to address this gap by analyzing the quality of data being reported in Uttar Pradesh's HMIS, which captures monthly facility-level data on (i) ranked, (ii) incentivized, (iii) ranked and incentivized, and (iv) unranked and unincentivized indicators. In this analysis, we hypothesize that ranked indicators, incentivized indicators, and ranked and incentivized indicators may have poorer data quality metrics compared to unranked and unincentivized indicators.

3.2 Methods

Data source

We conducted this assessment using data from January – December 2019 in the Uttar Pradesh Health Management Information System (UP-HMIS), the government administrative data for UP, which captures self-reported monthly health facility reports from different levels of the health system (subcenters, primary health centers, community health centers, district hospitals) across 75 districts in UP. Among these, 25 districts are high priority districts (HPDs) that receive additional financial support from the Government of Uttar Pradesh (GOUP) and technical assistance from the Uttar Pradesh Technical Support Unit (UP-TSU). In each HPD, one monitoring and evaluation staff member from the UP-TSU is placed at the district-level to support HMIS data quality and data use processes through activities such as analyzing data to check quality and performing HMIS supportive supervision visits within the district.

The UP public health system serves an estimated population of roughly 230 million people (Census Population, 2020), and each month up to 28,241 health facilities, including subcenters, primary health centers, community health centers and hospitals, report to the UP-HMIS. Of these, 19,610 health facilities are in non-HPDs, and the remaining 8,631 are in HPDs.

Our study included a census all health facilities reporting to the UP-HMIS, and all monthly health facility reports submitted to the UP-HMIS were analyzed. Therefore, no power and sample size calculations were performed..

The UP-HMIS dataset analyzed in this study captures 919 indicators, and includes 4 types of indicators:

(i) ranked indicators, i.e., indicators used to compute the monthly ranks of each district relative to 74 other districts in the state. With respect to the district rankings, the GOUP's expectation was that district health and administrative officials review the district's ranking indicators every month during their program review meetings; and identify low performing ranking indicators in order to develop corresponding strategies for their improvement.

(ii) incentivized indicators, i.e., indicators that capture health services associated with financial incentives, for example, antenatal care, institutional deliveries, cesarean sections (C-sections), intrauterine contractual devices (IUCD) insertions, postpartum IUCDs insertions, and childhood immunizations (UP-TSU, 2019);

(iii) ranked and incentivized indicators, i.e., indicators that have characteristics of both (i) and (ii).

(iv) unranked and unincentivized indicators, i.e., indicators that capture data for health services, which are not incentivized and not used to compute district rankings.

Research hypotheses

Four hypotheses were examined in this study using the UP-HMIS dataset from January to December 2019. First, we hypothesized that the reporting of ranked and incentivized indicators would be *more complete* than unranked and unincentivized indicators in the monthly facility reports (H_1). Second, we hypothesized that *the proportion of outliers* among ranked and incentivized indicators *would be higher than* those for unranked and unincentivized indicators in the monthly facility reports (H_2). Third, we hypothesized that there would be a *systematic bias towards overreporting positive indicators* (such as, number of services delivered) among ranked and incentivized indicators compared to unranked and unincentivized indicators in the monthly facility reports (H_3). Finally, we hypothesized that the quality of all indicators reported in monthly facility reports from high-priority districts (HPDs) would be higher in terms of *completeness* ($H_{4\text{-}a}$), *number of outliers* ($H_{4\text{-}b}$), and *degree of systematic overreporting* ($H_{4\text{-}c}$) compared to indicators reported in monthly facility reports from non-HPDs.

Indicator selection

Our analytical dataset consisted of 41 UP-HMIS indicators. With respect to the selection of *ranked indicators,* we only selected those reported in the UP-HMIS, relating to the provision of health services, and excluded indicators capturing inputs, like the availability of human resources. *Incentivized indicators* in the UP-HMIS were selected based on a review of Government of India (GOI) and Government of Uttar Pradesh (GOUP) policy documents from January to December 2019 that describe the incentives given to Accredited Social Health Activists, who are community health workers, for achieving outlined targets or completing pre-defined activities (UP-TSU, 2019). Finally, we selected unranked and unincentivized indicators that pertained to health services that were not associated with a financial incentive nor captured by the district ranking indicators, however, belonged to the same health domains as ranked indicators, incentivized indicators, and ranked and incentivized indicators. The classification of the UP-HMIS indicators into the four indicator categories was reviewed by colleagues at the UP-TSU who were involved in designing the UP-HMIS and who continue to provide managerial support to the UP-HMIS state-level team in the GOUP. **Table 4** lists the indicators included in this analysis.

Table 4. UP-HMIS indicators included in the study analysis

Indicator classification	Indicator list
Ranked and incentivized (n= 6)	1) Number of injectable contraceptives, depot medroxyprogesterone acetate (DMPA) first dose 2) Number of children aged between 9 and 11 months fully immunized- male 3) Number of children aged between 9 and 11 months fully immunized - female 4) Number of pregnant women with 4 or more antenatal care (ANC) check ups 5) Number of institutional deliveries conducted (including cesarean sections) 6) Number of pregnant women screened for HIV
Ranked (n=4)	1) Number of pregnant women tested for hemoglobin (Hb) 4 or >4 times in ANC visits 2) Number of women receiving 1st post-partum checkup within 48 hours of delivery 3) Number of children who received the third dose of pentavalent vaccine 4) Number of children who received Bacille Calmette-Guérin (BCG) dose

Incentivized (n=9)	1) Number of interval intrauterine device (IUCD) insertions (excluding post-partum IUCD/post-abortion IUCD) 2) Number of post-partum IUCD insertions (within 48 hours of delivery) 3) Number of post-abortion IUCD insertions (within 12 days) 4) Number of newborns who received 6 home based newborn care (HBNC) visits after institutional delivery 5) Number of newborns who received 7 HBNC visits after home delivery 6) Number of new pregnant women identified as high-risk pregnancy (HRP), who are 35 years and older 7) Number of new pregnant women identified as HRP due to previous history with any complication 8) Number of new pregnant women identified as HRP due to any other reasons not due to age or previous history 9) Number of pregnant women registered in 1st trimester (within 12 weeks) out of the total ANC registrations that month
Unranked and unincentivized (n=22)	1) Number of women aged 15-49 years receiving the first dose of DMPA after abortion 2) Number of women aged 15-49 years receiving the first dose of DMPA after delivery (post-partum) 3) Number of women aged 15-49 years receiving first dose of DMPA in 'interval' period (6 weeks after delivery/ any time when woman is not pregnant other than post-partum or post-abortion) 4) Number of IUCD inserted on the fixed day services (FDS) days 5) Number of IUCD inserted on the fixed day off-service (FDOS) days 6) Number of children who received measles and rubella (MR) vaccine 1st dose (9-11months) 7) Number of children who received measles vaccine 1st dose (9-11 months) 8) Number of pregnant women who received full ANC check-ups by the end of the reporting month. 9) Number of PW having severe anemia (Hb<7) treated 10) Number of pregnant women with Hb<7 gm received iron sucrose by the end of the reporting month. 11) Number of home deliveries attended by a skill birth attendant (SBA) 12) Number of home deliveries attended by a non-SBA 13) Number of oral polio virus – birth doses (OPV 0) delivered 14) Number of hepatitis B – birth dose delivered 15) Number of vitamin K1 doses delivered after delivery - birth dose 16) Number of pregnant women registered for ANC 17) Number of women receiving 1st post-partum checkup between 48 hours and 14 days 18) Number of HIV tests found positive during ANC visits 19) Number of mothers provided full course of 180 Iron/Folic Acid (IFA) tablets after delivery 20) Number of pregnant women tested for syphilis 21) Number of pregnant women tested for blood sugar (oral glucose tolerance test) 22) Number of new cases of pregnant women with hypertension detected

Analysis

Methods for characterizing data quality were drawn from the WHO Data Quality Review Framework, which outlines four dimensions of data quality: (1) completeness and timeliness of data; (2) internal consistency of reported data; (3) external consistency of reported data; and (4) external comparisons of population data (World Health Organization, 2017). Given the lack of access to publicly available survey data, district-level census data, and information on timestamps associated with monthly health facility report submissions to the UP-HMIS, our analysis focused on examining the four metrics in dimensions 1 and 2 as shown in **Table 5**. All four hypotheses relating to these measures were tested for significance at the 0.05 level (alpha error) by examining the difference between proportions using t-tests.

Table 5. Data quality dimensions adapted from the World Health Organization Data Quality Review Framework

Measures	Definition
Dimension 1: Completeness of data	
(a) Completeness of health facility reporting	The percentage of expected monthly health facility reports submitted in the UP-HMIS web-based portal
(b) Completeness of indicator reporting	The percentage of missing values for indicators in the submitted monthly health facility reports
Dimension 2: Internal consistency of reported data	
(c) Identification of moderate and extreme outliers	The percentage of moderate (+/-2 standard deviations) and extreme outliers (+/- 3 standard deviations) from the mean for each indicator reported in the submitted monthly facility report
(d) Consistency between indicators	The ratio of events reported for two sets of indicators that are expected to be equal

With respect to completeness of data (dimension 1), we first examined the completeness of monthly facility reports by calculating the percentage of expected monthly reports submitted from health facilities to the online UP-HMIS web-based portal. Second, we examined completeness of indicators in monthly facility reports by examining the percentage of missing data for the four indicator categories (ranked; incentivized; ranked and incentivized; and unranked and unincentivized).

With respect to internal consistency of reported data (dimension 2), we calculated the percentage of moderate outliers by identifying values that lie above or below two standard deviations from the mean for each indicator reported in the monthly facility reports. However, in instances when two times the standard deviation was less than 1, we used 1 as the corresponding value to determine a moderate outlier. The percentage of extreme outliers was calculated by identifying values that lie above or below three standard deviations from the mean for each indicator reported in the monthly facility reports. Similarly, in instances when three times the standard deviation was less than 1, we used 1 as the corresponding value to determine an extreme outlier. This calculation prevented us from classifying values for indicators reported in the monthly facility reports as outliers when absolute changes were small. For example, a change in value from 0 to 1 for an indicator (that rarely reports a non-zero value, like HIV tests found positive during ANC visits) was not counted as a moderate or extreme outlier. With regard to outliers, we also quantified the proportion of outliers that lie above the mean and below the mean to gauge potential overreporting (>2 standard deviations *above* the mean) and underreporting (>2 standard deviations *below* the mean) of indicators.

Next, we developed internal consistency checks to examine whether the observed relationships between the values of indicators were as expected based on our programmatic knowledge and in consultation with the UP-TSU colleagues. We found two methods to calculate the same metric, one using ranked and incentivized indicators, and another using unranked and unincentivized indicators. Then, we calculated the ratio of the values calculated from the two methods. Since the two methods calculate the same metric, we expect the resultant ratio to equal 1.0. A ratio >1.0 may suggest overreporting of the ranked and incentivized indicators relative to unranked and unincentivized indicators, and a ratio < 1.0 may suggest underreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators. To account for potential, unintentional, data entry errors, we considered a 10% difference in ratios as acceptable for internal consistency based on the WHO Data Quality Assessment Toolkit guidelines (World Health Organization, 2017). Therefore, accounting for this 10% threshold, we interpreted ratios > 1.1 as potential evidence for overreporting, and ratios <0.9 as potential evidence for underreporting. For this analysis, we only included monthly facility reports with non-missing data for the indicators used to calculate the internal consistency checks for both methods. These internal consistency ratios were calculated for each monthly facility report. **Table 6** presents the six consistency checks which were examined in this analysis.

All the analyses were conducted using STATA 14.0.

Table 6. Internal consistency checks examined in the analysis

#	Internal consistency check	Measure #1 (ranked & incentivized indicators)	Measure #2 (unranked and unincentivized indicators)	Expected ratio (Measure #1/ Measure #2)
1	Total number of first DMPA[1] contraceptive dose should equal number of first DMPA doses given across programs	Total number of first DMPA contraceptive doses given	Number of women receiving first DMPA contraceptive dose post-abortion, post-delivery or any other time	~ 1.0
2	Total number of IUCDs[2] provided should equal total number provided during on and off-services days	Total number of IUCDs provided	Number of IUCDs provided during on and off-service days	~ 1.0
3	Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (vitamin K vaccine birth dose)	Total number of institutional deliveries	Total number of birth doses for Vitamin K vaccine plus stillbirths	~ 1.0
4	Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (oral polio virus vaccine birth dose)	Total number of institutional deliveries	Total number of birth doses for oral polio virus vaccine plus stillbirths	~ 1.0
5	Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (hepatitis B birth dose)	Total number of institutional deliveries	Total number of birth doses for hepatitis B plus stillbirths	~ 1.0
6	Total number of fully immunized child should be no greater than the number of doses of the measles-rubella vaccine	Total number of fully immunized children (9-11 months)	Total number of measles-rubella vaccine given (9-11 months)	~ 1.0

[1] Depot medroxyprogesterone acetate; [2] Intra-uterine contraceptive device

3.3 Results

The results are presented below by the two data quality dimensions examined in this study.

Dimension 1: Completeness of data

A. Completeness of monthly health facility reporting

Each facility is expected to submit a monthly report; therefore 338,892 facility reports were expected in the UP-HMIS dataset from January 2019 – December 2019. Overall, we found that 99.7% (n=337,907) of expected monthly health facility reports were submitted to the UP-HMIS across all districts with roughly the same percentage of monthly health facility reports submitted from HPDs (99.5%) and non-HPDs (99.8%).

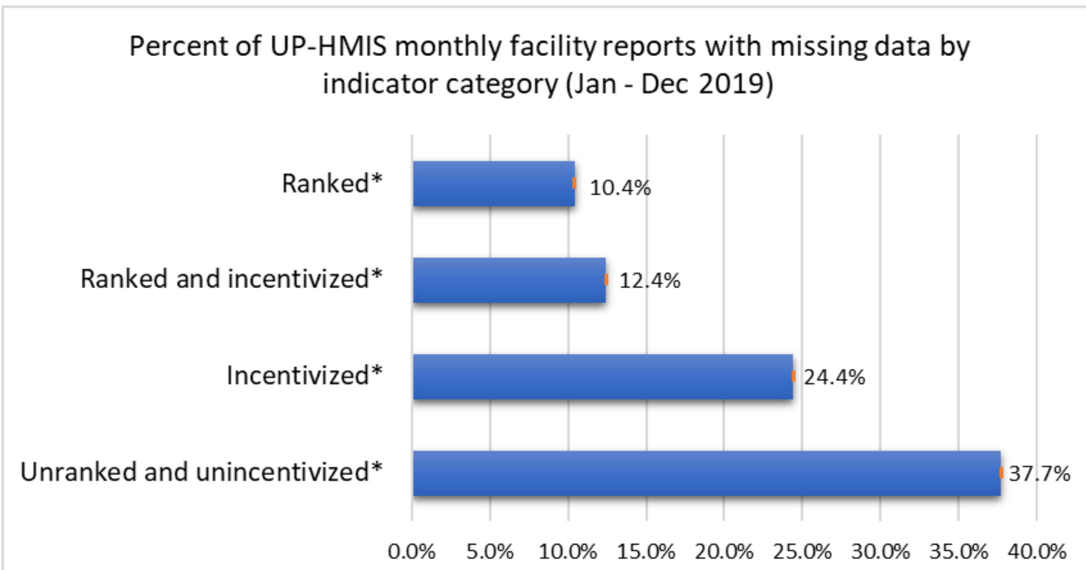
B. Completeness of indicator reporting in monthly health facility reports

With respect to the completeness of indicator reporting in the monthly facility reports, consistent with our hypothesis (H_1), we found that ranked indicators, and ranked and incentivized indicators were more completely reported compared to unranked and unincentivized indicators.

As shown in **Figure 5**, the average percentage of missing data was lowest among ranked indicators (10.42%; 95% CI: 10.37%, 10.48%) followed by ranked and incentivized indicators (12.45%; 95% CI: 12.40%, 12.49%) and incentivized indicators (24.42%; 95% CI: 24.37%, 24.47%), with unranked and unincentivized indicators having the highest average percentage of missing data (37.70%; 95% CI: 37.66%, 37.73%). The completeness of indicator reporting across all the four indicator categories were statistically different from one another at the 0.05 level ($p<0.01$).

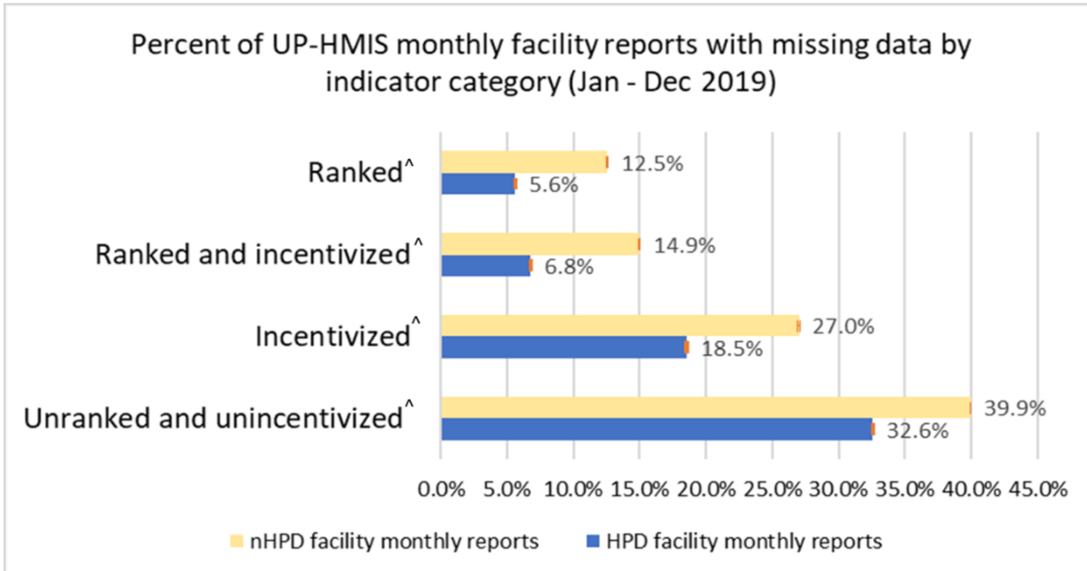
The same pattern of completeness observed by indicator category was observed for monthly facility reports in HPDs and non-HPDs (**Figure 6**), however for each indicator category, there were significantly fewer missing values observed in HPD monthly facility reports compared to non-HPD monthly facility reports ($p<0.01$) consistent with $H_{4\text{-}a}$. **Appendix 5** presents the average percentage of indicator completeness, and confidence intervals for each indicator category disaggregated by HPD status. When examining the percentage of indicator completeness over time, we found that indicators reported in the monthly facility reports from HPDs had higher levels of completeness relative to those reported in monthly facility reports from non-HPDs (**Appendices 6 and 7**).

Figure 5. The average percentage of missing data reported by indicator category in the monthly facility reports gathered from January to December 2019



Note: Completeness was examined in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. * indicates that the percentage of completeness of indicator reporting across all the four indicator categories (examined as pairwise comparisons) are significantly different from one another at the 0.05 level ($p<0.01$).

Figure 6. The average percentage of missing data being reported by indicator category in monthly facility reports from high priority districts (HPDs) and non-high priority districts (non-HPDs) gathered from January to December 2019



Note: Completeness was examined in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. ^ indicates that within each indicator category the percentage of missing values observed in HPD monthly facility reports compared to non-HPD monthly facility reports are significantly different from one another ($p<0.01$).

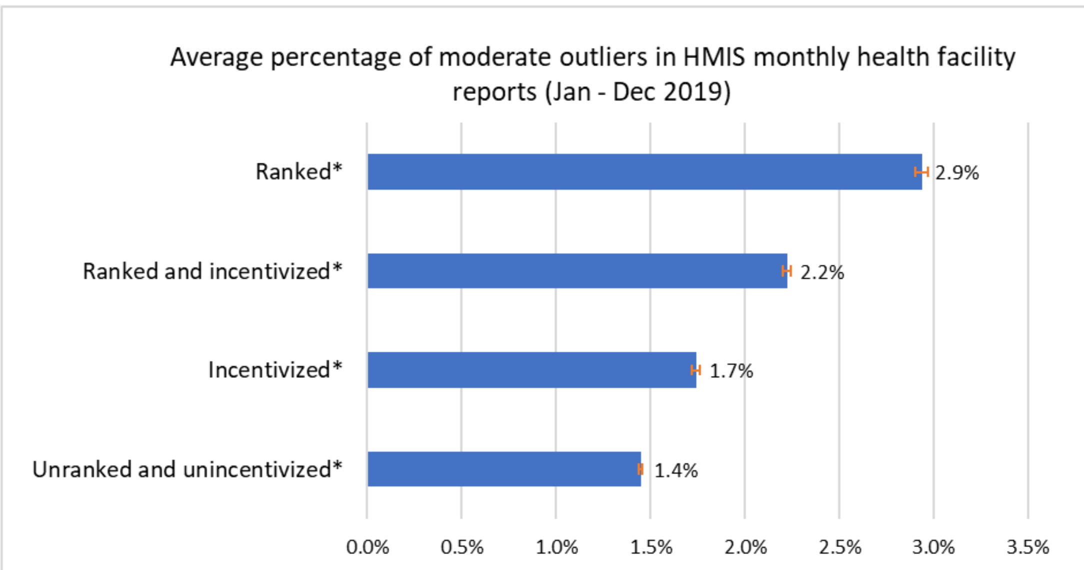
Dimension 2: Internal consistency of reported data

A. Identification of moderate and extreme outliers

Overall, about 8.2% of all monthly facility reports had moderate outliers (**Figure 7**). When examining moderate outliers by district status, nearly 8.7% of monthly facility reports from HPDs had moderate outliers, whereas roughly 8.1% of monthly facility reports from non-HPDs had moderate outliers (**Figure 8**).

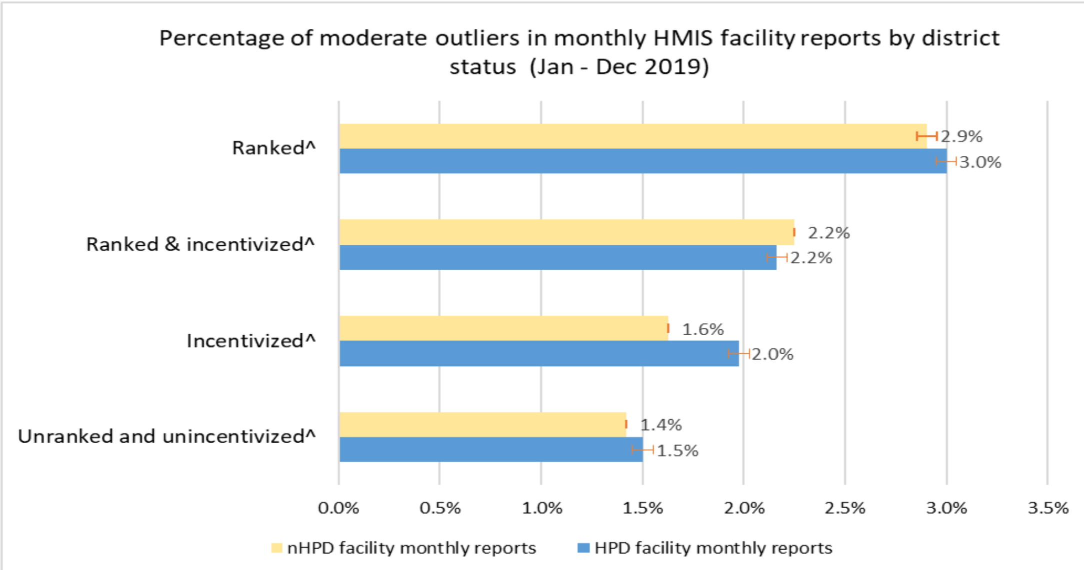
Supporting our hypothesis (H_2), we observed the highest average percentage of moderate outliers reported in the monthly facility reports among ranked indicators (2.94%; 95% CI: 2.91%, 2.97%), followed by ranked and incentivized indicators (2.22%; 95% CI: 2.20%, 2.24%) and incentivized indicators (1.74%; 95% CI: 1.72%, 1.76%), with the lowest average percentage of moderate outliers observed among unranked and unincentivized indicators (1.45%; 95% CI: 1.44%, 1.46%). A similar pattern was observed in monthly facility reports across HPDs and non-HPDs (**Figure 8**). However, we identified a significantly higher average percentage of moderate outliers for two indicator categories - ranked indicators and incentivized indicators – in HPD monthly facility reports compared to non-HPD monthly facility reports ($p<0.01$), contradicting our hypothesis ($H_{4\text{-}b}$). **Appendix 8** presents the average percentage of moderate outliers and the corresponding confidence intervals for each indicator category disaggregated by HPD status.

Figure 7. The average percentage of moderate outliers reported by indicator category in the monthly facility reports gathered from January to December 2019



Note: Moderate outliers was identified by indicator category in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. * indicates that the percentage of moderate outliers identified across all the four indicator categories (examined as pairwise comparisons) are significantly different from one another at the 0.05 level ($p<0.01$).

Figure 8. The average percentage of moderate outliers observed in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019



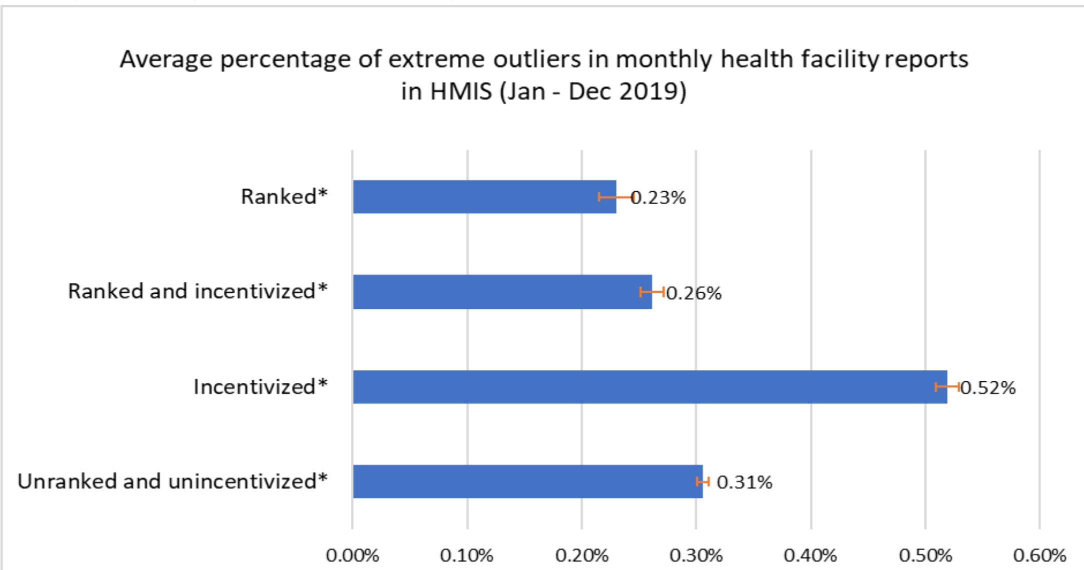
Note: Moderate outliers was identified by indicator category in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. ^indicates that within each indicator category the percentage of moderate outliers identified in HPD monthly facility reports compared to non-HPD monthly facility reports are significantly different from one another ($p<0.01$).

In comparison to moderate outliers, extreme outliers were identified in 1.3% of monthly facility reports (**Figure 9**). Contradicting our hypothesis (H_2), the highest average percentage of extreme outliers were observed among incentivized indicators (0.52%; 95% CI: 0.51%, 0.53%), followed by unranked and unincentivized indicators (0.31%; 95% CI: 0.30%, 0.31%), ranked and incentivized indicators (0.26%; 95% CI: 0.25%, 0.27%), and ranked indicators (0.23%; 95% CI: 0.22%, 0.25%).

The same pattern was observed in monthly facility reports among HPDs and non-HPDs (**Figure 10**). However, we identified a significantly higher average percentage of extreme outliers for three indicator categories - ranked and incentivized indicators, incentivized indicators, and unranked and unincentivized indicators – in HPD monthly facility reports compared to non-HPD monthly facility reports ($p<0.01$), contradicting our hypothesis (H4-c). **Appendix 9** presents the average percentage of extreme outliers and the corresponding confidence intervals for each indicator category disaggregated by HPD status. The number of moderate and extreme outliers for each indicator in monthly facility reports in HPDs and non-HPDs are reported in **Appendix 10**.

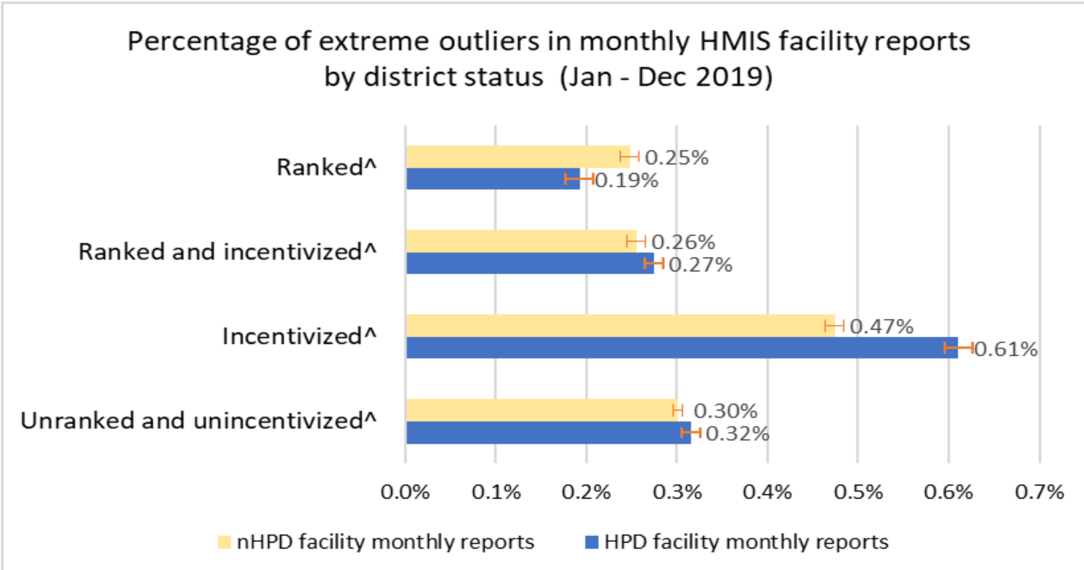
Overall, a majority of the outliers were overreported (**Table 7**). Among the underreported outliers, about 97.2% were moderate outliers. Among the overreported outliers, roughly 82.4% were moderate outliers, and 17.5% were extreme outliers.

Figure 9**.** The average percentage of extreme outliers reported by indicator category in the monthly facility reports gathered from January to December 2019



Note: Extreme outliers was identified by indicator category in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. *indicates that the percentage of extreme outliers identified across all the four indicator categories (examined as pairwise comparisons) are statistically different from one another at the 0.05 level (p<0.01).

Figure 10. The average percentage of moderate outliers observed in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019



Note: Extreme outliers was identified by indicator category in 337,907 monthly health facility reports that had been submitted. Confidence intervals are presented in orange. ^indicates that within each indicator category the percentage of extreme outliers identified in HPD monthly facility reports compared to non-HPD monthly facility reports are statistically different from one another ($p<0.01$).

Table 7. Percentage of moderate and extreme outliers that were overreported or underreported

	Outliers observed in monthly health facility reports from HPDs (n=102,845)	**Outliers observed in monthly health facility reports from non-HPDs** (n=235,062)	**Outliers observed in monthly health facility reports from all districts** (n=337,907)
Total number of *underreported* outliers			**26,005 (7.70%)**
Moderate	8,934 (8.69%)	16,887 (7.18%)	25,821 (7.64%)
Extreme	54 (0.05%)	130 (0.06%)	184 (0.05%)
Total number of *overreported* outliers			**189,608 (56.11%)**
Moderate	52,970 (51.50%)	103,292 (43.94%)	156,262 (46.24%)
Extreme	11,693 (11.37%)	21,653 (9.21%)	33,346 (9.86%)

B. Consistency between indicators

Consistent with our hypothesis (H_3), we found evidence of possible overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators in all six consistency checks as reflected in ratios greater than 1.1, which account for the 10% threshold to allow for potential inconsistency (**Table 8**). When these ratios were disaggregated by district status, the same pattern of substantial overreporting (ratios > 1.1) was observed in monthly facility reports from HPDs and monthly facility reports from non-HPDs. While there were no significant differences observed in ratios for two internal consistency checks reported in monthly facility reports from HPDs and non-HPDs ($H_{4\text{-}c}$), three consistency checks had significantly higher ratios reported in monthly facility reports from HPDs compared to those non-HPDs.

Table 8. Internal consistency checks in monthly health facility reports in high priority districts (HPDs) and non-high priority districts (non-HPDs)

Internal consistency check	Ratio[a]	Ratio HPD[b]	Ratio nHPD[c]	p-value
Total number of first DMPA[1] contraceptive doses should equal number of first DMPA doses given across programs	1.60 (1.57, 1.63)	1.69 (1.64, 1.74)	1.55 (1.51, 1.60)	<0.01
Total number of IUCDs[2] provided should equal total number provided during on and off-services days	6.64 (6.40, 6.89)	6.73 (6.32, 7.14)	6.59 (6.29, 6.89)	0.59
Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (vitamin K vaccine birth dose)	4.41 (4.33, 4.49)	4.22 (4.12 , 4.33)	4.52 (4.41, 4.62)	<0.01
Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (oral polio virus vaccine birth dose)	1.84 (1.80, 1.88)	2.00 (1.95, 2.06)	1.76 (1.71, 1.81)	<0.01
Total number of institutional deliveries resulting in a live birth should equal number of birth dose vaccine (hepatitis B birth dose)	2.97 (2.92, 3.02)	3.21 (3.13, 3.28)	2.84 (2.78, 2.91)	<0.01
Total number of fully immunized children should be no greater than the number of doses of the measles-rubella vaccine	1.15 (1.12, 1.17)	1.11 (1.07, 1.15)	1.16 (1.13, 1.19)	0.05

[1] Depot medroxyprogesterone acetate; [2] Intra-uterine contraceptive device; [a]Ratio based on monthly health facility reports across all districts; [b]Ratio based on monthly health facility reports from high priority districts (HPDs); [c]Ratio based on monthly health facility reports from non-high priority districts (nHPDs); Note: all ratios for all internal consistency checks are between ranked and incentivized indicators versus unranked and unincentivized indicators.

3.4 Discussion

This study examined the data quality of four indicator categories (ranked, ranked and incentivized, incentivized and unranked and unincentivized) using an administrative health dataset with 337,907 monthly health facility reports from over 28,000 health facilities during a one-year time period.

Our analyses show that data quality metrics for completeness and internal consistency varied by the four indicator categories (ranked, incentivized, ranked and incentivized, and unranked and unincentivized). With respect to completeness of indicator reporting, largely consistent with the first hypothesis (H_1), we found a higher percentage of complete reporting for ranked indicators, closely followed by ranked and incentivized indicators. When examining the percentage of outliers by indicator category, we found that ranked indicators had the highest percentage of moderate outliers followed by ranked and incentivized indicators, incentivized indicators, and unranked and unincentivized indicators, supporting our second hypothesis (H_2). However, this trend differed for extreme outliers. Incentivized indicators had the highest percentage of extreme outliers, followed by unranked and unincentivized indicators, ranked and incentivized indicators, and ranked indicators.

The analyses comparing internal consistency revealed higher levels of systematic overreporting of ranked and incentivized indicators compared to unranked and unincentivized indicators, providing evidence for our third hypothesis (H_3). Finally, with respect to the above data quality metrics by district status (HPDs and non-HPDs), consistent with our hypothesis ($H_{4\text{-}a}$), we observed higher levels of completeness across the four indicator categories in monthly facility reports from HPDs. However, contrary to our hypothesis ($H_{4\text{-}b}$), we found at least the same percentage or a higher percentage of moderate and extreme outliers by the four indicator categories in the monthly health facility reports from HPDs compared to non-HPDs. Similarly, contradicting our hypothesis ($H_{4\text{-}c}$), we observed potential overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators in monthly facility reports from both HPDs and non-HPDs. Furthermore, in three out of the six internal consistency checks, we observed significantly higher ratios in monthly facility reports from HPDs as compared to non-HPDs.

The differences in completeness of reporting by indicator type may be explained by the higher demand of UP-HMIS indicators used to calculate district rankings, which were routinely reviewed by district and state leadership across all districts during monthly review meetings. In contrast, the high percentage of missing data for unranked and unincentivized indicators may reflect the low prioritization and demand for those data for decision-making.

Our analyses also support previous studies, which have attributed high reporting burdens contributing to incomplete data and poor data quality (AbouZahr *et al.*, 2007). More broadly across low- and middle-income countries (LMICs), the high burden of data collection and entry has been attributed to the implementation of vertical health programs and the requirements of funders (Chan *et al.*, 2010). Similarly, in UP, high reporting burden has been attributed to a large number of national health programs and the concomitant rise in demand for those program data (Meghani *et al.*, 2020). Our study suggests that data entry was prioritized for indicators associated with district rankings or financial incentives and highlights a need to rationalize the number of indicators in the UP-HMIS, which currently captures 919 indicators.

In our analysis, we found a much lower percentage of extreme outliers reported in monthly health facility reports compared to moderate outliers across all districts (1.3% vs. 8.2%). We offer three potential explanations. First, close monitoring and demand of ranked indicators, ranked and incentivized indicators, and incentivized indicators may have improved the accuracy of reporting.

Second, these indicators may be consistently overreported resulting in a lower percentage of detectable extreme outliers. Or, third, building on the first and second explanations, indicators may not be overreported at extreme levels to avoid undue attention from superiors, which may prompt investigations to examine potential overreporting.

As seen in the internal consistency ratios (H_3), the higher levels of systematic overreporting of ranked and incentivized indicators compared to unranked and unincentivized indicators may provide evidence for the second and third explanation. This finding resonates with the results from another data validation study in UP, which found overreporting of HMIS indicators that are associated with financial incentives (Phillips *et al.*, 2019). More broadly, overreporting of data has also been observed in the context of achieving external donor-outlined targets and performance-based aid (Sandefur and Glassman, 2015; Closser, 2019),

In the context of UP, our finding highlights how specific measures, like district ranking indicators, which are associated with rewards and punishments (described further in Chapter 4), may perversely incentivize individuals to adopt behaviors that maximize potential awards and minimize punishment possibly to the detriment of the broader good (Goodhart, 1989). This point is also represented in a study from Burkina Faso, which described how a data auditing verification process created perverse incentives for auditors to falsify the data because they were paid based on the number of patients they covered during each data verification exercise (Turcotte-Tremblay *et al.*, 2017).

By placing additional monitoring and evaluation staff in HPDs, the GOUP attempted to improve overall UP-HMIS data quality. Our findings suggest that the presence of additional technical staff may have contributed to improvements in data completeness, however this approach may be insufficient for improving internal consistency and accuracy of HMIS data. Improving these two data quality metrics may require a different set of strategies, such as strengthening the implementation of data quality audits that compare source documents in health facilities or managed by frontline health workers, with data being reported in the UP-HMIS, and ensuring those results are used to guide improvements. It is also possible that given the recent UP-HMIS reform, districts may first be prioritizing processes to improve the completeness of data being reported to the UP-HMIS before turning their attention to issues relating to data accuracy.

Many of the challenges with UP-HMIS data quality presented here have not gone unnoticed by the GOUP. To streamline data collection efforts and improve the completeness of UP-HMIS data, the GOUP in collaboration with the UP-TSU has been conducting data rationalization consultations with state- and district-level decision-makers to reduce the number of indicators in the UP-HMIS. In addition, the GOUP has been actively working on addressing data quality gaps by scaling up the implementation of state-level data quality audits, quarterly state-level data quality meetings with district-level staff, and establishing a new cadre of monitoring and evaluation staff at the division level who can supervise and support data quality initiatives across all the 75 districts.

At the national level, Niti Aayog, the national planning commission, has also been paying increasing attention to issues of data quality, by explicitly incorporating a measure for data integrity in its state-health index, which is published annually to show the variations in health outcomes across different states and union territories of India (Niti Aayog, The World Bank, Ministry of Health & Family Welfare, 2019). Recently, the Ministry of Health and Family Welfare (MoHFW) also reiterated its commitment to conducting a National Family Health Survey to generate district-level estimates for health indicators, and launched the development of a tablet-based data entry application to facilitate digital data entry by frontline health workers "at source" (Press Information Bureau, Government of India, 2017). Currently, the GOUP is scaling up trainings to enable tablet-based data entry by frontline health workers across all 75 districts to reduce the burden of data entry at the block-level, which plays the critical role of entering monthly paper-based reports collected from the frontline health workers and primary health workers to the UP-HMIS web-based portal.

As the GOUP and the national-level government strengthen data quality processes, and strive towards improving HMIS data quality, it will be important to ensure that other factors that determine HMIS performance – like gaps in availability of human resources, both in number and technical skill, are addressed so that basic functions like supportive supervision and data validation activities are implemented at lower administrative levels. Similarly, it will also be important to move towards building an organizational culture that values good quality, and use of good quality data in decision-making, so that data quality processes and activities are successfully institutionalized within the UP health system over time.

While this analysis provides some evidence of differences in data quality metrics by indicator category, it is important to note several study limitations. First, we did not examine all the indicators reported in the UP-HMIS, as our focus was limited to examining the data quality of maternal and child health program indicators because they are a priority of the GOUP. Second, we recognize that calculating the number of outliers can be particularly problematic for indicators that are dependent on the availability of health commodities in health facilities. For these indicators, sudden increases in availability of health commodities in health facilities may coincide with higher completeness of data, which may lead to potential misclassification of values being identified as outliers. Third, our study had a small number of internal consistency checks because we were limited by our approach to calculate one construct in two different ways – one using ranked and incentivized indicators and the other using unranked and unincentivized indicators. Related to this point, while our findings on internal consistency suggest potential overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators, we were unable to explore whether this phenomenon was being driven by the potential underreporting of unranked and unincentivized indicators. Facility-level audits measuring the agreement of HMIS web-based portal data with source documents, like health facility registers would have provided a direct measure of data accuracy (e.g., development of data verification ratios), however due to time and resource constraints this was not feasible. Related to resource constraints, lastly, we could not conduct an independent survey and measure the external consistency of coverage data for the indicators in our analysis, another data quality metric.

3.5 Conclusion

To conclude, our study provides initial evidence for how data quality varies for indicators that are associated with performance measures like district rankings and financial incentives. While completeness of data may have improved for ranked and incentivized indicators, we found evidence for potential overreporting of these indicators relative to unranked and unincentivized indicators. Routinely examining data accuracy would be important for ensuring that real progress and achievement is being reflected in the district rankings, and effectively guiding decision-making. Data quality audits that are currently being scaled up by the GOUP may help quantify potential data manipulation, however additional qualitative research may shed light on the underlying drivers that may be leading to this practice. As GOUP scales up the initiatives to improve HMIS data quality, effective implementation of those initiatives will be critical for achieving the intended objective of good data quality.

Chapter 4. Understanding when, how and why administrative health data are manipulated in Uttar Pradesh, India

4.1 Introduction

The Performance of Routine Information Systems (PRISM) framework identifies technical, organizational and behavioral determinants that are critical for improving the quality and use of health management information system (HMIS) or administrative data for decision-making (Aqil *et al.*, 2009). While these determinants are useful for identifying interventions to improve administrative data quality and use, there are no conceptual frameworks or theories that explain how and why administrative data are manipulated, and equally importantly, how one might intervene to prevent data manipulation.

A number of parallels can be drawn between data manipulation and corruption; for example, both entail officials misusing their power or coercing others to misuse their power for private gain; and corruption, like data manipulation, often happens "quietly," in clandestine ways. There is a well-developed body of theory on corruption in the health sector that may be used to study data manipulation (Sardan, 1999; Brinkerhoff, 2004; Lewis, 2006; Savedoff and Hussmann, 2006). Therefore, to better understand the forces that result in data manipulation and how best to respond to this practice in a health system, we drew upon a theoretical framework that consolidated previously proposed concepts on corruption in the health sector (Vian, 2008). In this study, we define the manipulation of administrative health data or data manipulation, as the fabrication or alteration of data, done with the aim of furthering one's personal interests or to cope with systemic pressures; for example, by giving falsely positive impressions of health sector achievements, or hiding negative data.

Public health researchers have observed data manipulation in the unreliability of national statistics (Jerven, 2013; Sandefur and Glassman, 2015); they have reported on the falsification of administrative data (Qazi and Ali, 2009; Mercader *et al.*, 2017), and explored how perceptions of compromised data quality affect data use (Mutemwa, 2006; Setel *et al.*, 2007). The consequences of making decisions based on manipulated and poor quality data have been far-reaching, resulting in poor planning and inequitable distribution of resources and delivery of health services (Mackey *et al.*, 2018), and a breakdown in transparency and accountability processes within a health system (Transparency International, 2019). Therefore, ensuring the accuracy of Health Management Information Systems (HMIS) data, the largest routinely collected data source about the health services delivered to a population, is of paramount importance.

To improve the quality of HMIS data, many low- and middle-income countries have introduced district health information systems (DHIS2, 2019). These systems have been replacing paper-based reports with mobile health (mHealth) applications by enabling frontline health workers to record data directly on mobile phones (Asangansi *et al.*, 2013; Ethiopian FMoH, 2014; Biemba *et al.*, 2017); automating and implementing data validation processes to detect data quality errors (Government Of India, Ministry of Statistics and Program Implementation, 2018; Burnett *et al.*, 2019); and establishing web-based health data dashboards to promote visibility and real-time monitoring of collected data to support communication and decision-making (Nutley *et al.*, 2013; Mutale *et al.*, 2018).

While these technical processes are expected to improve data management, data quality and data use, some researchers acknowledge that they are insufficient to ensure good data quality and data use (Garrib *et al.*, 2008; Karuri *et al.*, 2014). In fact, the quality of administrative data remains a persistent challenge (Kiberu *et al.*, 2014; Ndabarora *et al.*, 2014; Morton *et al.*, 2016; Phillips *et al.*, 2019). For example, quantitative studies have shown a systematic overreporting of certain HMIS health indicators (Singh *et al.*; Sharma *et al.*, 2016; Phillips *et al.*, 2019), and qualitative studies have found that the inability to uphold data quality standards stems from multiple individual and organizational factors, including the lack of interest and ownership in the data (Hernández-Ávila *et al.*, 2013), poor accountability processes, and even personal associations with political elites that condone the failure to comply with HMIS standards (Qazi and Ali, 2009, 2011; Ramesh *et al.*, 2012). A key question remains: why are data manipulated or misreported in the first place?

Answering this question requires unpacking contextual factors, organizational factors, and interpersonal dynamics of actors who may be incentivized to allow corrupt practices to thrive. In this paper, we first describe the types of data manipulation observed in Uttar Pradesh (UP), India and then using a theoretical framework on corruption in the health system (Vian, 2008) examine the (i) pressures and (ii) opportunities for data manipulation; and (iii) the rationalization of data manipulation by those involved. A deeper understanding of these collective factors driving data manipulation may provide insights into how to address this problem.

4.2 Methods

Study Context

The Government of Uttar Pradesh (GOUP) implemented a series of initiatives in 2015 to address barriers affecting HMIS performance like, complex reporting formats, weak processes for HMIS data quality, and low use of HMIS data in decision-making (Meghani *et al.*, 2020).

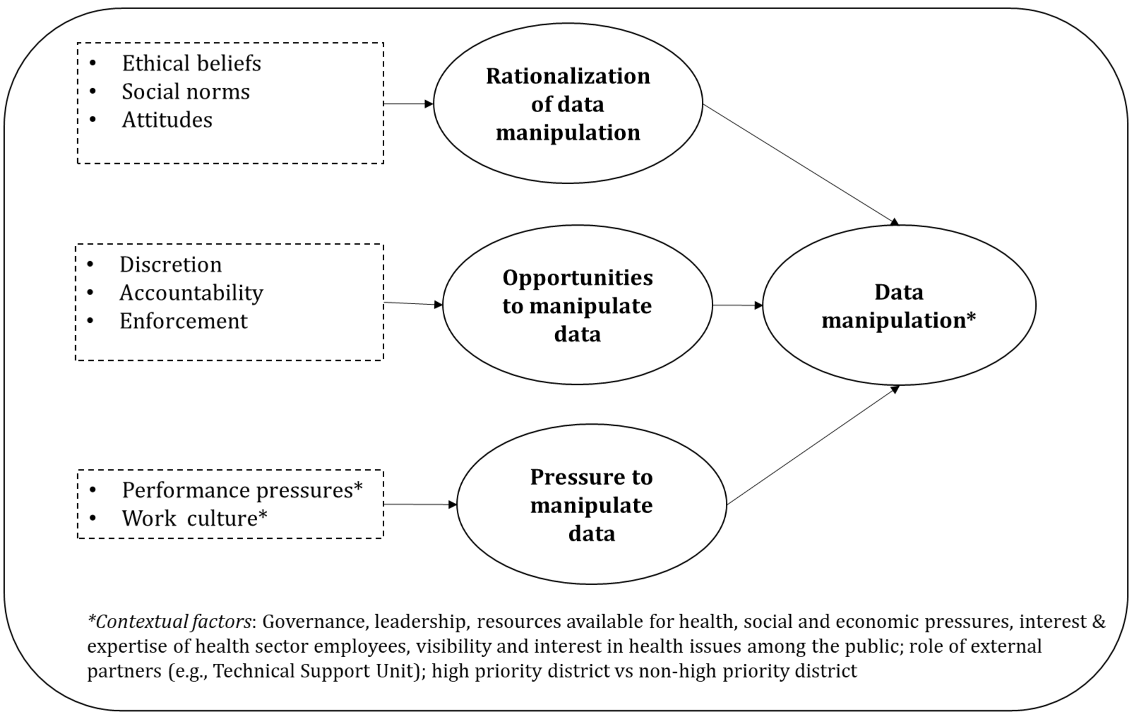
First, the GOUP implemented a new online HMIS, known as the UP-HMIS to gather relevant data, largely on maternal and child health programs, to meet the state's managerial and decision-making needs. Among the 919 data elements in HMIS, some were used to calculate the monthly district rankings (Uttar Pradesh Technical Support Unit, 2018), others captured services that have been incentivized by the national government, like antenatal care, and institutional deliveries (Government of India, 2018), and the remaining data elements were collected for routine monitoring.

Second, to improve data quality, the GOUP established data validation committees at two administrative levels below the state – at block and district levels – to ensure accurate data were available for decision-making. Relatedly, the GOUP also built automated data validation checks within UP-HMIS web-based portals to identify data errors, but also instituted data quality audits and supportive supervision visits at both levels. Finally, to facilitate the use of these validated data for decision-making across the health system, the GOUP developed a UP Health Dashboard. Populated using the UP-HMIS data, the Dashboard ranked each of the 75 districts in UP relative to one another based on their performance on priority health indicators every month. The policy did not outline any explicit awards or punishments for high or low ranking districts, however, the GOUP expected that these district ranking indicators would be examined during program review meetings at the district level to identify program weaknesses and develop action plans to target improvements in performance. Given this context, UP offered an opportunity to investigate why data are manipulated or misreported despite the implementation of technical solutions to improve data quality.

Conceptual framework

Based on our formative research, we adapted Vian's framework on corruption in the health sector (Vian, 2008) to investigate key factors driving data manipulation in UP (**Figure 12**). First, to identify factors that created opportunities for data manipulation, we examined the level of discretion and autonomy of actors, the accountability mechanisms for performance and data quality, and processes for detecting data manipulation and enforcing sanctions to curb future occurrences. Second, we studied pressures that incentivized data manipulation, e.g., performance pressures from one's superiors and peers, as well as pressures associated with the organization's work culture. Third, we explored the social norms, ethical beliefs and attitudes of health staff to understand how data manipulation was rationalized by those involved. Finally, acknowledging the importance of context, we remained open to studying how related health systems factors like availability of resources, workload, and leadership styles may influence data manipulation and its drivers.

Figure 11. Conceptual framework for the study



**Denotes the adaptations to the original framework on corruption in the health sector developed by Vian (2008)*

Sampling

We conducted 83 interviews with officials at the district, division and state levels. Following the principal of maximum variation sampling, we purposively selected 16 high, middle and low ranked districts based on their rankings in the UP-Health Dashboard, which included a combination of both high priority and non-high priority districts (Government of India, 2015). To ensure broad representation of district respondents, within each district, we purposively interviewed respondents who were involved in at least one data-related activity, such as data analysis, data validation or data review (e.g., reviewing data to monitor program performance or make a program-related decision), and included both government employees of the state's Directorates of Medical Health and Family Welfare (DOMHFW), as well as contractual employees of the National Health Mission (NHM) and the UP Technical Support Unit. Overall, we interviewed 48 district-level respondents. To better understand the organizational context, we also interviewed 35 division- and state-level officials in NHM and the DOMHFW responsible for monitoring district health programs. Finally, we observed 14 district-level data validation and program review meetings in the 8 of the 16 districts where we conducted interviews to corroborate and triangulate findings from the in-depth interviews.

Data collection

Our district-level interview guide aimed to elicit respondents' perceptions on: (1) the data quality of existing administrative data; (2) current practices to promote data quality; (3) the prioritization of data quality initiatives within the health department; (4) individual, organizational and contextual factors that influence data quality processes; and (5) potential opportunities to uphold data quality standards within the health system. Our division- and state-level guide focused on understanding which data are used for decision-making, how they are used, and potential challenges and opportunities for improving the use of data for decision-making in UP.

Interviews were conducted primarily in respondents' offices in Hindi or English depending on their preference. Before each interview, we obtained written informed consent. Interviews were audio-recorded except for 22 interviews when respondents preferred hand-written notes be taken. Interviews generally lasted between 30-90 minutes. All audio recorded interviews were transcribed verbatim and translated to English as needed by a qualified transcription agency; AM reviewed all transcripts for accuracy.

Interviews (**Table 9**) and meeting observations (**Table 10**) were conducted in three phases: December 2018; February-March 2019; and August-October 2019. During data collection, the study team debriefed biweekly to discuss emerging findings, triangulate data by respondent type, and identify probes for subsequent interviews.

Table 9. Types of positions held by respondents

<table>
<tr><th>Level</th><th>Type of position</th><th>Description</th><th>Number of respondents</th></tr>
<tr><td rowspan="4">District</td><td>Administrative officials</td><td>District magistrates, chief development officers</td><td>2</td></tr>
<tr><td>Health officials</td><td>Chief medical officers</td><td>2</td></tr>
<tr><td rowspan="2">District staff</td><td>Program staff[1]</td><td rowspan="2">46</td></tr>
<tr><td>Data staff[2]</td></tr>
<tr><td colspan="2">Division</td><td>Monitoring and evaluation specialists</td><td>5</td></tr>
<tr><td colspan="2">State</td><td>DOMHFW: Directors, Joint Directors,
NHM: Program managers and additional research officers</td><td>30</td></tr>
<tr><td colspan="3">Total</td><td>83</td></tr>
</table>

[1] Responsible for managing and monitoring implementation of health programs; positions include: assistant chief medical officers and district immunization officers; [2]Responsible for collating, reviewing and analyzing health program data; positions include: assistant research officers, district program managers, district data managers, data entry operators, monitoring and evaluation specialists

Table 10. Meeting observed at the district level in Uttar Pradesh

Meeting types	Number of observations
Data validation committee meetings	6
Program review meetings	8
Total	**14**

Analysis

We conducted a thematic analysis using the framework method (Gale *et al.*, 2013). First, we inductively coded twenty transcripts line-by-line, and used our conceptual framework (**Figure 12**) to develop an analytical framework that captured data on: (1) rationalization of data manipulation; (2) opportunities for data manipulation; (3) pressures and work-related stressors; and (4) other factors. The detailed sub-categories in the analytical framework are in **Appendix 11**. Relevant data were extracted from the interview transcripts, notes and meeting observations into the excel-based analytical framework. Then, memos for each category were prepared, summarizing the overall findings, identifying deviant cases, comparing/contrasting potential conflicting findings reported by respondents (Boeije, 2002), and triangulating meetings observations with interview findings (Carter *et al.*, 2014). Memos were shared with team members to deepen the discussion and understanding of the data. After the analysis, a meeting was conducted with a couple of respondents as a way of member checking.

4.3 Ethical Considerations

The study was approved for ethical research by the Institutional Review Board of SIGMA Research and Consulting in New Delhi, India (10047/IRB/D/18-19). Johns Hopkins Bloomberg School of Public Health deemed this research as IRB exempt (00009106). In some cases, we have not directly quoted respondents to ensure anonymity since they come from a tightly knit pool of actors whose speaking styles may be revealing. Furthermore, we do not identify the respondent's organizational affiliation in our results, and only indicate their administrative level and position type.

4.4 Results

Despite recent improvements in data quality, district level respondents perceived that data manipulation and the pressures to manipulate data were common at the district level across both high-priority and non-high priority districts. Therefore, we do not present our results by this stratification. Similarly, because district rankings significantly fluctuated month-to-month over the course of our study, we decided not to present our results stratified by low, middle and high performing districts. Below, we describe types of data manipulation, opportunities and pressures to change data, and how respondents rationalize these actions.

Types of data manipulation

District staff observed direct (overreporting and underreporting) and indirect forms of data manipulation at the block and district levels (**Table 11**).

Table 11. Types of administrative data manipulation observed at the block and district levels in Uttar Pradesh, India

Type of data manipulation	How it works	Examples of indicators being manipulated
Direct forms		
Overreporting progress	The numerator, i.e., the number of services provided, reflect a longer time-period (e.g., 45 days), while the denominator is assumed to be for the typical 30-day reporting period. In other instances, data may be made up to reflect progress.	Observed for indicators that are: (i) difficult to cross-validate with other indicators (e.g., supplies distributed, community activities conducted); (ii) associated with financial incentives (e.g., identification of high-risk pregnancies, institutional deliveries, bed occupancy rates); and (iii) for priority programs and national campaigns that are closely monitored (e.g., institutional deliveries, high risk pregnancies)
Underreporting indicators	Reporting fewer incidents than actually occur	Observed for indicators that may reflect poorly on health workers (e.g., maternal deaths)
Indirect forms		
Retrofitting service data to match inventory	Distribution of health commodities are calculated based on stocks/inventory left in the health facilities at the end of the month compared to the inventories at the beginning of the month. Inventory data do not reflect the actual number of commodities distributed by health workers.	Observed for data pertaining to health commodities, like oral contraceptive pills, and multi-dose vaccine vials
Hiding data	Data reflecting low progress on certain health indicators are not presented during review meetings with senior officials	Any information about health programs with low performance are not presented in reports or PowerPoint slides prepared for high-level review meetings with superiors

A. Overreporting progress

District staff described overreporting of health indicators that were (i) monitored in the district rankings and (ii) associated with financial incentives. Overreporting involved inflating the number of services (numerator) provided over a fixed reporting period (denominator). According to district data staff, ranking indicators (e.g., the ratio of health worker incentives paid against total institutional deliveries) were often overreported to demonstrate higher than actual progress before meetings with district administrative officials, as one district data staff described:

> *"To prepare for the District Health Society meeting [with district magistrates/district administrative officials], I collect the data till 20th of the month. I see that the ASHA payments till 20th is not so good, so they [chief medical officers/district health officials] ask to change the data of ASHA payments [numerator] but the number of [institutional] deliveries should be same [denominator]" (I-5).*

District staff observed similar practices in some blocks, where block health officials requested that their data staff overreport before meetings with their superiors, district health officials. Similar practices were observed at the field level by community health workers before their monthly meetings with their supervisors:

> *"Our ANMs [health workers] come and say that this is the actual amount of work done and this is the amount of work that is yet not done … they create the report where even if 4 people have been vaccinated, they write it as 14 people vaccinated. They say they will vaccinate the remaining 10 people when they come the next day" (I-32, District program staff).*

While personal financial gain may influence community health workers to overreport incentivized indicators like high risk pregnancies, district staff explained that those who manipulated the data were not always community health workers, who were the direct beneficiaries of financial incentives. Their supervisors at the block-level may change the data (e.g., identify pregnant women as high risk pregnancies even if they are not) and through complex kick-back systems receive a portion of the incentives given to community health workers.

B. Underreporting poor performance

Overall, district-level respondents felt that maternal and neonatal deaths were systematically underreported within the health system (e.g., by documenting fewer or no deaths than actual) because such indicators reflected poorly on a health worker's performance. This challenge was also broadly acknowledged by district leadership, who emphasized the importance of changing this practice:

> *"Staff are afraid that if they report a maternal death then they will get some punishment. They feel that they may be blamed for not taking care of the mother. They escape by not mentioning maternal or child deaths… If the message goes to a higher level, then some action may be taken, some investigation may be conducted to find out the reason for death. Like if the HB [hemoglobin] was less, then superiors will ask 'why was this not taken care of?'" (I-36, District administrative official)*

C. Indirect forms of data manipulation

Drawing on experiences from their supportive supervision visits, district staff observed other subtle forms of data manipulation. For example, they often felt data on the distribution of health commodities (e.g., oral contraceptive pills) were retrofitted to match the existing health facility inventories and were not based on verifiable data reported in health workers' registers. Before meetings with district administrative officials, district staff also described requests by district health officials to hide data on poorly performing indicators from meeting presentations to avoid bringing attention to low provision of health services or commodities in the district.

Opportunities for data manipulation

A. Discretion

Many district staff observed that unchecked power and authority exercised by senior block and district health officials created opportunities for data manipulation. Their high level of discretion coupled with little demand for accurate data resulted in low prioritization of data quality processes, which was problematic for two main reasons.

First, without explicit support from their health officials, data staff in blocks and districts were unable to convene data validation meetings and unable to create accountability for other health staff to deliver on their data quality-related tasks. Second, other lower-level staff's lack of seniority limited their ability to prevent district and block health officials from requiring data manipulation. For example, when district health officials demanded that data be fixed or changed, district data staff described their reluctance to push back because their job security was directly tied to district health officials' opinion of them. Furthermore, the lack of avenues available to district staff, particularly data staff, to report their grievances was problematic; as one stated, *"who would they raise their voices to when all the feedback goes back to one person?"* (I-16). Similar challenges were described at the block-level between block staff and block health officials.

B. Accountability

District staff described the implementation of two competing forms of accountability within the health system: district- and state-level leadership created strong accountability mechanisms for performance, while weakly enforcing accountability for data quality. For accurate data to inform district rankings, enforcement of both forms of accountability are needed.

1. Accountability for performance

District-level performance was largely based on the monthly district rankings in the UP-Health Dashboard. A district's rank was routinely reviewed during meetings with district health and administrative officials. If the district's ranking was low, district staff felt the focus shifted to pinpointing blame rather than examining the drivers of low performance:

> *"They [District administrative officials] just want to see their A grading of the district. No one wants to know that we cannot do well in the outpatient department because we do not have doctors" (I-32, District data staff).*

Following these meetings, district health and administrative officials reportedly sanctioned punishments via official letters or requests for "action taken reports" requiring explanations for poor performance. Unofficial forms of communication like threats to withhold salaries or delay approval of holidays were also reportedly used by district leadership, a point corroborated by the district health officials and administrative leaders we interviewed.

The district leadership's emphasis on accountability for performance was seen to mirror state-level priorities, as meetings between districts and states predominantly focused on monitoring targets and performance based on the district rankings. Most state-level respondents corroborated this, saying they used data to monitor performance as opposed to identify or address issues of data quality.

2. Accountability for data quality

Despite the presence of two formal mechanisms to improve data quality – supportive supervision visits and data validation committee meetings – six factors appeared to weaken their enforcement: (i) poor understanding of data quality; (ii) high workload; (iii) overemphasis on performance data; (iv) perception that district performance reflects one’s own performance, (v) systemic corruption; and (vi) weak processes for disciplining or dismissing staff.

First, district-level respondents described an inadequate level of understanding about data quality – what good data quality means and how it is measured – among district administrative and health leadership. Often “good data” were interpreted as “good performance” and not necessarily “good quality data.” Relatedly, some district- and state-level respondents rationalized poor performance by explaining that services were being systematically underreported:

> *“We are doing very good work, our doctors, paramedics… but it is not reflected in the data because you [they] are not managing the data. It is not that the doctors are not seeing the patients, day by day the OPD [Outpatient Department] load is increasing… but it is not reflected in the data”* (I-58, State-level respondent).

This perception that services are being delivered but being underreported may also explain why reporting errors were not given due consideration when identified during district data validation meetings:

> *"They [data entry operators or community health workers] do not worry about writing the wrong data. They just say, ‘Oh, it went wrong, tell me what to fill here.’ Here, data does not mean true data"* (I-18, District data staff).

Some district-level data staff further explained that less time was invested in recording, reviewing and assessing the data quality of data that did not inform the district-level rankings and were not associated with financial incentives.

Second, high workload associated with the implementation of a number of national health programs and fortnightly health campaigns also contributed to the low prioritization of data quality accountability mechanisms, like supportive supervision. As one district data staff noted: *"In practice, we have so much work that supportive supervision actually becomes too much…there is no time to do actually do it"* (I-27). District data staff also reported that some of them preferred *"changing the data"* rather than conducting supportive supervision (I-43).

When supportive supervision did occur, district data staff questioned the quality of these visits, describing them as informal *"tea-visits"* rather than official validations of web-based data (I-43). This laxness was attributed to district staff's minimal training on using the supportive supervision checklist or lack of sincerity towards work.

Third, the state leadership's emphasis on performance over data quality contributed to weak enforcement of data quality at district and block levels. Several district data staff felt this was evident in the little attention given to data quality issues when data demonstrated good performance (e.g., a high district ranking): *"The trouble is, if the performance is good on the basis of data, no one is going to ask anything [about data quality]"* (I-43). In a similar vein, one state-level respondent explained if the focus is on demonstrating improvement, using the data source that fits that messaging becomes priority.

State-level respondents also said there was limited demand for data quality at the state-level. According to some, lack of consideration for data quality was perhaps most reflected in a decision to minimize the functions of a data unit within the DOMHFW. Until 2015, this cell was responsible for reviewing paper-based administrative data and hosting monthly meetings to review the quality of those data with district-level data staff. However, with the replacement of paper-based reporting for web-based reporting, some state-level respondents said that the state leadership felt a less prominent role for the data unit was justified. Regardless, district data staff and state-level respondents universally expressed the importance of establishing clear lines of reporting from district-level data units to the state-level data units. State-level respondents further articulated that building capacity for data analysis and data quality in DOMHFW would be critical for improving accountability for data quality.

Fourth, some district-level respondents explained the difficult tradeoff they faced between upholding data quality or using data to show good district performance, because the latter factored into their performance assessment: *"You can look at the data to actually see whether or not things are improving and to track health programs; or, you can focus on looking at the data mainly as a way to save your own job"* (I-13, District data staff). This conflict of interest was also applicable to community, block, and district staff/officials, as one district administrative official explained.

Fifth, district-level respondents explained how political or personal connections with members of the legislative assembly or district health and administrative officials weakened accountability for data quality and data manipulation at lower administrative levels. For example, district data staff described how those who manipulate data at community or block levels were protected by district health officials who they had bribed for their current positions or were connected with through existing systems of kick-back.

Finally, and related to the point above, influential connections coupled with high levels of discretion meant that senior block and district health officials rarely bore the consequences of engaging in corrupt practices like data manipulation. For example, a district data staff described being unable to enforce disciplinary measures against a block health official who was extorting a portion of the financial incentives given to community health workers for supporting institutional deliveries:

> *"If I tell the CMO [chief medical officers/district health official], the CMO will not take any action. The previous CMO would have called the MOIC [medical officer-in-charge/block health official] and said, 'Listen I heard this news. You need to give me this much for this problem to go away…'" (I-29).*

Politics aside, many district-level respondents pointed to the lengthy process for dismissing and suspending government employees (Legal Service India, 2018), which made holding them accountable very difficult. Despite being aware of the problems associated with corruption, district administrative officials submitted that in light of significant human resources constraints, making do with the staff they had was their only option.

3. Examples of strong enforcement of district-level data quality accountability mechanisms

District staff identified two factors contributing to the strong enforcement of data quality accountability mechanisms at the district-level. First, district health and administrative officials who prioritized good quality data, through their enforcement of supportive supervision visits and review or presentation of those reports during meetings. Second, many district health officials with better enforcement of data quality processes held weekly meetings with block-level officials/staff to ensure consistent achievement of targets, troubleshoot problems, and safeguard against data manipulation.

On a broader scale, there was a consensus across respondents of all levels that the replacement of paper-based reporting with digital reporting increased accountability for good quality data and reduced opportunities to manipulate data at lower administrative tiers:

"Now with HMIS/UP-HMIS [web-based reporting platforms], manual [paper-based] reporting is decreasing, things are improving. Previously, it was difficult to catch errors but now with digitization, it's easier for us to go back in time and see what data were being reported. With data coming online, we have capacity to do more analytical work." (I-78, State-level respondent)

Interviews with division- and state-level respondents also signaled increasing prioritization of data quality at higher administrative levels with the recent development of a division-level monitoring and evaluation unit, as well as a state-level data validation committee and audit team. State-level respondents also noted that demand for the states, including UP, to improve data quality was coming from the national-level, particularly, the Niti Aayog, India's planning commission:

"Niti Aayog is not accepting [paper-based] data so all are focusing on HMIS data and that has to be correct and complete… they are ensuring HMIS should have correct data entry, data validation committee should be there, data should be checked and data output should be maximized, so this process is beginning now." (I-55, State-level respondent)

Pressures to manipulate data

A. Performance pressures

A high-pressure environment geared towards results and achievement of targets was evident in the content and number of meetings held at the district, and between districts and the state. Low achievement in the district rankings resulted in videoconferences with senior state-level leadership, which many district data staff described as a "one-way communication" where the state-leadership restated its performance expectations (I-25, District data staff).

District staff felt this top-down pressure was reiterated during district-level meetings with district administrative officials. If achievements were lagging on certain priority programs based on the district rankings, district administrators (e.g., district magistrates) would demand improvement. District staff universally stated that the district magistrates would never suggest "changing or manipulating the data," however, to steer clear of their "scolding" during the next meeting, district and block health officials would demand their staff to "increase the reporting" of priority health indicators. As one district data staff explained:

> *"The thing is that they [block health officials and staff] have already understood that in the previous meeting, I was scolded for this. … So, if any one of the MOIC [medical-officer-in charge/block-level health official] was scolded for this HBNC [home-based newborn care] thing in the last month; to take care of that next month they will do this [data manipulation]"* (I-43, District data staff).

Many district staff described feeling "frustrated," "burnt out," and "overburdened." However, one district staff noted that the most severe performance pressure was yet to come: rankings of district program managers, who are contractual data staff of the NHM. At the time of these interviews, these rankings were being developed by the GOUP, and the expectation was that they would be released every month alongside the district rankings (UP NHM, 2019).

B. Punitive work environment

Fear-based tactics, such as transfers or holding back salaries were often employed by district health and administrative officials to increase accountability for program performance. These tactics were observed during district-level meeting observations and confirmed by the district health and administrative officials we interviewed, who noted using similar approaches.

Many district program and data staff described "holding their breath" when attending district-level or state-level meetings where district-rankings were reviewed, fearing repercussions for poor performance. The pressures to "fix" or "improve" performance fostered an organizational culture where data manipulation became a coping strategy, which was operationalized via informal networks with district and block health officials, and data staff at the block and district levels. In particular, to draw less attention and scrutiny during meetings with district administrative officials or state-level officials if ranked as a top district, district staff said their district health officials preferred to be "somewhere in the middle" of the district rankings as one noted: "*CMO [District health official] is satisfied as long as we are ranked somewhere in the middle. Same with DM [District Magistrate/district administrative official]"* (I-43, district data staff).

Rationalization

Not all district staff succumbed to the pressures of their environment. Many responded to these pressures by using existing technical reasons for being unable to manipulate data. One district data staff recalled refusing a request by clearly stating: *"We [assistant research officers/district data staff] are not data generators. We compile data"* (I-37).

Other district data staff also described flatly ignoring requests to change data. For example, district data staff, who were aware of data being manipulated, refused from clicking the "submit" button on the online UP-HMIS that would record those data on the UP-HMIS web-based data portal. In another example, a district data staff described a peer's strong adherence to data quality principles, who continued to report actual attendance data of block-level medical officers despite facing high levels of pressure to inflate their attendance. However, persistently ignoring these requests resulted in a hostile work environment, which eventually led to the data staff's resignation.

District data staff also noted how many districts had *"rapid increases in district ranking even though those improvements should happen overtime and gradually"* (I-54). These quick spikes in ranking were attributed to manipulating the district rankings indicators. In such situations, when it was obvious that other districts were engaging in the practice, resisting data manipulation was socially unpopular. This challenge was reiterated by another district data staff who described how the district health official felt peer pressure to demonstrate progress when comparable districts had high district ranks, which the respondent speculated was due to overreporting (I-37). In short, data manipulation was seen as the way to survive within the broader system that appeared to condone the practice.

District-level respondents also felt job security and family financial security were often used as justification for data manipulation. One district data staff reflected on a personal transformation from wanting "to change the system" and abiding by abstract ethical norms to the current realization that "challenges to address are too many" and the importance of prioritizing that "family is taken care of" (I-13).

4.5 Discussion

Our study identified the main forms of administrative health data manipulation (**Table 11**) and the informal networks that operationalized the practice to provide a clearer view of the underlying factors that incentivize data manipulation. This analysis also presents the first application of the Vian corruption in the health system framework to study data manipulation. While the topic of data manipulation has been peripherally examined in the context of falsification of records for personal financial gain, and misreporting of administrative data to meet targets or benefit from results-based aid programs (Qazi and Ali, 2011; Sandefur and Glassman, 2015; Closser, 2019), our goal through this study is to explicitly situate data manipulation as a corrupt practice in the health systems literature.

Based on our analysis, we find that the problem of data manipulation, in part, reflects the persistent disconnect between "brilliantly formulated policies" and "realities on the ground"(Pritchett, 2009). In UP, HMIS policies clearly stated the objective of using good quality data in decision-making. However, the uneven implementation of data use and data quality policies at local levels resulted in competing systems of accountability. More specifically, the overemphasis on one aspect of the data use policies (i.e., using district rankings to create accountability for performance, and not the related aspect of identifying gaps and devising actions plans for improvement) - created unrealistic expectations of achieving significant improvements in a short time (or, before the next monthly district ranking).

Top-down pressures from the state translated to stronger system-wide enforcement of accountability for performance rather than data quality. The absence of functional state-level data units reflected the void in state-level demand for better data quality, further amplifying these pressures. At the district-level, performance pressures were reinforced by a punitive performance management system, where district staff/health officials were chastised during high-level meetings for low district rankings. Furthermore, a major conflict of interest emerged: the performance of district/block health officials, who were responsible for data quality were also judged on those same data (via the district ranking). This situation perversely incentivized data manipulation and led to a break down in the formal channels of accountability, transparency, and enforcement of practices for good data quality. Since job security of lower level staff was strongly tied to their obedience to superiors' directives, the discretionary powers of officials often remained unchecked. Finally, the widespread social acceptability of data manipulation, in part to cope with the performance pressures, resulted in the rationalization of the practice.

Our study mirrors findings from other studies where data were manipulated for personal financial gain and to achieve outlined targets (Qazi and Ali, 2011; Sandefur and Glassman, 2015; Closser, 2019). However, unlike these studies, which have explored pressures to manipulate data in the context of achieving external donor-outlined targets and performance-based aid (Sandefur and Glassman, 2015; Closser, 2019), we found that data manipulation was a coping strategy to manage pressures associated with a punitive work culture which demanded achievements of aggressive targets quickly. The approaches to performance management - naming, shaming and blaming – more commonly affected contractual staff working in data units, who were less capable of effectively responding to pressures from their superiors. As observed in other studies, we found the data units lacked functional independence and had little discretionary power at the district-level, and were incapacitated at the state-level, allowing data manipulation to persist (Sandefur and Glassman, 2015).

Consistent with other studies, we also found that enforcement of accountability for data quality were weaker for those connected with influential politicians or those who had bought their positions from them because they had impunity for non-performance (Closser, 2019). In addition, we found that the overwhelming influence of indirect social pressures via socially acceptable working norms created a tension between delivering on the expectations of peers and supervisors in the district and abiding by abstract ethical norms. One corruption theory grounded in behavioral sciences explains that individuals who are likely to be involved in corruption are “those who internalize the sanction (experience guilt, shame or embarrassment)” for not participating in their organization’s corrupt practices, and “conclude they have in fact done wrong” by rebuking those corrupt practices; though their actions chastising corruption would be considered correct outside their networks (Smith-Crowe and Warren, 2014). This point further demonstrates the challenges of working in punitive environment, where possibly false impressions of reality (e.g., feeling embarrassed for not achieving an unrealistic target) perpetuate corrupt practices, like data manipulation.

While our analysis describes the main forces of data manipulation and how they interact with one another, we were unable to fully examine if pressures to manipulate data subside when technical and resources constraints within the system are addressed. In our interviews with respondents from high priority districts, which receive additional technical support, we anticipated fewer pressures to manipulate data. However, contrary to expectation, they reported similar experiences with data manipulation to those articulated by respondents in non-high priority districts, suggesting that issues of data manipulation and corruption are not a mere reflection of insufficient resources but broader organizational cultural issues.

There have been louder calls for countries to implement top-down anti-corruption approaches and strengthen system-wide governance initiatives (Sudarshan and Prashanth, 2011). In 2013, the Government of India (GOI) instituted *Lokpal and Lokayukta* to investigate corruption at the national and state-levels respectively (The Times of India, 2013). States like Karnataka, also expanded Lokayukta into vigilance cells within health departments (The Times of India, 2013). While it is currently unclear, whether these units are able to identify or even address issues of data manipulation, the Government of India has started implementing national data quality audits to strengthen data quality. The frequency, breadth (in terms of indicators and geography), and feasibility of conducting data quality audits seems challenging in large states like UP with nearly 29,000 public health facilities. Even if they are implemented as intended, it would be critical for the national government to penalize practices of data manipulation to curb recurrences, as well as devise strategies to address the root causes of it.

Our study has several limitations worth highlighting. First, we examined the drivers of data manipulation, and while our respondents spoke with us extensively about data manipulation practices, we were unable to quantify the prevalence of these practices across all 75 districts. Second, we recognize that the sensitive nature of this research may have resulted in social desirability bias. However, we attempted to address this limitation through prolonged engagement in the field, rapport building with participants, and generating detailed and nuanced accounts that would reveal a full picture. Third, due to their busy schedules, we were unable to extensively capture the views senior district health and administrative officials (e.g., chief medical officers and district magistrates) whose insights may have further illuminated the findings from this study.

4.6 Conclusion

This study unpacks the main drivers of data manipulation and shows why these practices persist despite the strong initiatives to improve data quality by the GOUP. A deeper understanding of the underlying barriers to data manipulation is the first step towards identifying strategies to curb this practice. While stakeholder engagements in UP will be required to identify context-appropriate strategies in UP, our study identifies three main entry points to mitigate data manipulation: (1) changing the incentive structures, for there to be equal emphasis on data quality as there is on performance data; (2) strengthening checks and balances to reinforce the integrity of data-related processes at all levels; and (3) implementing system-wide policies that make data manipulation an unacceptable anomaly. Future evidence on context-relevant top-down and bottom-up strategies to effectively counter data manipulation are required.

Chapter 5. Discussion and conclusions

5.1 Research purpose

Leveraging both qualitative and quantitative methods, this dissertation explored the non-technical determinants of Health Management Information System (HMIS) performance, such as organizational and behavioral factors, that are often less examined in the literature. Chapter 2 explained the observed gap between well-intentioned HMIS policies and their implementation by analyzing how organizational factors and culture shaped implementation processes. Chapter 3 quantitatively analyzed the variations in data quality for HMIS indicators that are used in performance metrics (like district rankings) and are associated with financial incentives with those that are only collected for routine monitoring. Finally, Chapter 4 described the types of HMIS data manipulation observed in Uttar Pradesh (UP), and their underlying drivers.

This chapter summarizes the key results from each of the three papers, presents the strengths and limitations of the overall study, and describes the broader policy implications as well as recommendations for future research.

5.2 Summary of findings

Chapter 2 identified four key factors that affected HMIS policy implementation and performance in Uttar Pradesh. First, respondents described the human resource shortages, including the lack of block-level data entry operators, which overburdened existing staff and weakened the implementation of HMIS activities. A second implementation gap was the inadequate knowledge about UP-HMIS policy guidelines, and limited computer literacy among block- and district-level staff. The issue of hierarchy emerged as a third important factor influencing HMIS implementation.

District data staff, particularly contractual data staff, described how their limited power and authority required them to escalate minor issues to the level of the district-leadership in order to create accountability among other staff for UP-HMIS activities. However, district-level data staff also noted that working within a very hierarchical organizational system meant having to follow their supervisors' directives– even if they contradicted HMIS policy guidelines. A fourth gap affecting HMIS performance was the overemphasis on using monthly district rankings to create accountability for performance. Though the primary policy intention was to use district rankings to guide improvements in program implementation, district-level respondents described how their superiors' "fixation" with becoming a top-ranking district, often meant disregarding the quality of data informing district rankings.

Chapter 3 showed that data quality metrics for completeness and internal consistency varied by the four HMIS indicator categories (ranked, incentivized, ranked and incentivized, and unranked and unincentivized). The highest level of completeness in the monthly health facility reports was observed for ranked indicators, closely followed by ranked and incentivized indicators, incentivized indicators and finally, unranked and unincentivized indicators, which had the highest percentage of missing data. The high percentage of completeness for ranked indicators may be explained by the demand by district and state leadership to review these data during monthly meetings.

Contrary to expectation, when examining the percentage of outliers, we found that ranked indicators had the smallest percentage of extreme outliers and unranked and unincentivized indicators had the highest percentage of extreme outliers. However, findings from internal consistency ratios revealed higher levels of systematic overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators. Together, these findings suggest that ranked and incentivized indicators may be overreported, but not at extreme levels, perhaps to avoid undue attention from superiors that may prompt investigations. Finally, with respect to the performance of the three data quality metrics (completeness, outliers, internal consistency) by monthly facility reports in high priority districts (HPDs) and non-high priority districts (non-HPDs), as expected, we observed higher levels of completeness across the four indicator categories in monthly facility reports from HPDs. However, we observed the same percentage of moderate and extreme outliers, and evidence for potential overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators (based on internal consistency ratios) in monthly facility reports from both HPDs and non-HPDs.

Chapter 4 described the four types of data manipulation observed by district-level respondents and the underlying drivers of data manipulation in UP. The four types of data manipulation described were: (i) the overreporting of positive indicators, for example, health service indicators like institutional deliveries; (ii) the underreporting of negative indicators, e.g., reporting of maternal deaths or stillbirths; (iii) the retrofitting of health commodities data to match health facility inventories at the end of the month; and (iv) hiding data that showed low progress from presentations to senior district or state officials.

Many district respondents observed that unchecked power and authority exercised by senior block and district health officials created opportunities for data manipulation. Their high level of discretion coupled with little demand for accurate data resulted in low prioritization of data quality processes. Relatedly, district-level respondents emphasized that opportunities for data manipulation were created, when accountability mechanisms for data quality were weakly enforced, which they attributed to six factors: (i) poor understanding of data quality; (ii) high workload; (iii) overemphasis on performance data; (iv) perception that district performance reflects one's own performance, (v) systemic corruption; and (vi) weak processes for disciplining or dismissing staff.

Performance pressures and punitive work culture were also identified as key factors that created pressure to manipulate data. A high-pressure environment geared towards results and achievement of targets was evident in the content and number of meetings held at the district-level, and between districts and the state. Many district-level respondents also described the use of fear-based tactics, such as transfers or holding back salaries to increase accountability for program performance. Finally, district-level respondents explained the social pressure to manipulate data and described job security and financial security for one's family as reasons to justify data manipulation.

Some district-level staff described resisting manipulating data by drawing on technical reasons for being unable to change data or flatly ignoring requests. However, as potential elements of a broader strategy to mitigate data manipulation, district- and state-level respondents identified several potential avenues for exploration, including, the replacement of paper-based reports with digital reporting and the implementation of skills-based trainings to build technical knowledge among data and program staff. However, respondents noted that the most important factor to address data manipulation is having leadership that values, demands, and prioritizes good quality data in decision-making.

Conclusions from all three research papers demonstrate that issues of a weak HMIS implementation are not merely a reflection of insufficient resources or the lack of technical guidelines. Our qualitative findings (in Chapters 2 and 4) describe how organizational cultural factors – particularly, challenges associated with working within a strict hierarchy, and broader performance pressures and punitive work culture resulted in weak enforcement of data quality mechanisms, and created perverse incentives to manipulate district ranking indicators to show high achievement of performance metrics. The HMIS data quality analysis (in Chapter 3) corroborated these assessments and presented evidence to show the potential overreporting of HMIS indicators that are associated with performance measures like district rankings and financial incentives. Findings from all three chapters demonstrate the lack of alignment in goals among health actors in data units and those in leadership positions, which resulted in data quality goals often being at odds with the goal of achieving a high district ranking. Findings also point to the need for strengthening the integrity of data-related processes at all levels of the health system, and implementing system-wide policies that make data manipulation an anomaly, not a norm.

5.3 Strengths and limitations

Since the strengths and limitations of each paper are highlighted in Chapters 2-4, this section reflects on the overall strengths and weaknesses of the dissertation. A major strength of the dissertation is the collaboration with technical partners of the GOUP - the Uttar Pradesh Technical Support Unit (UP-TSU), who had intimate understanding of the state's governance structure and the UP-HMIS policy guidelines - throughout the dissertation research. First, research questions were designed to be policy relevant and were developed in consultation with the UP-TSU. The study tools, which were based on an initial document review, were further refined following discussions with colleagues at the UP-TSU, and interviews with HMIS program implementers at the block and district levels. During data collection, emerging themes were also shared with colleagues at the UP-TSU. At this time, findings presented in Chapters 2-4 have been shared with UP-TSU colleagues for their written feedback, and meetings have been planned in August 2020 to discuss the interpretation of the dissertation's findings, and the policy implications of this work in greater detail.

Second, this dissertation leverages both qualitative and quantitative methods, such as in-depth interviews, meeting observations, document review, and descriptive quantitative analyses, which has helped shed light on different aspects of HMIS performance. For example, we were able to triangulate findings from in-depth interviews with district-level meeting observations, which provided direct empirical evidence on behaviors and interactions pertaining to hierarchy and performance management. Similarly, the quantitative component of this dissertation (Chapter 3) corroborated qualitative findings (Chapters 2 and 4) by quantifying the level of potential overreporting of ranked and incentivized HMIS indicators compared to unranked and unincentivized HMIS indicators.

Finally, being able to conduct all the in-depth interviews and meeting observations myself over the span of one year has had several advantages. My prolonged engagement in UP helped me build and gain the trust of my respondents and allowed me to better understand the organizational and health system culture that my respondents operate within. My long-term presence in UP also exposed me to a wide a range of respondents across different districts, which allowed me to iterate on the in-depth interview guide, develop nuanced accounts of my respondents' experiences with HMIS implementation, and conduct interviews until data saturation was achieved.

While the strengths described above improved the quality of the overall dissertation, there are shortcomings worth noting. In addition to those specified in each chapter, one major limitation of this dissertation was being unable to quantify the prevalence of data manipulation observed across districts in UP, even though we were able to identify the drivers of HMIS data manipulation (Chapter 4) and quantitatively present evidence for potential overreporting, a type of data manipulation (Chapter 3). To enhance the quantitative findings presented, a data validation audit that verifies the HMIS data entered in source documents, like facility-level registers with UP-HMIS web portal data could have provided direct evidence on the practice of data manipulation. Second, the qualitative data collection for this dissertation happened in three phases over the span of one-year, and districts may have been at different phases of their UP-HMIS implementation processes during data collection, which may have shaped their responses to some questions. However, because all the district-level policies examined in this dissertation had already been released by the GOUP at the start of data collection, this limitation is unlikely to significantly modify the findings presented here.

5.4 Policy implications

The findings from this dissertation have immediate- and long-term policy implications for strengthening HMIS performance in UP. The first three recommendations focus on drawing on technical strategies to improve HMIS performance in the state. The remaining recommendations largely focus on building an organizational culture that demands and values good HMIS data quality for decision-making.

(1) *Improve the number of qualified staff who can carry out data-related activities at all levels health systems*

One of the most critical gaps affecting HMIS performance is the overburdened block-level data entry operators, who are responsible for entering paper-based facility reports from 26 to 31 health facilities (depending on block size) to up to 16 web-based health program portals every month. Hiring additional data entry operators is the most obvious solution for reducing the reporting burden, and the current scale up of electronic data entry platforms like ANMOL (Auxiliary Nurse Midwives Online) by the GOUP may drastically help reduce the reporting burden on block-level data entry operators. However, as the findings in Chapter 2 explained, ensuring the availability of data entry operators (and human resources, generally) is not enough, as they are often redirected to other activities at the behest of their supervisors. To improve the performance of HMIS in the state, the GOUP must ensure that job descriptions of data and program staff are closely followed.

In particular, alleviating the workload placed on district-level staff (e.g., assistant chief medical officers/program staff) would require addressing the uneven distribution of responsibilities among them. For example, the GOUP may consider establishing a cutoff for the maximum number of health programs one program staff is allowed to manage. Implementation of such a directive may help reduce situations which disproportionately overburden few program staff and in turn may encourage all program staff to take on greater ownership of their programs, including their program data.

Second, the GOUP should consider developing an ongoing collaboration with staffing agencies to establish a staffing pool that can be drawn upon in times of acute need. These staffing agencies can vet and assign the most qualified candidates to support the block or district's short-term needs, for example, to support the implementation of monthly national health campaigns and short-term health drives, which often result in existing staff being redirected to support these "urgent" activities, thereby disrupting the implementation of routine data-related activities.

Relatedly, findings showed how the lower status of contractual data staff relative to permanent staff inhibited them from effectively overseeing the implementation of HMIS data-related activities. Strategies that bridge the hierarchical divide between permanent and contractual staff and integrate contractual staff into the existing workforce would be critical for creating and enforcing accountability for HMIS-related activities.

Lastly, addressing the persistent human resources shortages across different cadres who are required to support HMIS processes at different levels will require the GOUP to identify sustainable mechanisms and strategies for producing, retaining, and equitably distributing health workers in the UP health system.

(2) *Invest in skill-based trainings, and automate data analysis to close existing technical knowledge gaps affecting HMIS performance*

Trainings during the scale-up of the UP-HMIS assumed a key competency: computer literacy and basic computer skills among block- and district-level staff. This oversight, in part, reflects the changing workforce in UP: new hires are often computer literate but lack technical knowledge of HMIS; whereas, older staff, who are nearing retirement, are better-versed in HMIS processes but remain less skilled with computers. In this context, the GOUP should consider developing targeted training sessions that address gaps in technical knowledge and computer literacy to ensure effective implementation of HMIS processes by all cadres in the health system. Developing and implementing an effective training program may involve drawing on theories about adult learning techniques, which outline the distinct styles with which adults learn and retain materials (Knowles, 1970) especially for those who continue to show deficiencies in their technical understanding of the HMIS despite have received prior trainings. In addition, the GOUP should consider routinely updating training content and implementing trainings (virtually or in-person) when data collection formats or data collection processes are changed so that health cadres responsible for data entry and analysis remain up-to-date with data demands for new and existing health programs.

Aside from trainings, to close technical and computer literacy gaps, automating basic technical analyses, such as the generation of monthly reports, and building additional data validation checks (including those proposed in Chapter 3), may be helpful to block-level data staff, who often rely on their district-level counterparts to support them with data analysis.

(3) *Draw on technical strategies to improve data quality and increase the transparency of data being reported at all levels of the health system*

Technical strategies that promote data entry at source may inhibit "fixing" of data at the block levels, and bring transparency and accountability, especially as data are entered in real-time. As of July 2020, the GOUP has been scaling up the use of electronic data entry platforms like ANMOL (auxiliary nurse midwives online), which will enable frontline staff to directly enter data into web-based portals via tablets. The state-wide implementation of such platforms would increase the availability of real-time data, which may encourage greater use of data for decision-making and help enhance transparency as more staff within the heath system would be able to view the data, making it harder to make changes to the data and establish informal networks for data manipulation (Press Information Bureau, Government of India, Ministry of Health and Family Welfare *et al.*, 2016). Similarly, technical approaches, such as incorporating additional data validation metrics as proposed in Chapter 3 to identify potential overreporting of ranked and incentivized indicators relative to unranked and unincentivized indicators may help identify data quality errors early on, which may be followed up or verified during supportive supervision visits or audits at the facility-level.

(4) *Build leadership, and ownership to generate accountability for good quality data at all levels of the health system*

Having strong leadership that values, demands, and prioritizes good quality data in decision-making is critical for creating an organizational culture where data quality is prioritized, and mechanisms to strengthen HMIS data quality are enforced at all levels of the health system. Instilling among leadership at all levels of health system the value of data quality is critical and may require additional trainings to illustrate the benefits of good data quality and to further develop relevant skills for analyzing and using data for decision-making.

Aside from leadership being a critical factor in creating accountability for good quality data within the health system, the GOUP should strengthen the capacity of existing data units or establish a new, integrated data unit within the Directorate to coordinate, monitor and evaluate data quality processes across the state. To effectively lead, state-level data units must have sufficient financial and decision-making authority to develop and implement data quality initiatives, as well as enforce accountability mechanisms to promote good HMIS data quality at all levels of the health system.

Most importantly, state-level data units could help strengthen existing GOUP initiatives, such as, the implementation of the state-level data validation committee meetings, and data quality audits, which have been weakly implemented. Relatedly, the state-level data units could play a broader analytic role to support better planning and monitoring of health programs being implemented in the state.

(5) *Create incentives for good data quality, and disincentives for data manipulation*

At the district-level, findings clearly demonstrated the tangible benefits of achieving high district rankings, such as better postings and promotions of health and administrative officials from top-ranking districts. In addition, top-ranking district officials were also less likely be to "named and shamed" for poor performance during district and state high-level meetings. Consequently, maintaining or achieving top district rankings took precedence over enforcing data quality mechanisms, especially when the incentives for good data quality and the disincentives for bad data quality were both lacking.

The GOUP may consider the following incentives to improve HMIS data quality: (i) computing a metric for data accuracy, which is calculated into the monthly district rankings; (ii) implementing a "naming and faming" strategy (Zomer, 2018) that recognizes block and district officials, whose districts show excellent data quality, for example, based on data quality audit results; and (iii) requiring district and state officials to review the data quality results from supportive supervision visits and data validation committee meetings, just as the GOUP guidelines mandate the review of the monthly district rankings from the UP Health Dashboard during these meetings.

To disincentivize data manipulation, the GOUP should clearly articulate the consequences of data manipulation in policy guidelines and enforce those guidelines. This policy should be considered as a part of a broader anti-corruption agenda which should include: (i) requiring district health officials to disclose conflicts of interests that could influence the recruitment, appointment or promotions of staff in the district; and (ii) expanding the *Lokpal* and *Lokayukta's* role by establishing vigilance cells to strengthen system-wide governance and employment grievance redressal mechanisms in the GOUP health system (The Times of India, 2013). Successful implementation of these initiatives will require strong leaders, who are passionate about defeating corruption and able to navigate political repercussions.

In addition, the GOUP should consider removing any direct or indirect "incentives" for potential data manipulation. By introducing "randomness" in the selection of indicators used to compute the monthly district rankings, the GOUP may reduce the perverse incentive for data manipulation. Relatedly, by expanding the pool of district ranking indicators, the GOUP could also increase attention given to health programs that are overlooked. Lastly, it is important to recognize that "urgencies," like, the immediate implementation of a national campaign and the expectation of high achievement often opens an opportunity for data manipulation because of the high pressure health officials feel to deliver on results in a short period of time. The GOUP may like to consider strategies that could alleviate such pressures to avoid data manipulation from becoming a coping strategy.

(6) *Build respect for data managers and data staff within the health system*

Building respect for data managers and data staff within the health system, who are responsible for implementing and overseeing data-related activities will be critical to improving HMIS performance. Creating a collaborative working environment based on mutual respect and one that recognizes their essential role in the health system may increase the status of data managers and staff. Some tangible approaches may include a combination of financial and non-financial approaches, such as, increasing salaries to retain employees but also recognizing staff who have exceeded expectations. The government may also consider establishing mechanisms for absorbing contractual data staff into established government positions, which may also help address the power dynamics that exist between permanent staff and contractual staff, many of whom were hired to support data-related activities.

(7) *Strengthen the public health capacity to ensure leadership and staff at different levels of the health system are well-equipped to make strategic decisions to guide program improvement*

District-level respondents described that high-level meetings with their supervisors generally focused on the importance of achieving a high district ranking, but seldom in those meetings did they discuss "how" to improve the program performance within the district. While this observation certainly underscores the need to reshape organizational incentives (as discussed in point 3-5 above), it possibly also reflects a mismatch of expectations between district health staff and officials, and their superiors. District health officials and staff expect their superiors to provide them with technical and analytical guidance. Yet many district administrative officials have limited formal public health training, given their role is to govern across all sectors within the district, not just health. At the same time, there is an implicit assumption by district administrative officials that their district health officials and staff have the relevant technical public health competencies to single-handedly manage and lead health programs successfully because of their medical training. However, as many have already suggested, “public health is not clinical medicine” (McPherson, 2001). Effective public health governance, which is inherently complex, requires the intersection of multiple skillsets, disciplines, and sectors.

Therefore, addressing this challenge requires considering several issues, such as: (i) establishing or strengthening technical units with public health experts, possibly at the division- or state-levels, that can provide targeted guidance to districts on how to improve the implementation and performance of their health programs; (ii) clarifying the roles and responsibilities of which units or teams are expected to provide the technical leadership necessary for improving program performance at the district, division and state-levels; and (iii) ensuring those units have access to the relevant resources and skillsets necessary to achieve their intended goals.

To take this work forward, perhaps, the most important next step would be to host one or more roundtable discussions with government stakeholders from block, district, division and state levels to identify strategies for improving data quality and strengthening HMIS performance in UP. These discussions could happen over four stages, for example: (i) first, present evidence from this dissertation and other resources to collectively frame the key problems affecting HMIS data quality and broader HMIS performance; (ii) second, brainstorm and map relevant strategies to address the problems identified based on best practices from districts in UP and those from other states; (iii) third, identify the key stakeholders (by role, and authority) whose involvement would be critical for championing the implementation of identified strategies; and (iv) finally, synthesize the discussions from parts (i-iii) into actionable policy briefs for consultation with a broader set of government stakeholders and the leadership before the designing strategies for implementation.

5.5 Future research

While this dissertation addressed a number of questions, it also gave rise to further questions summarized in two key areas presented below.

(1) Explore incentives to improve HMIS performance, particularly data quality, at the state and national levels

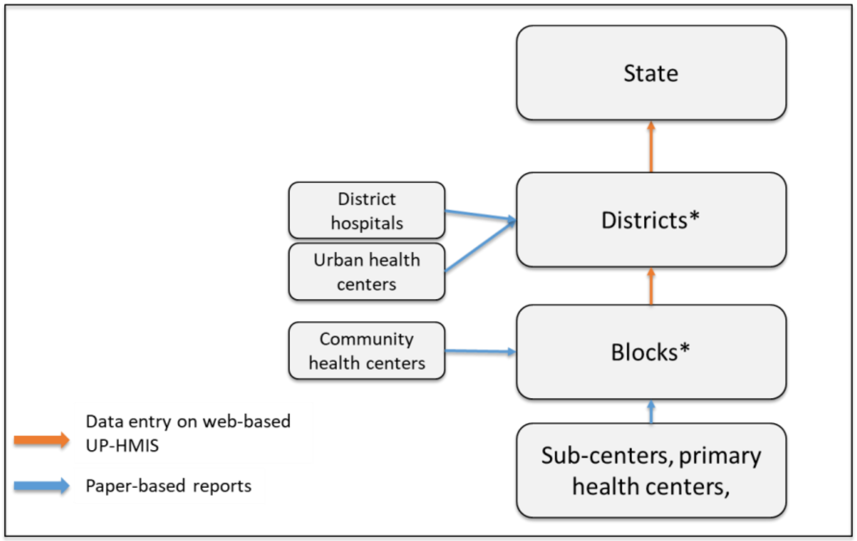
Organizational incentives and disincentives to strengthen HMIS performance at the district-level were greatly shaped by the expectations of leadership at the division, state, and national levels. While this study was able to shed light on the incentives and disincentives for strengthening data quality based on the perspective of district-level staff and health officials, future research should unpack the incentives and disincentives for creating accountability for performance and data quality experienced by division, state and national leadership, who collectively represent three different organizations (Departments of Medical Health and Family Welfare, the National Health Mission and the Indian Administrative Services). A holistic understand of existing incentives and disincentives of leaders at different levels of the health system and across the three organizations that are involved in overseeing public health in UP, would be critical for creating alignment on the GOUP's goal of improving the state's health performance and using quality data to measure progress against that goal.

(2) Conduct facility-level audits across high-priority and non-high priority districts

Building on findings from chapter 3, which provided initial evidence on potential overreporting of ranked and incentivized UP-HMIS indicators relative to unranked and unincentivized indicators, conducting health facility audits across high priority and non-high priority districts would be an important next step for verifying data quality at different levels of the health system. Specifically, with a representative random sample of health facilities, one would be able to examine the level of consistency between data reported in the web-based UP-HMIS portal, with data reported in the source documents and registers found in the sub-centers, primary health centers, and community health centers of a district. This exercise could help identify where inconsistencies are introduced and help establish a baseline of data quality within the state, which future facility-level audits could be compared against to evaluate improvements over time.

Appendices

Appendix 1. The flow of information in the Uttar Pradesh Health Management Information System (HMIS) in Uttar Pradesh



*At block- and district-levels, data entry operators are responsible to enter facility-level reports into UP-HMIS and other web-based portals for national programs

Appendix 2. UP-HMIS policy expectations for data quality and data use meetings at the block- and district-levels in Uttar Pradesh, India

	Data validation committee meetings		**Data use meetings**	
	Block-level	**District-level**	**District-level Executive Committee**	**District-level Governing Body meeting: District Health Society**
Purpose	Ensure quality (completeness, validation, consistency, accuracy) of data reported by the sub-centers, primary health centers and community health centers in the block Ensure timely uploading and forwarding of data to districts	Ensure the completeness, validation, consistency, and accuracy of data being reported from all blocks Ensure availability of quality data for district-level data use meetings	Examine data, including the district ranking to measure relative performance of a district in UP based on priority health indicators Help district administration to identify the reasons for poor performance (e.g., availability, quality, utilization issues) and take appropriate actions	
Timeline	Between 1^{st}-5^{th} of every month	Between 6-10^{th} of every month	Last week of the month	Last week of the month
Chairperson	Medical officer-in-charge	Assistant chief medical officer for reproductive and child health programs	Chief medical officer	District magistrate
Participants	Block attendees: (1) permanent data staff: assistant research officer; (2) permanent program staff: health education information officers; (3) contractual data staff: block program manager, data entry operators	District attendees: (1) permanent data staff: assistant research officers; (2) contractual data staff: district program managers, district data manager, data entry operators Block attendees: (1) permanent staff: medical officers-in-charge; (2) contractual data staff: block program managers, data entry operators	District attendees: (1) permanent program staff: assistant chief medical officers, district community process managers; (2) permanent data staff: assistant research officers; (3) contractual data staff: district program managers, district data managers, district accounts managers, data entry operator	District attendees: (1) permanent program staff: assistant chief medical officers, district community process managers; (2) permanent data staff: assistant research officers; (3) contractual data staff: district program managers, district data managers, district accounts managers, data entry operator Block attendees: (1) permanent program staff: medical officers-in-charge; (2) contractual data

			Block attendees: (1) permanent staff: medical officers-in-charge; (2) contractual data staff: block program managers, data entry operators	staff: block program managers, data entry operators Partners: (1) World Health Organization; (2) United Nations partners (e.g., UNICEF and UNDP); (3) UP-TSU

Appendix 3. The primary data-related roles and responsibilities of health staff/officials in the Uttar Pradesh health system

Level	Employment	Staff type	Actors	Data-related responsibility	Specific responsibility
State	Permanent	N/A	Directors & Joint Directors - Department of Medical Health & Family Welfare	Data review & feedback	▪ Review data quality ▪ Use data to monitor performance
	Contractual	N/A	General Managers from the National Health Mission		
District	N/A	Administrative official	District Magistrate; Chief Development Officer	Data review & feedback to district	▪ Chair Governing Body - District Health Society meetings ▪ Use data to monitor performance
	Permanent	Health officials	Chief Medical Officer (CMO)	Data review & feedback to block level	▪ Chair Executive Committee Meetings ▪ Use data to monitor performance
		Program staff	Assistant Chief Medical Officer & Deputy CMO	Data validation, review, validation, and feedback	▪ Feedback to block ▪ Programs officers to screen reports for accuracy & share reports with AROs/DDMs before data validation committee meeting
		Data staff	Assistant Research Officer	Data analysis, validation, and feedback	▪ Review the data shared by district program nodal officers, prepare for the data validation committee meeting
	Contractual	Data staff (NHM)	District Program Managers		
			District Data Managers		
		Data (external agency)	HMIS Operators	Data entry and compilation	▪ Following the data validation committee meetings, data are uploaded to the HMIS portal
Block	Permanent	Health official	Medical office-in-charge	Data review, validation and feedback	▪ Preside over the block-level data validation committee meeting
		Data staff	Assistant Research Officer	Data analysis, validation, and feedback to block	▪ Screen the reports received from ANMs for accuracy ▪ AROs review the data and conduct a data validation committee meeting before sharing the data with the DEOs

Level	Employment	Staff type	Actors	Data-related responsibility	Specific responsibility
	Contractual	Data staff (NHM)	Block Program Managers	Data analysis, validation, and review	▪ Support data validation committee meetings
		Data staff (external agency)	Data entry operators	Data entry	▪ Validated data are uploaded by the DEOs into digital portals
Sub-center	Permanent / contractual	Program	Auxiliary Nurse Wives (ANMs)	Data entry, compilation, and verification	▪ ANMs/Facilities will compile the reports collected from ASHAs & submit them to Block-level AROs
Community	Permanent / contractual	Program	ASHAs	Data entry	▪ Record health services provided in registers

Appendix 4. Analytical framework used for the analysis

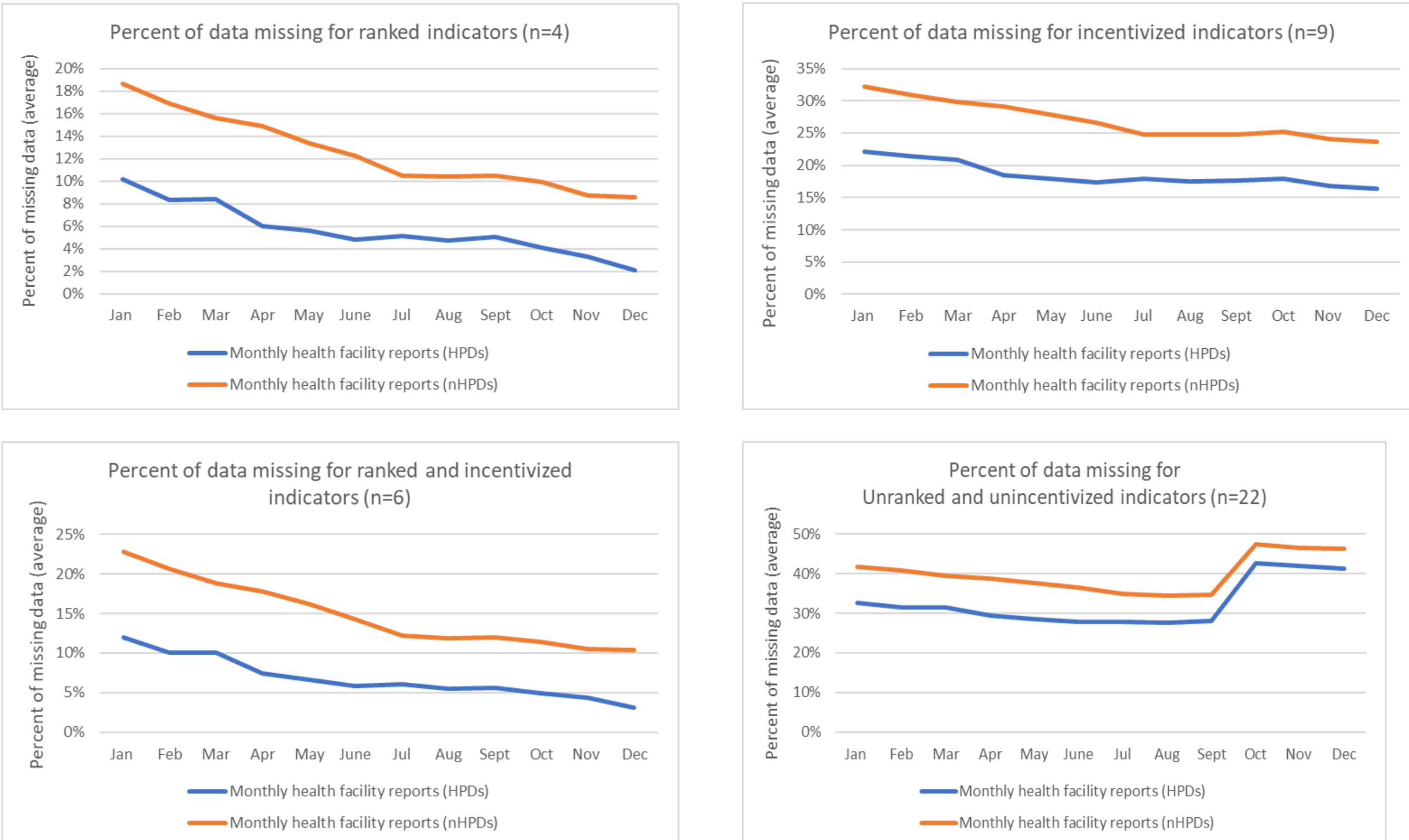
#	Domains	Codes	Sub-codes
1	Policy environment	National policy expectation	National targets, national Schemes
		State policy expectations	Blocks, districts, states
2	Factors affecting policy implementation	Technical factors	Reporting processes and complexity, availability of materials
		Resources	Human resources distribution, human resources availability, trainings, technical skills
		Processes	Supportive supervision
		Work culture	Authority/discretion, accountability, collaboration/coordination, workload
		Behavioral factors	Commitment to work, attitudes towards data quality/use
3	Characteristics of actors	District permanent staff	Responsibilities, incentives
		District contractual staff	Responsibilities, incentives
		Senior district officials (district magistrates)	Responsibilities, incentives
		Divisional staff	Responsibilities, incentives
		State officials	Responsibilities, incentives
4	UP-HMIS policy implementation observed in practice	Data quality meetings	Processes, platforms
		Data use	Processes, platforms
5	Effects of UP-HMIS policy implementation	Data quality	Positive, negative, other
		Data use	Positive, negative, other

Appendix 5. Percentage of missing data (overall) by indicator category for monthly health facility reports from high priority districts (HPDs) and non-high priority districts (non-HPDs) from January to December 2019

COMPARISON	MEAN[#]	STANDARD DEVIATION	95% CONFIDENCE INTERVAL
Ranked indicators (HPD)	0.056	0.230	(0.055, 0.056)
Ranked indicators (non-HPD)	0.125	0.330	(0.124, 0.125)
P-VALUE*	<0.01		
Ranked and incentivized indicators (HPD)	0.067	0.251	(0.067, 0.068)
Ranked and incentivized indicators (non-HPD)	0.149	0.356	(0.148, 0.149)
P-VALUE*	<0.01		
Incentivized indicators (HPD)	0.185	0.388	(0.184, 0.186)
Incentivized indicators (non-HPD)	0.269	0.443	(0.269, 0.270)
P-VALUE*	<0.01		
Unranked and unincentivized indicators (HPD)	0.325	0.468	(0.325, 0.326)
Unranked and unincentivized indicators (non-HPD)	0.399	0.489	(0.399, 0.399)
P-VALUE*	<0.01		

[#]not presented as a percentage ;*P-VALUE: diff = mean(HPD) - mean(non-HPD)

Appendix 6. Trends in the percentage of missing data over time by indicator category for monthly health facility reports from high priority districts and non-high priority districts from January to December 2019



Appendix 7. Trends in the percentage of missing data over time by indicator (n=41) reported in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019

Ranked indicators

A. Percentage of missing data among ranked indicators in the monthly health facility-reports from high priority districts

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Number of pregnant women tested for hemoglobin (Hb) 4 or >4 times in ANC visits	10%	8%	9%	6%	5%	4%	5%	4%	5%	4%	3%	2%
Number of women receiving 1st post-partum checkups within 48 hours of delivery	11%	9%	9%	7%	6%	5%	5%	5%	5%	4%	3%	2%
Number of children who received pentavalent 3 dose	10%	7%	7%	5%	5%	5%	5%	5%	5%	4%	3%	2%
Number of children who received Bacille Calmette-Guérin (BCG) dose	10%	8%	8%	6%	6%	5%	5%	5%	5%	4%	3%	2%

B. Percentage of missing data among ranked indicators in the monthly health facility-reports from non-high priority districts

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Number of pregnant women tested for hemoglobin (Hb) 4 or >4 times in ANC visits	19%	17%	16%	15%	14%	13%	11%	11%	11%	10%	8%	9%
Number of women receiving 1st post-partum checkups within 48 hours of delivery	22%	20%	19%	18%	16%	15%	12%	12%	12%	11%	10%	10%
Number of children who received pentavalent 3 dose	16%	15%	14%	13%	12%	11%	9%	9%	9%	9%	8%	8%
Number of children who received Bacille Calmette-Guérin (BCG) dose	17%	15%	14%	13%	12%	11%	9%	9%	10%	9%	8%	8%

Incentivized indicators

C. Percentage of missing data among incentivized indicators in the monthly health facility-reports from high priority districts

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Number of interval intrauterine device (IUCD) insertions (excluding post-partum IUCD/post-abortion IUCD)	11%	9%	9%	7%	6%	6%	6%	6%	6%	5%	4%	4%
Number of post-partum IUCD insertions (within 48 hours of delivery)	13%	11%	11%	8%	8%	7%	8%	8%	7%	7%	7%	5%
Number of post-abortion IUCD insertions (within 12 days)	84%	83%	83%	81%	81%	81%	80%	80%	80%	79%	78%	77%
Number of newborns received 6 home based newborn care (HBNC) visits after institutional delivery	12%	10%	11%	8%	7%	7%	8%	7%	7%	5%	5%	4%
Number of newborns received 7 HBNC visits home delivery	18%	16%	17%	15%	14%	14%	14%	14%	14%	14%	14%	13%
Number of new pregnant women identified as high-risk pregnancy (HRP), who are 35 years and older	17%	18%	17%	14%	13%	13%	13%	13%	14%	15%	13%	13%
Number of new pregnant women identified as HRP (previous history with any complication)	17%	18%	17%	14%	13%	13%	13%	13%	14%	16%	14%	14%
Number of new pregnant women identified as HRP (any other reasons)	17%	18%	16%	14%	13%	13%	13%	13%	13%	16%	14%	14%
Number of pregnant women registered in 1st trimester (within 12 weeks) out of the total ANC registrations that month	9%	8%	8%	5%	5%	4%	5%	4%	5%	4%	3%	2%

D. Percentage of missing data among incentivized indicators in the monthly health facility-reports from non-high priority districts

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Number of interval intrauterine device (IUCD) insertions (excluding post-partum IUCD/post-abortion IUCD)	20%	18%	17%	17%	15%	14%	11%	11%	11%	11%	10%	9%
Number of post-partum IUCD insertions (within 48 hours of delivery)	25%	23%	21%	21%	19%	18%	16%	15%	15%	15%	14%	13%
Number of post-abortion IUCD insertions (within 12 days)	88%	88%	86%	85%	85%	84%	83%	83%	83%	82%	81%	81%

Number of newborns received 6 home based newborn care (HBNC) visits after institutional delivery	23%	21%	20%	19%	18%	16%	14%	14%	14%	14%	12%	12%
Number of newborns received 7 HBNC visits home delivery	27%	26%	25%	25%	23%	22%	21%	21%	21%	22%	21%	20%
Number of new pregnant women identified as high-risk pregnancy (HRP), who are 35 years and older	30%	29%	28%	27%	26%	25%	23%	23%	23%	24%	24%	23%
Number of new pregnant women identified as HRP (previous history with any complication)	31%	30%	29%	28%	27%	26%	24%	24%	24%	25%	24%	24%
Number of new pregnant women identified as HRP (any other reasons)	30%	29%	28%	27%	27%	25%	23%	23%	24%	24%	24%	24%
Number of pregnant women registered in 1st trimester (within 12 weeks) out of the total ANC registrations that month	17%	15%	14%	13%	12%	11%	9%	9%	10%	9%	7%	7%

Ranked and incentivized indicators

E. Percentage of missing data among ranked and incentivized indicators in the monthly health facility-reports from high priority districts

	Jan	**Feb**	**Mar**	**Apr**	**May**	**June**	**Jul**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Number of injectable contraceptive, Antara program - first dose	15%	13%	13%	10%	9%	9%	8%	7%	7%	6%	5%	3%
Number of children aged between 9 and 11 months fully immunized- male	10%	8%	8%	5%	5%	4%	5%	5%	5%	4%	3%	2%
Number of children aged between 9 and 11 months fully immunized - female	10%	8%	8%	5%	5%	4%	5%	5%	5%	4%	3%	2%
Number of pregnant women with 4 or more antenatal care (ANC) check ups	10%	8%	8%	5%	5%	4%	5%	4%	5%	4%	3%	2%
Number of institutional deliveries conducted (including cesarean sections)	12%	10%	10%	7%	7%	6%	7%	6%	6%	6%	7%	6%
Number of pregnant women screened for HIV	15%	13%	14%	11%	9%	8%	7%	6%	6%	6%	5%	3%

F. Percentage of missing data among ranked and incentivized indicators in the monthly health facility-reports from non-high priority districts

	Jan	**Feb**	**Mar**	**Apr**	**May**	**June**	**Jul**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Number of injectable contraceptive, Antara program - first dose	27%	26%	24%	22%	20%	19%	16%	15%	15%	15%	14%	13%

Number of children aged between 9 and 11 months fully immunized- male	20%	16%	15%	14%	12%	11%	10%	10%	10%	9%	8%	8%
Number of children aged between 9 and 11 months fully immunized - female	20%	16%	15%	14%	12%	11%	10%	10%	10%	9%	8%	8%
Number of pregnant women with 4 or more antenatal care (ANC) check ups	18%	15%	14%	14%	12%	11%	9%	9%	10%	9%	8%	9%
Number of institutional deliveries conducted (including cesarean sections)	23%	22%	20%	18%	17%	14%	12%	12%	12%	12%	12%	12%
Number of pregnant women screened for HIV	30%	28%	26%	25%	23%	20%	17%	16%	15%	14%	13%	12%

Unranked and unincentivized indicators

G. Percentage of missing data among unranked and unincentivized indicators in the monthly health facility-reports from high priority districts

	Jan	**Feb**	**Mar**	**Apr**	**May**	**June**	**Jul**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after abortion during the reporting month.	28%	28%	28%	25%	23%	22%	21%	22%	23%	100%	100%	100%
Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after delivery (post-partum) during the reporting month.	28%	29%	28%	25%	24%	22%	21%	22%	23%	100%	100%	100%
Number of women aged 15-49 years receiving first dose of DMPA (Inj. Antara) in 'interval' period (6 weeks after delivery/ any time when woman is not pregnant other than post-partum or post-abortion) during the reporting month.	27%	28%	27%	25%	24%	22%	21%	22%	23%	100%	100%	100%
Number of IUCD inserted on the fixed day services (FDS) days during the reporting month.	88%	88%	87%	87%	86%	86%	86%	86%	86%	100%	100%	100%
Number of IUCD inserted on the fixed day off-service (FDOS) days during the reporting month	88%	88%	87%	87%	86%	87%	86%	86%	86%	100%	100%	100%
Number of children who received measles and rubella (MR) vaccine 1st dose (9-11months)	15%	12%	11%	8%	7%	7%	7%	7%	7%	4%	3%	2%

Number of children who received measles vaccine 1st dose (9-11 months)	12%	9%	9%	8%	8%	7%	8%	8%	8%	8%	7%	7%
Number of pregnant women received full ANC check-ups by the end of the reporting month.	29%	29%	29%	27%	27%	26%	26%	26%	27%	100%	100%	100%
Number of PW having severe anemia (Hb<7) treated	83%	82%	82%	81%	81%	80%	80%	79%	79%	79%	78%	77%
Number of pregnant women with Hb<7 gm received iron sucrose by the end of the reporting month.	87%	87%	87%	86%	86%	86%	86%	86%	86%	86%	85%	86%
Number of home deliveries attended by skill birth attendant (SBA)	20%	18%	19%	16%	15%	15%	16%	15%	15%	15%	15%	15%
Number of home deliveries attended by non-SBA	17%	15%	16%	14%	13%	13%	14%	14%	14%	14%	14%	14%
Number of oral polio virus – birth dose (OPV 0)	11%	9%	9%	7%	6%	6%	5%	6%	6%	5%	4%	3%
Number of hepatitis B – birth dose	13%	11%	12%	9%	8%	7%	7%	7%	7%	7%	5%	4%
Number of vitamin K1 after delivery - birth dose	17%	15%	15%	12%	11%	10%	10%	10%	9%	8%	7%	6%
Number of total number of pregnant women registered for ANC	10%	7%	8%	5%	5%	4%	5%	4%	5%	4%	3%	2%
Number of women receiving 1st post-partum checkup between 48 hours and 14 days	11%	9%	9%	7%	6%	5%	6%	5%	5%	4%	4%	3%
Number of HIV tests found positive during ANC visits	15%	14%	14%	11%	9%	8%	8%	7%	7%	7%	5%	4%
Number of mothers provided full course of 180 Iron/Folic Acid (IFA) tablets after delivery	11%	10%	9%	7%	6%	5%	5%	5%	5%	5%	4%	2%
Number of pregnant women tested for syphilis	15%	12%	13%	10%	9%	8%	8%	8%	8%	7%	5%	4%
Number of pregnant women tested for blood sugar (oral glucose tolerance test)	84%	83%	83%	82%	81%	81%	80%	79%	80%	80%	79%	77%
Number of new cases of pregnant women with hypertension detected	11%	9%	10%	7%	6%	5%	6%	5%	5%	4%	3%	2%

Note: missingness increases to 100% of some of the indicators suggesting potential changing in reporting forms where the GOUP may be stopped requesting electronic reporting on those indicators

H. Percentage of missing data among unranked and unincentivized indicators in the monthly health facility-reports from non-high priority districts

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after abortion during the reporting month.	41%	41%	40%	38%	38%	36%	34%	33%	35%	100%	100%	100%
Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after delivery (post-partum) during the reporting month.	41%	41%	40%	39%	39%	36%	34%	33%	35%	100%	100%	100%
Number of women aged 15-49 years receiving first dose of DMPA (Inj. Antara) in 'interval' period (6 weeks after delivery/ any time when woman is not pregnant other than post-partum or post-abortion) during the reporting month.	41%	41%	40%	38%	38%	36%	34%	33%	35%	100%	100%	100%
Number of IUCD inserted on the fixed day services (FDS) days during the reporting month.	90%	90%	90%	89%	89%	89%	88%	88%	89%	100%	100%	100%
Number of IUCD inserted on the fixed day off-service (FDOS) days during the reporting month	91%	91%	90%	90%	90%	90%	89%	89%	90%	100%	100%	100%
Number of children who received measles and rubella (MR) vaccine 1st dose (9-11months)	24%	20%	17%	16%	14%	12%	10%	10%	11%	10%	9%	9%
Number of children who received measles vaccine 1st dose (9-11 months)	24%	22%	21%	20%	19%	19%	17%	17%	18%	18%	17%	16%
Number of pregnant women received full ANC check-ups by the end of the reporting month.	36%	35%	35%	34%	34%	33%	32%	32%	34%	100%	100%	100%
Number of PW having severe anemia (Hb<7) treated	87%	87%	85%	85%	84%	84%	82%	82%	82%	82%	81%	81%
Number of pregnant women with Hb<7 gm received iron sucrose by the end of the reporting month.	90%	89%	89%	89%	89%	88%	88%	88%	88%	88%	87%	87%
Number of home deliveries attended by skill birth attendant (SBA)	28%	27%	26%	26%	24%	23%	22%	22%	22%	23%	22%	21%

Number of home deliveries attended by non-SBA	26%	24%	24%	24%	22%	21%	20%	20%	20%	21%	20%	20%
Number of oral polio virus – birth dose (OPV 0)	19%	17%	16%	15%	14%	12%	11%	11%	11%	11%	9%	9%
Number of hepatitis B – birth dose	25%	24%	22%	21%	20%	18%	16%	16%	15%	16%	15%	14%
Number of vitamin K1 after delivery - birth dose	28%	28%	26%	25%	23%	22%	19%	18%	18%	17%	16%	15%
Number of total number of pregnant women registered for ANC	16%	14%	13%	13%	12%	10%	9%	9%	10%	9%	8%	7%
Number of women receiving 1st post-partum checkup between 48 hours and 14 days	22%	20%	19%	18%	16%	14%	13%	13%	12%	12%	10%	10%
Number of HIV tests found positive during ANC visits	31%	30%	28%	27%	26%	23%	20%	19%	18%	16%	15%	14%
Number of mothers provided full course of 180 Iron/Folic Acid (IFA) tablets after delivery	23%	21%	20%	19%	17%	16%	13%	13%	13%	12%	11%	11%
Number of pregnant women tested for syphilis	27%	25%	24%	23%	21%	19%	16%	15%	15%	14%	13%	12%
Number of pregnant women tested for blood sugar (oral glucose tolerance test)	87%	87%	86%	85%	85%	84%	83%	83%	82%	82%	81%	81%
Number of new cases of pregnant women with hypertension detected	23%	22%	20%	20%	18%	16%	14%	14%	14%	13%	12%	12%

Appendix 8. Percentage of moderate outliers identified by indicator category for monthly health facility reports from high priority districts (HPDs) and non-high priority districts (non-HPDs) from January to December 2019

COMPARISON	MEAN	STANDARD DEVIATION	95% CONFIDENCE INTERVAL
Ranked indicators (HPD)	0.030	0.170	(0.029, 0.030)
Ranked indicators (non-HPD)	0.029	0.167	(0.028, 0.029)
P-VALUE*	<0.01		
Ranked and incentivized indicators (HPD)	0.021	0.145	(0.021, 0.022)
Ranked and incentivized indicators (non-HPD)	0.022	0.148	(0.022, 0.022)
P-VALUE*	<0.01		
Incentivized indicators (HPD)	0.019	0.139	(0.019, 0.020)
Incentivized indicators (non-HPD)	0.016	0.126	(0.016, 0.016)
P-VALUE*	<0.01		
Unranked and unincentivized indicators (HPD)	0.015	0.121	(0.014, 0.015)
Unranked and unincentivized indicators (non-HPD)	0.014	0.118	(0.014, 0.014)
P-VALUE*	<0.01		

[#]not presented as a percentage ;*P-VALUE: diff = mean(HPD) - mean(non-HPD)

Appendix 9. Percentage of extreme outliers identified by indicator category for monthly health facility reports from high priority districts (HPDs) and non-high priority districts (non-HPDs) from January to December 2019

COMPARISON	MEAN	STANDARD DEVIATION	95% CONFIDENCE INTERVAL
Ranked indicators (HPD)	0.0019	0.043	(0.0017, 0.0020)
Ranked indicators (non-HPD)	0.0024	0.049	(0.0023, 0.0025)
P-VALUE*	<0.01		
Ranked and incentivized indicators (HPD)	0.0027	0.052	(0.0026, 0.0028)
Ranked and incentivized indicators (non-HPD)	0.0025	0.050	(0.0024, 0.0026)
P-VALUE*	<0.01		
Incentivized indicators (HPD)	0.0061	0.077	(0.0059, 0.0062)
Incentivized indicators (non-HPD)	0.0047	0.068	(0.0046, 0.0048)
P-VALUE*	<0.01		
Unranked and unincentivized indicators (HPD)	0.0031	0.056	(0.0030, 0.0032)
Unranked and unincentivized indicators (non-HPD)	0.0030	0.054	(0.0029, 0.0030)
P-VALUE*	<0.01		

#not presented as a percentage ;*P-VALUE: diff = mean(HPD) - mean(non-HPD)

Appendix 10. Trends in the percentage of moderate and extreme outliers over time by indicator (n=41) reported in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019

A. Moderate outliers observed in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019

	Variable name	# mod outliers – HPD reports (n=102,845)	# mod outliers: non-HPD reports (n=235,062)	# mod outliers overreported: HPD reports (n=102,845)	# mod outliers overreported: non-HPD reports (n=235,062)	# mod outliers underreported: HPD reports (n=102,845)	# mod outliers underreported: non-HPD reports (n=235,062)	% mod outliers in monthly health facility reports (All districts)	% mod outliers in monthly health facility reports (HPDs)	% mod outliers in monthly health facility reports (non-HPDS)
RANKED	Number of pregnant women tested for hemoglobin (Hb) 4 or >4 times in ANC visits	2,919	6,239	2,317	5,077	602	1,162	3.032%	3.005%	3.044%
	Number of women receiving 1st post-partum checkups within 48 hours of delivery	2,650	4,298	2,309	3,959	341	339	2.342%	2.741%	2.149%
	Number of children who received pentavalent 3 dose	3,052	6,657	2,253	4,977	799	1,680	3.169%	3.133%	3.185%
	Number of children who received Bacille Calmette-Guérin (BCG) dose	3,029	6,703	2,474	5,443	555	1,260	3.185%	3.123%	3.214%
INCENTIVIZED	Number of interval intrauterine device (IUCD) insertions (excluding post-partum IUCD/post-abortion IUCD)	2,048	4,768	1,922	4,320	126	448	2.278%	2.128%	2.349%
	Number of post-partum IUCD insertions (within 48 hours of delivery)	337	568	317	541	20	27	0.315%	0.358%	0.294%
	Number of post-abortion IUCD insertions (within 12 days)	30	77	30	77	0	0	0.186%	0.150%	0.205%
	Number of newborns received 6 home based newborn care (HBNC) visits after institutional delivery	2,047	3,479	1,715	3,044	332	435	1.895%	2.154%	1.770%

	Number of newborns received 7 HBNC visits home delivery	2,378	3,284	2,126	3,090	252	194	2.102%	2.712%	1.807%
	Number of new pregnant women identified as high-risk pregnancy (HRP), who are 35 years and older	2,000	2,442	1,936	2,358	64	84	1.687%	2.276%	1.392%
	Number of new pregnant women identified as HRP (previous history with any complication)	1,283	1,436	1,237	1,391	46	45	1.043%	1.464%	0.829%
	Number of new pregnant women identified as HRP (any other reasons)	1,759	2,296	1,714	2,239	45	57	1.546%	2.005%	1.315%
	Number of pregnant women registered in 1st trimester (within 12 weeks) out of the total ANC registrations that month	3,015	6,776	2,503	5,787	512	989	3.191%	3.091%	3.238%
RANKED AND INCENTIVIZED	Number of injectable contraceptive, Antara program - first dose	365	772	359	759	6	13	0.400%	0.389%	0.405%
	Number of children aged between 9 and 11 months fully immunized-male	3,012	6,997	2,382	5,566	630	1,431	3.289%	3.096%	3.379%
	Number of children aged between 9 and 11 months fully immunized - female	3,018	6,884	2,487	5,808	531	1,076	3.256%	3.105%	3.326%
	Number of pregnant women with 4 or more antenatal care (ANC) check ups	2,957	6,715	2,367	5,322	590	1,393	3.166%	3.034%	3.228%
	Number of institutional deliveries conducted (including cesarean sections)	953	2,001	709	1,526	244	475	1.005%	1.001%	1.006%
	Number of pregnant women screened for HIV	2,145	3,626	2,027	3,324	118	302	2.042%	2.276%	1.926%
UNRANKED AND	Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after abortion during the reporting month.	133	162	133	159	0	3	0.175%	0.229%	0.147%
	Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after delivery	96	159	94	157	2	2	0.152%	0.165%	0.145%

	(post-partum) during the reporting month.									
	Number of women aged 15-49 years receiving first dose of DMPA (Inj. Antara) in 'interval' period (6 weeks after delivery/ any time when woman is not pregnant other than post-partum or post-abortion) during the reporting month.	223	436	213	425	10	11	0.391%	0.383%	0.395%
	Number of IUCD inserted on the fixed day services (FDS) days during the reporting month.	147	284	143	275	4	9	1.458%	1.438%	1.468%
	Number of IUCD inserted on the fixed day off-service (FDOS) days during the reporting month	70	129	69	127	1	2	0.712%	0.693%	0.723%
	Number of children who received measles and rubella (MR) vaccine 1st dose (9-11months)	2,955	6,518	2,223	5,209	732	1,309	3.173%	3.114%	3.201%
	Number of children who received measles vaccine 1st dose (9-11 months)	1,011	2,213	1,007	2,107	4	106	1.132%	1.072%	1.162%
	Number of pregnant women received full ANC check-ups by the end of the reporting month.	1,829	3,678	1,565	3,205	264	473	3.194%	3.270%	3.157%
	Number of PW having severe anemia (Hb<7) treated	238	359	230	347	8	12	1.009%	1.171%	0.924%
	Number of pregnant women with Hb<7 gm received iron sucrose by the end of the reporting month.	236	321	234	311	2	10	1.335%	1.652%	1.170%
	Number of home deliveries attended by skill birth attendant (SBA)	438	1,371	435	1,313	3	58	0.681%	0.508%	0.000%
	Number of home deliveries attended by non-SBA	2,531	3,413	2,208	3,222	323	191	2.183%	2.868%	1.855%
	Number of oral polio virus – birth dose (OPV 0)	2,486	5,598	2,245	5,044	241	554	2.685%	2.581%	2.734%
	Number of hepatitis B – birth dose	520	1,155	418	945	102	210	0.585%	0.551%	0.602%

	Number of vitamin K1 after delivery - birth dose	407	639	314	540	93	99	0.377%	0.443%	0.345%
	Number of total number of pregnant women registered for ANC	3,140	6,805	2,296	5,182	844	1,623	3.240%	3.218%	3.250%
	Number of women receiving 1st post-partum checkup between 48 hours and 14 days	2,473	4,216	2,257	3,899	216	317	2.256%	2.563%	2.108%
	Number of HIV tests found positive during ANC visits	67	80	67	80	0	0	0.053%	0.072%	0.044%
	Number of mothers provided full course of 180 Iron/Folic Acid (IFA) tablets after delivery	2,281	3,670	2,076	3,363	205	307	2.021%	2.367%	1.852%
	Number of pregnant women tested for syphilis	700	1,640	665	1,514	35	126	0.823%	0.747%	0.860%
	Number of pregnant women tested for blood sugar (oral glucose tolerance test)	131	196	114	181	17	15	0.563%	0.659%	0.514%
	Number of new cases of pregnant women with hypertension detected	795	1,119	780	1,079	15	40	0.654%	0.824%	0.570%

B. Extreme outliers observed in monthly health facility reports from high priority districts and non-high priority districts from January to December 2019

	Variable name	**# ext outliers –HPD reports (n=102, 845)**	**# ext outliers: non-HPD reports (n=235,06 2)**	**# ext outliers overrepor ted: HPD reports (n=102, 845)**	**# ext outliers overrepor ted: non-HPD reports (n=235,06 2)**	**# ext outliers underrep orted: HPD reports (n=102, 845)**	**# ext outliers underrep orted: non-HPD reports (n=235,06 2)**	**% ext outliers in monthly health facility reports (All districts)**	**% ext outliers in monthly health facility reports (HPDs)**	**% ext outliers in monthly health facility reports (non-HPDS)**
RANKED	Number of pregnant women tested for hemoglobin (Hb) 4 or >4 times in ANC visits	125	285	177	285	0	0	0.162%	0.189%	0.150%
	Number of women receiving 1st post-partum checkups within 48 hours of delivery	359	0	0	0	0	0	0.000%	0.000%	0.000%

	Number of children who received pentavalent 3 dose	111	0	0	0	0	0	0.000%	0.000%	0.000%
	Number of children who received Bacille Calmette-Guérin (BCG) dose	153	0	1	0	0	0	0.001%	0.002%	0.000%
INCENTIVIZED	Number of interval intrauterine device (IUCD) insertions (excluding post-partum IUCD/post-abortion IUCD)	753	1,405	752	1,382	1	23	0.721%	0.783%	0.692%
	Number of post-partum IUCD insertions (within 48 hours of delivery)	300	369	300	369	0	0	0.233%	0.319%	0.191%
	Number of post-abortion IUCD insertions (within 12 days)	60	63	60	63	0	0	0.213%	0.299%	0.168%
	Number of newborns received 6 home based newborn care (HBNC) visits after institutional delivery	702	0	0	0	0	0	0.000%	0.000%	0.000%
	Number of newborns received 7 HBNC visits home delivery	503	0	0	0	0	0	0.000%	0.000%	0.000%
	Number of new pregnant women identified as high-risk pregnancy (HRP), who are 35 years and older	602	424	89	417	1	7	0.169%	0.093%	0.205%
	Number of new pregnant women identified as HRP (previous history with any complication)	593	469	97	466	1	3	0.186%	0.101%	0.227%
	Number of new pregnant women identified as HRP (any other reasons)	985	488	92	486	1	2	0.195%	0.098%	0.240%
	Number of pregnant women registered in 1st trimester (within 12 weeks) out of the total ANC registrations that month	106	1,503	723	1,503	0	0	0.782%	0.766%	0.789%
RANKED AND	Number of injectable contraceptive, Antara program - first dose	177	395	122	380	3	15	0.172%	0.129%	0.193%

	Number of children aged between 9 and 11 months fully immunized-male	90	380	123	372	3	8	0.166%	0.129%	0.183%
	Number of children aged between 9 and 11 months fully immunized - female	98	0	0	0	0	0	0.000%	0.000%	0.000%
	Number of pregnant women with 4 or more antenatal care (ANC) check ups	126	111	45	111	0	0	0.264%	0.221%	0.286%
	Number of institutional deliveries conducted (including cesarean sections)	208	114	59	114	0	0	0.415%	0.413%	0.416%
	Number of pregnant women screened for HIV	882	1,275	695	1,273	7	2	0.678%	0.739%	0.649%
UNRANKED AND UNINCENTIVIZED	Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after abortion during the reporting month.	0	971	500	969	3	2	0.547%	0.574%	0.534%
	Number of women aged 15-49 years receiving the first dose of DMPA (Inj. Antara) after delivery (post-partum) during the reporting month.	0	869	601	862	1	7	0.559%	0.685%	0.495%
	Number of women aged 15-49 years receiving first dose of DMPA (Inj. Antara) in ‘interval’ period (6 weeks after delivery/ any time when woman is not pregnant other than post-partum or post-abortion) during the reporting month.	1	752	592	750	1	2	0.516%	0.677%	0.434%
	Number of IUCD inserted on the fixed day services (FDS) days during the reporting month.	0	1,263	982	1,261	3	2	0.857%	1.123%	0.723%
	Number of IUCD inserted on the fixed day off-service (FDOS) days during the reporting month	0	545	334	544	1	1	0.332%	0.389%	0.304%
	Number of children who received measles and rubella (MR) vaccine 1st dose (9-11months)	93	665	247	663	4	2	0.336%	0.284%	0.361%

	Number of children who received measles vaccine 1st dose (9-11 months)	723	450	208	450	0	0	0.224%	0.219%	0.226%
	Number of pregnant women received full ANC check-ups by the end of the reporting month.	0	1,045	573	1,044	1	1	0.538%	0.596%	0.510%
	Number of PW having severe anemia (Hb<7) treated	45	783	407	783	0	0	0.416%	0.431%	0.408%
	Number of pregnant women with Hb<7 gm received iron sucrose by the end of the reporting month.	59	305	282	305	0	0	0.212%	0.307%	0.165%
	Number of home deliveries attended by skill birth attendant (SBA)	335	272	105	261	3	11	0.124%	0.111%	0.130%
	Number of home deliveries attended by non-SBA	251	357	105	349	1	8	0.151%	0.109%	0.171%
	Number of oral polio virus – birth dose (OPV 0)	574	970	358	969	1	1	0.448%	0.371%	0.485%
	Number of hepatitis B – birth dose	407	1,086	501	1,084	7	2	0.538%	0.527%	0.543%
	Number of vitamin K1 after delivery - birth dose	282	369	108	358	3	11	0.157%	0.114%	0.177%
	Number of total number of pregnant women registered for ANC	108	306	147	297	6	9	0.150%	0.158%	0.147%
	Number of women receiving 1st post-partum checkup between 48 hours and 14 days	508	1,058	881	1,050	1	8	0.687%	0.936%	0.562%
	Number of HIV tests found positive during ANC visits	117	91	117	91	0	0	0.075%	0.125%	0.050%
	Number of mothers provided full course of 180 Iron/Folic Acid (IFA) tablets after delivery	497	1,035	497	1,034	0	1	0.520%	0.516%	0.522%
	Number of pregnant women tested for syphilis	337	734	337	734	0	0	0.377%	0.360%	0.385%
	Number of pregnant women tested for blood sugar (oral glucose tolerance test)	60	88	60	88	0	0	0.255%	0.302%	0.231%
	Number of new cases of pregnant women with hypertension detected	417	488	416	486	1	2	0.309%	0.432%	0.248%

Appendix 11. Categories and sub-categories in the analytical framework

Categories	Sub-categories
Rationalization of data manipulation	1. Perceptions of being empowered in the workplace a. autonomy b. self-efficacy c. ability to make a difference d. meaning or commitment to one's work 2. Morality/ethics 3. Social Norms
Opportunities to manipulate data	1. Discretion a. Level b. Controls 2. Accountability for performance a. Measurement of goals b. Monitoring mechanisms c. Sanctions/Consequences 3. Accountability for data quality a. Measurement of goals b. Monitoring mechanisms c. Sanctions/Consequences
Pressures to manipulate data	1. Pressures a. Performance b. Fear-based (job security, withholding pay, scolding) 2. Workload (including time pressure)
Other factors	[Open-ended]
Types of data manipulation	1. Types of data 2. Level 3. Participants/Network

Appendix 12. In-depth interview guide

Note: This in-depth interview guide was largely used for the district-level interviews. The guide reflects the range of questions asked during the interviews, however not all questions were asked of each respondent. A subset of these questions was used for interviews with division- and state-level respondents. These interview guides were also translated into Hindi.

I. Background characteristics

Interviewer: Document the following information in a separate document

a) Respondent current position/designation
b) District affiliation (HPD vs non-HPD)
c) Length of service in the district
d) Length of service in the GOUP
e) Educational background
f) Any experience working outside the gov't sector

II. Interview guide

Thank you for taking the time to speak with me. Before we begin our conversation, I would like us to read through the informed consent to review the aims of the study and then I would like to seek your consent to participate in this study. I would learn more about the quality of routine data sources, and how these data are used to make decisions about health programs in UP. Learning from your perspective would give me an opportunity to learn more about the current context around data use/quality, and how we may be able to bring improvements to these existing processes.

<u>Roles & responsibilities</u>

Let's begin our conversation by first discussing the general roles and responsibilities of officials who are involved in data-related activities

1) At the district-level, who is responsible for reviewing the data, analyzing the data, and making decisions based on the program data?
    a. What are the <u>expected</u> roles and responsibilities of the following individuals with respect to data?
        i. Permanent staff: CMO, ACMO/DIO, ARO, DEO
        ii. Contractual staff: DPM, DDM, HMIS operator, DEO
        iii. Supervisors: District Magistrate
        iv. Other staff (perhaps located in the DM's office): any statistical officer?
    b. What roles and responsibilities do they <u>actually carry</u> out?
        i. How does this affect the quality of routine data available at the district level?
        ii. Are those who are responsible for carrying out these activities, able to do so in practice? Why or why not?
        iii. If they are not able to carry out those responsibilities, then who does?
    c. How does this affect how data are used for making decisions at the district-level?
    d. How do they view the data? How do you know that?

2) Now, let's talk about the officials at the block-level – who is responsible for reviewing the data, analyzing the data, and making decisions based on the program data?
    a. What are the <u>expected</u> roles and responsibilities of the following individuals with respect to data?
        i. Permanent staff: MOIC, HMIS operator
        ii. Contractual staff: BPM, HMIS operator

        iii. Other staff?
   b. What roles and responsibilities do they <u>actually carry</u> out?
   c. How does this set up affect the quality of routine data available at the block level?
        i. Are those who are responsible for carrying out these activities, able to do so in practice? Why or why not?
        ii. If they are not able to carry out those responsibilities, then who makes those decisions, and why?
   d. How does this affect how data are used for making decisions at the block-level?
   e. How do they view the data? How do you know that?

<u>Interactions of the district with the block-level and state-level</u>

Now, I would like to learn more about your interactions with block, district and state level officials.

3) How and when do you interact with block officials on data-related issues (e.g., discuss the quality of HMIS/UP-HMIS, MCTS/RCH and so on)?
    a. Who do you speak with from the block-level, and when?
        i. PROBE: program review meetings, data validation meetings, other meetings?
    b. How frequently do you meet with them?
    c. When these meetings occur, how are these meetings run?
        i. What is discussed during these meetings?
            1. Are data reviewed during these meetings?
                a. If so, what types? What types of data tend to be reviewed mostly frequently? And, why?
        ii. Who attends these meetings from the block level?
        iii. What type of feedback do you provide blocks? Do block-level staff also provide any feedback during these meetings?
    d. What types of decisions are made during these meetings? Who monitors these decisions, and follows up on them?

4) How and when do you interact with state officials on data-related issues?
    a. Who do you interact with at the state-level?
        i. PROBE: Program Managers (NHM), Directors/Joint Directors (Directorates of Medical Health and Family Welfare), MD-NHM, Principal Secretary
    b. How frequently do you meet them?
    c. How do they view the data? How do you know that?
    d. When meetings occur, how are they run?
        i. What is discussed during these meetings?
            1. Are data reviewed during these meetings?
                a. If so, what types? What types of data tend to be reviewed mostly frequently? And, why?
        ii. Who attends these meetings from the state level, district level, block level?
        iii. What type of feedback does the state provide districts? Do district-level (or block-level) staff also provide any feedback during these meetings?
    e. What types of decisions are made during these meetings? Who monitors these decisions, and follows up on them?

5) How and when do you interact with the district magistrate on data-related issues?
    a. When do you meet the district magistrate, and how frequently?
        i. PROBE: District Health Society meetings, during campaigns, other program-related meetings?
    b. When these meetings occur, how are they run?

            i. What is discussed during these meetings?
                1. Are data reviewed during these meetings?
                    a. If so, what types? What types of data tend to be reviewed most frequently? And, why?
            ii. Who attends these meetings?
                1. PROBE: block level? district level? other partners?
            iii. What type of feedback do you receive from the District Magistrate or other officials during these meetings? Do you also provide any feedback during these meetings?
    c. What types of decisions are made during the meeting? Who monitors these decisions, and follows up on them?

<u>Reflection on how meetings are run & the types of feedback received</u>

6) Overall, what types of feedback do you receive about your work from different supervisors (e.g., District Magistrate, NHM officials, Directorate officials?
    a. How do they provide this feedback, and when?
    b. How fair is the feedback you receive?
    c. How does their feedback affect how you do your work – e.g., how you modify/implement data quality processes, or use data when making decisions?

7) Now, specifically reflecting on meetings, tell me about:
    a. What you think has worked well or not?
    b. Are there specific issues that come up again and again during these meetings?
    c. Are there problems that should be raised but are not?
    d. Are there individuals or participants that should participate but do not?
    e. How would you change how these meetings are conducted?

<u>General perceptions around prioritizing data and data quality</u>

Now, I would like to learn more about your perceptions about data quality, and the use of data when making decisions about health programs and so on.

8) In the health department, do you feel that superiors and staff feel that data quality is an important activity? Why or why not?
    a. What types of issues pertaining to data quality do they bring up?
    b. When do they bring them up?
        i. PROBE: during meetings? when reviewing reports, etc.?
    c. How do their perceptions on this issue of data quality influence how the district or block views data quality efforts?
        i. Can you provide examples?

9) In the health department, do superiors encourage staff to make decisions based on data? Why or why not?
    a. Can you give examples of when this happens, for example, what types of decisions are made, what types of data sources are used?

<u>Existing practices around data quality and how this affects decision-making</u>

Now, let's talk about issues of data quality. Data quality is affected for various reasons. For example, sometimes this is because there is lack of sufficient understanding around the data; in other situations, data are misreported.

10) When you review block level data at the district, for example, during a program review meeting or data validation meeting – are there situations when you observe that data are not reported accurately?
    a. How do you know that data have been misreported?
    a. What types of data tend to be misreported?
    b. Do you have a sense about why these data are being misreported?
    c. How frequently does this happen?
    d. How is reporting of unusual data/indicators identified?
        i. Probes: during meetings when data are shared; in advance of meetings; in-built validation checks in UP-HMIS?
    e. What are the reasons that prompt/encourage/pressure people to change the data?
    f. What causes people to change the data more than others?
    g. What happens when someone misreports?
        i. What are the consequences for misreporting data? Is any action taken, and if so, by whom?
        ii. How well are these consequences working to address problems with misreporting?
        iii. What else could be done to address misreporting?

<u>Reflecting on your own role pertaining to data-related processes</u>

Now, I would like to learn more about your own experiences

11) What are the processes in place for data quality (e.g., data validation meetings are held to ensure data are properly reviewed and validated)?
    a. How well are these processes being implemented?

12) What are the factors that are driving how well these processes are running or not running?
    a. What are the expectations in terms of how data should be used for programmatic decision-making? How do you think data are actually being used?

13) How important do you feel data-related activities are with respect to other things? What are the types of factors that affect how much attention you give to data-related activities versus other activities?

14) Are you able to make decisions to ensure appropriate processes are in place for there to be good quality data (e.g., data validation meetings are held to ensure data are properly reviewed and validated) and so on? Why or why not?
    a. If you are not able to make decisions, then who generally does?

15) Do you feel district-level staff are able to perform data-related activities that are expected of them (e.g., data compilation, data review, data analysis)? Why or why not?
    a. Tell me, how you would reflect on your performance in this regard?

16) Do you feel that district-level staff are committed to performing data-related activities? For example, do they see value in collecting data, engaging in data validation activities, and making decision based on data? Why or why not?

17) How do you think your work is making a difference in improving health programs and health status of people? Why do you feel this way?

Fixing the status quo

18) Given all that we have discussed, what can be done to improve the overall data quality at the district level?
    a. Based on your experiences, which initiatives have shown improvement? Why or why not?
    b. What would you recommend?

Data use for decision-making

19) How likely are you to use the data to make decisions about health programs implemented in your district? Why or why not?
    a. Would you use data for certain types of decisions or programs, but not others? Can you give me an example?
    b. If you use data to inform a program decision, what types of data sources do you use most frequently? Why?
    c. Are there decisions for which you would like to have data, but for which data aren't available or don't exist?

Appendix 13. Meeting observations

Objective: Examine if, how and when data are being referred to or are being used during discussions/decision-making processes during meetings at the district-level

General questions

Type of meeting	☐ Monthly MOIC review meeting ☐ Validation committee meeting ☐ Other, please specify ______________
District Name	
Meeting Location	
Name of meeting room	
Note if meeting location rotates	
Date	
Observer name	

Observation checklist

Observation Category	Prompts	Notes		
Purpose of meeting	N/A			
Attendees	N/A			
Gender distribution				
Types of stakeholders represented (e.g., Block-level, district-level, positions)				
Note how the listed objects are used or being referred to during meetings	Objects:	Present (check)	Pertinent to meeting (note)	Pertinent to study (note)
	Agendas			
	Notes			
	Guidelines			
	PowerPoint presentations			
	Mission statement			

	Strategy documents			
	Other, please note here:			
Room setting	▪ What is the seating arrangement of the attendees?			
	▪ Who is sitting at the head of the table?			
	▪ Draw a quick sketch of the meeting seating arrangement (if easier)			
Organization and content of the meeting	▪ Who starts and closes the meetings?			
	▪ Who runs the meetings (e.g., who controls who speaks during the meeting)?			
	▪ What is the agenda of the meeting? *Request a copy of the agenda*			
	▪ What topics are discussed during the meetings? Can participants add to the agenda items?			
	▪ What types of issues are discussed during the meetings?			
	▪ How are decisions discussed? For example, is input requested from most participants during these discussions?	f		
	▪ What types of discussions (or decisions) dominant the meeting? For which topics is the largest amount of time devoted to during meetings? Do discussions about decisions appear to favor a set of activities or programs?			

	▪ Who has opportunity to speak and raise concerns? How formal is that process?	
	▪ Are these opportunities to speak openly and voice concerns granted? When people get called on what they are saying?	
	▪ How is positive or negative feedback taken by the group? And does this vary by the position of the participant?	
	▪ What are the arguments are raised to support or negate a decision?	
Organizational Style	▪ How do participants address one another during the meeting?	
	▪ Any practices or behaviors reflected by those who may have more status or authority (e.g., dismissiveness of certain ideas)?	
	▪ What formalities are observed in the meetings?	
Common language used	▪ Are any labels or language use to dismissive (or indicate receptiveness to) certain participants during the meeting?	
Discussion of data during the meeting	▪ What types of data/information are discussed or referred to during the meeting and in what context? o List data sources o List how they are used	
	▪ Are data or evidence used during a decision-making process or discussion? If yes, how so?	

	▪ Are there issues for which data were needed but were missing? What were they? ▪ How were decisions made in the absence of data?	
	▪ What types of data are most commonly referred to during meetings?	
	▪ For which issues, are data most commonly used?	
Requests for data/information between levels	▪ What types of information or questions do the district cadre ask of the block-level cadre? Who (indicate position) tends to make these asks during these meetings?	
	▪ How do block level cadre respond to requests for information or data from the district level?	
	▪ What types of information or questions do the block-level cadre ask of the district-level cadre?	
	▪ How do district level cadre respond to requests for information or data from the block level?	

Bibliography

AbouZahr C, Adjei S, Kanchanachitra C. 2007. From data to policy: good practices and cautionary tales. *Lancet (London, England)* **369**: 1039–46.

Akhlaq A, McKinstry B, Muhammad KB, Sheikh A. 2016. Barriers and facilitators to health information exchange in low- and middle-income country settings: a systematic review. *Health Policy and Planning* **31**: 1310–25.

Al Laham H, Khoury R, Bashour H. 2001. Reasons for underreporting of notifiable diseases by Syrian paediatricians. *EMHJ-Eastern Mediterranean Health Journal, 7 (4-5), 590-596, 2001*.

Andargie G. 2006. Assessment of utilization of health information system at district level with particular emphasis to HIV/AIDS program in North Gondar zone Amhara National Regional State. PhD Thesis, Addis Abeba University.

Aqil A, Lippeveld T. 2009. PRISM: Performance of Routine Information System Management Framework — MEASURE Evaluation.

Aqil A, Lippeveld T, Hozumi D. 2009. PRISM framework: a paradigm shift for designing, strengthening and evaluating routine health information systems. *Health Policy and Planning* **24**: 217–28.

Asangansi I, Macleod B, Meremikwu M, *et al.* 2013. Improving the Routine HMIS in Nigeria through Mobile Technology for Community Data Collection. *Journal of Health Informatics in Developing Countries* **7**.

Basinga P, Gertler PJ, Binagwaho A, Soucat AL, Sturdy J, Vermeersch CM. 2011. Effect on maternal and child health services in Rwanda of payment to primary health-care providers for performance: an impact evaluation. *The Lancet* **377**: 1421–8.

Belay H, Azim T, Kassahun H. 2013. Assessment of health management information system (HMIS) performance in SNNPR, Ethiopia. *Measure Evaluation*.

Bhojani U, Prashanth N, Devedasan N. 2010. Under reported deaths and inflated deliveries: making sense of health management information systems in India. In: Chennai

Biemba G, Chiluba B, Yeboah-Antwi K, *et al.* 2017. A Mobile-Based Community Health Management Information System for Community Health Workers and Their Supervisors in 2 Districts of Zambia. *Global Health: Science and Practice* **5**: 486–94.

Boeije H. 2002. A purposeful approach to the constant comparative method in the analysis of qualitative interviews. *Quality & quantity* **36**: 391–409.

Boerma JT, Stansfield SK. 2007. Health statistics now: are we making the right investments? *The Lancet* **369**: 779–86.

Boerma T. 2013. Public health information needs in districts. *BMC Health Services Research* **13**: S12.

Braa J, Heywood A, Sahay S. 2012. Improving quality and use of data through data-use workshops: Zanzibar, United Republic of Tanzania. *Bulletin of the World Health Organization* **90**: 379–84.

Brinkerhoff DW. 2004. Accountability and health systems: toward conceptual clarity and policy relevance. *Health Policy and Planning* **19**: 371–9.

Brodkin EZ. 2012. Reflections on Street-Level Bureaucracy: Past, Present, and Future. *Public Administration Review* **72**: 940–9.

Burnett SM, Wun J, Evance I, *et al.* 2019. Introduction and Evaluation of an Electronic Tool for Improved Data Quality and Data Use during Malaria Case Management Supportive Supervision. *The American Journal of Tropical Medicine and Hygiene* **100**: 889–98.

Business Standard News. 2016. UP govt ranking districts on health indicators.

Carter N, Bryant-Lukosius D, DiCenso A, Blythe J, Neville AJ. 2014. The use of triangulation in qualitative research. In: *Oncology nursing forum*

Census Population. 2020. Uttar Pradesh Population Sex Ratio in Uttar Pradesh Literacy rate data 2011-2020.

Chan M, Kazatchkine M, Lob-Levyt J, *et al.* 2010. Meeting the demand for results and accountability: a call for action on health data from eight global health agencies. *PLoS Medicine* **7**.

Chaulagai CN, Moyo CM, Koot J, *et al.* 2005. Design and implementation of a health management information system in Malawi: issues, innovations and results. *Health policy and planning* **20**: 375–384.

Chimhutu V, Lindkvist I, Lange S. 2014. When incentives work too well: locally implemented pay for performance (P4P) and adverse sanctions towards home birth in Tanzania - a qualitative study. *BMC Health Services Research* **14**: 23.

Closser S. 2019. The Corruption Game: Health Systems, International Agencies, and the State in South Asia. *Medical Anthropology Quarterly* **n/a**.

DHIS2. 2019. District Health Information System 2 (DHIS2).

Djibuti M, Gotsadze G, Zoidze A, Mataradze G, Esmail LC, Kohler JC. 2009. The role of supportive supervision on immunization program outcome-a randomized field trial from Georgia. *BMC international health and human rights* **9**: S11.

Ethiopian FMoH. 2014. Ethiopian National eHealth Strategic Report., Addis Ababa.

First Post Staff. 2017. Farrukhabad tragedy: After 49 children die in a month, govt transfers district magistrate, CMO. *Firstpost*.

Foreit K, Moreland S, LaFond A. 2006. Data demand and information use in the health sector: conceptual framework. *Chapel Hill, NC: MEASURE Evaluation, Carolina Population Center*: 1–17.

Gale NK, Heath G, Cameron E, Rashid S, Redwood S. 2013. Using the framework method for the analysis of qualitative data in multi-disciplinary health research. *BMC Medical Research Methodology* **13**: 117.

Garrib A, Stoops N, McKenzie A, *et al.* 2008. An evaluation of the District Health Information System in rural South Africa. *South African Medical Journal* **98**: 549-552–552.

Goodhart CAE. 1989. *Money, information and uncertainty*. Macmillan International Higher Education.

Government of India. 2008. Establishment of Health Management Information System at State and District Level, Letter to the states by AS and MD-NHM.

Government of India. 2015. List of High Priority Districts (HPDs) in the country.

Government of India. 2018. Revised ASHA incentive guide. Ministry of Medical Health and Family Welfare, Delhi.

Government Of India, Ministry of Statistics and Program Implementation. 2018. Notification for General Guidelines on Quality Assurance for Official Statistics.

Government of Uttar Pradesh. 2013. Conditionality of 2013-14 approved Program Implementation Plan.

Government of Uttar Pradesh. 2015. Government order released by the Principal Secretary of the Department of Medical Health and Family Welfare.

Harrison T, Nutley T. 2010. A Review of Constraints to Using Data for Decision Making: Recommendations to Inform the Design of Interventions — MEASURE Evaluation.

Health Metrics Network. 2008. *Framework and standards for country health information systems*. World Health Organization: Geneva.

Health Metrics Network. 2020. Health Metrics Network Framework. *RHINO Routine Health Information Network*.

Hernández-Ávila JE, Palacio-Mejía LS, Lara-Esqueda A, *et al.* 2013. Assessing the process of designing and implementing electronic health records in a statewide public health system: the case of Colima, Mexico. *Journal of the American Medical Informatics Association* **20**: 238–244.

Husain Z, Saikia N, Bora RS. 2012. Opportunities and challenges of health management information system in India: a case study of Uttarakhand.

International Health Partnership+. 2009. Monitoring and evaluation of health systems strengthening: An operational framework. WHO, Geneva.

Jerven M. 2013. *Poor numbers: how we are misled by African development statistics and what to do about it*. Cornell University Press.

Kamadjeu R, Tapang E, Moluh R. 2005. Designing and implementing an electronic health record system in primary care practice in sub-Saharan Africa: a case study from Cameroon. *Journal of Innovation in Health Informatics* **13**: 179–86.

Karuri J, Waiganjo P, Orwa D, Manya A. 2014. DHIS2: The Tool to Improve Health Data Demand and Use in Kenya. *Journal of Health Informatics in Developing Countries* **8**.

Kiberu VM, Matovu JK, Makumbi F, Kyozira C, Mukooyo E, Wanyenze RK. 2014. Strengthening district-based health reporting through the district health management information software system: the Ugandan experience. *BMC Medical Informatics and Decision Making* **14**: 40.

KirungaTashobya C, Ssengooba F, Nabyonga-Orem J, *et al.* 2018. A critique of the Uganda district league table using a normative health system performance assessment framework. *BMC Health Services Research* **18**: 355.

Knowles MS. 1970. The modern practice of adult education: andragogy versus pedagogy New York. *NY: New York Association*.

Legal Service India. 2018. Doctrine of pleasure and its proviso article 311 of Indian Constitution.

Lewis M. 2006. Governance and corruption in public health care systems. *Center for Global Development working paper*.

Lipsky M. 2010. *Street-level bureaucracy, 30th ann. Ed.: dilemmas of the individual in public service*. Russell Sage Foundation.

MA4Health. 2015. Health Measurement and Accountability Post 2015: Five-Point Call to Action.

Macfarlane SB, AbouZahr C, Tangcharoensathien V. 2019. National Systems for Generating and Managing Data for Health. In: Macfarlane SB, AbouZahr C (eds). *The Palgrave Handbook of Global Health Data Methods for Policy and Practice*. Palgrave Macmillan UK: London, 3–23.

Mackey TK, Vian T, Kohler J. 2018. The sustainable development goals as a framework to combat health-sector corruption. *Bulletin of the World Health Organization* **96**: 634–43.

Maluka S, Kamuzora P, Sebastiån MS, *et al.* 2010. Decentralized health care priority-setting in Tanzania: Evaluating against the accountability for reasonableness framework. *Social Science & Medicine* **71**: 751–9.

McPherson K. 2001. Public health does not need to be led by doctors. *BMJ : British Medical Journal* **322**: 1593–6.

MEASURE Evaluation. 2019. Tools — MEASURE Evaluation.

Meghani A, Tripathi A, Bilal H, *et al.* 2020. Optimizing the health management information system in Uttar Pradesh, India: Implementation learnings. Unpublished.

Mercader HFG, Kabakyenga J, Katuruba DT, Hobbs AJ, Brenner JL. 2017. Female respondent acceptance of computer-assisted personal interviewing (CAPI) for maternal, newborn and child health coverage surveys in rural Uganda. *International journal of medical informatics* **98**: 41–46.

Moreland S, Misra S, Agrawal S, Gupta R, Harrison T. 2010. Data Use in the Indian Health Sector. Publication. Measure Evaluation.

Morse JM. 2015. "Data Were Saturated . . . ". *Qualitative Health Research* **25**: 587–8.

Morton M, Nagpal S, Sadanandan R, Bauhoff S. 2016. India's Largest Hospital Insurance Program Faces Challenges In Using Claims Data To Measure Quality. *Health Affairs (Project Hope)* **35**: 1792–9.

Mumtaz Z, Salway S, Waseem M, Umer N. 2003. Gender-based barriers to primary health care provision in Pakistan: the experience of female providers. *Health Policy and Planning* **18**: 261–9.

Mutale W, Chintu N, Amoroso C, *et al.* 2013. Improving health information systems for decision making across five sub-Saharan African countries: implementation strategies from the African Health Initiative. *BMC health services research* **13**: S9.

Mutale W, Cleary S, Olivier J, Chilengi R, Gilson L. 2018. Implementing large-scale health system strengthening interventions: experience from the better health outcomes through mentoring and assessments (BHOMA) project in Zambia. *BMC Health Services Research* **18**: 795.

Mutemwa RI. 2006. HMIS and decision-making in Zambia: re-thinking information solutions for district health management in decentralized health systems. *Health Policy and Planning* **21**: 40–52.

Nah F, Sæbø JI. 2017. Analysing inhibitors of integrating and routinizing Health Information Systems for Universal Health Coverage: the case of Cameroon. *Journal of Health Informatics in Africa* **4**.

National Health Mission. 2020. Janani Suraksha Yojana.

Ndabarora E, Chipps JA, Uys L. 2014. Systematic review of health data quality management and best practices at community and district levels in LMIC. *Information Development* **30**: 103–20.

Niti Aayog, The World Bank, Ministry of Health & Family Welfare. 2019. Healthy States Progressive India: Report on the ranks of states and union terrorities

Nutley T, McNabb S, Salentine S. 2013. Impact of a decision-support tool on decision making at the district level in Kenya. *Health Research Policy and Systems* **11**: 34.

Odhiambo-Otieno GW. 2005. Evaluation of existing District Health Management Information Systems: A case study of the District Health Systems in Kenya. *International Journal of Medical Informatics* **74**: 733–44.

Oliver K, Innvar S, Lorenc T, Woodman J, Thomas J. 2014. A systematic review of barriers to and facilitators of the use of evidence by policymakers. *BMC Health Services Research* **14**: 2.

Oni-Orisan A. 2016. The obligation to count: the politics of monitoring maternal mortality in Nigeria. *Metrics: What Counts in Global Health. V. Adams, ed*: 82–104.

Østmo IE. 2007. Exploring information use and information culture at health facility level in Cape Town, South Africa: a case study and discourse analysis. Master's Thesis.

Ostrom E. 2011. Background on the Institutional Analysis and Development Framework. *Policy Studies Journal* **39**: 7–27.

Phillips BS, Singhal S, Mishra S, Kajal F, Cotter SY, Sudhinaraset M. 2019. Evaluating concordance between government administrative data and externally collected data among high-volume government health facilities in Uttar Pradesh, India. *Global Health Action* **12**: 1619155.

Press Information Bureau, Government of India. 2017. Healthcare Data.

Press Information Bureau, Government of India, Ministry of Health and Family Welfare, Government of India, Ministry of Health and Family Welfare. 2016. On World Health Day, Health Minister launches new health initiatives and Mobile APPS.

Pritchett L. 2009. Is India a flailing state?: detours on the four lane highway to modernization.

Qazi MS, Ali M. 2009. Pakistan's health management information system: health managers' perspectives. *JPMA. The Journal of the Pakistan Medical Association* **59**: 10.

Qazi MS, Ali M. 2011. Health Management Information System utilization in Pakistan: challenges, pitfalls and the way forward. *Bioscience trends* **5**: 245–254.

Ramesh K, Shaikh BT, Chandio AK, Jamil A. 2012. Role of Health Management Information System in disease reporting at a rural district of Sindh. *Pakistan Journal of Public Health* **2**: 10–12.

Renmans D, Holvoet N, Orach CG, Criel B. 2016. Opening the 'black box'of performance-based financing in low-and lower middle-income countries: a review of the literature. *Health policy and planning* **31**: 1297–1309.

Sandefur J, Glassman A. 2015. The political economy of bad data: Evidence from African survey and administrative statistics. *The Journal of Development Studies* **51**: 116–132.

Sardan JPO de. 1999. A Moral Economy of Corruption in Africa? *The Journal of Modern African Studies* **37**: 25–52.

Savedoff WD, Hussmann K. 2006. The causes of corruption in the health sector: a focus on health care systems. *Transparency International. Global Corruption Report*.

Setel PW, Macfarlane SB, Szreter S, *et al.* 2007. A scandal of invisibility: making everyone count by counting everyone. *The Lancet* **370**: 1569–77.

Sharma A, Rana SK, Prinja S, Kumar R. 2016. Quality of Health Management Information System for Maternal & Child Health Care in Haryana State, India. *PLOS ONE* **11**: e0148449.

Sheikh K, Gilson L, Agyepong IA, Hanson K, Ssengooba F, Bennett S. 2011. Building the Field of Health Policy and Systems Research: Framing the Questions. *PLOS Medicine* **8**: e1001073.

Shortell SM, Jones RH, Rademaker AW, *et al.* 2000. Assessing the impact of total quality management and organizational culture on multiple outcomes of care for coronary artery bypass graft surgery patients. *Medical Care* **38**: 207–17.

Singh M, Goel MK, Behera BK, Punia JS, Labani S. Health Management Information System Data Quality under NRHM in District Sonipat, Haryana.

Smith-Crowe K, Warren DE. 2014. The emotion-evoked collective corruption model: The role of emotion in the spread of corruption within organizations. *Organization Science* **25**: 1154–1171.

Sudarshan H, Prashanth N. 2011. Good governance in health care: the Karnataka experience. *The Lancet* **377**: 790–2.

Tandon A, Murray CJL, Lauer J, Evans DB. 2016. Measuring overall health system performance for 191 countries. 2002. *World Health Organisation*.

Teklegiorgis K, Tadesse K, Mirutse G, Terefe W. 2014. Factors associated with low level of health information utilization in resources limited setting, eastern Ethiopia. *Inf Syst* **3**: 69–75.

The DHS Program. 2016. National, State and Union Territory, and District Fact Sheets - 2015-16 National Family Health Survey (NFHS-4) (English).

The Times of India. 2013. Lokpal Bill passed by Parliament; Anna Hazare breaks fast, cold-shoulders AAP | India News - Times of India. *The Times of India*.

Transparency International. 2019. Corruption: the Ignored Pandemic. Transparency International, UK.

Tribune News Service. 2020. NHM staff protest, seek regular jobs. *Tribuneindia News Service*.

Trostle J, Bronfman M, Langer A. 1999. How do researchers influence decision-makers? Case studies of Mexican policies. *Health Policy and Planning* **14**: 103–14.

Turcotte-Tremblay A-M, Gali-Gali IA, De Allegri M, Ridde V. 2017. The unintended consequences of community verifications for performance-based financing in Burkina Faso. *Social Science & Medicine* **191**: 226–36.

United Nations. 2016. Sustainable Development Goal 17. *Sustainable Development Knowledge Platform*.

UP NHM. 2019. District Review Meeting on 30 Key Indicators.

UP-TSU. 2019. ASHA Incentive Guidelines

US Census Bureau. 2020. Census.gov. *Census.gov*.

Uttar Pradesh Technical Support Unit. 2018. District & Block Health Ranking.

Vian T. 2008. Review of corruption in the health sector: theory, methods and interventions. *Health policy and planning* **23**: 83–94.

Vidaurre-Arenas M, Martínez-Piedra R, Castillo-Salgado C. 2005. Health Metrics Network: a global partnership to improve access to information for health care practitioners and policy-makers. *Epidemiological bulletin* **26**: 1–8.

Wandera SO, Kwagala B, Nankinga O, *et al.* 2019. Facilitators, best practices and barriers to integrating family planning data in Uganda's health management information system. *BMC health services research* **19**: 327.

Weiss CH, Bucuvalas MJ. 1980. *Social Science Research and Decision-making*. Columbia University Press.

Welay A, Tadesse K, G/tsadik T. 2017. Process Evaluation of Health Management Information System Implementation Status in Public Health Facilities of Mekelle Zone, Tigray, Ethiopia. *Research & Reviews : Journal of Computational Biology* **6**: 36–49.

WHO. 2020. WHO | Performance-based financing. *WHO*.

Wickremasinghe D, Hashmi IE, Schellenberg J, Avan BI. 2016. District decision-making for health in low-income settings: a systematic literature review. *Health Policy and Planning* **31**: ii12–24.

World Health Organization. 2007. Everybody's business–strengthening health systems to improve health outcomes: WHO's framework for action.

World Health Organization. 2009. Toolkit on monitoring health systems strengthening. *WHO. 2008b. WHO*: 17–3.

World Health Organization. 2017. WHO | Data Quality Review (DQR) Toolkit. *WHO*.

World Health Organization. 2019. WHO | Health statistics and information systems. *WHO*.

Zomer A. 2018. Naming and faming (not shaming) to hold public officials accountable. *MIT GOV/LAB*.

Ankita Nigam Meghani

Ankita N. Meghani has over seven years of experience in health systems research, monitoring and evaluation, and health policy analysis in low-and middle-income countries, with a keen interest in strengthening health systems, promoting accountability for health by considering institutional incentives and digital tools, and examining the role of the private sector in healthcare delivery. Meghani has designed and implemented quantitative and qualitative research studies in India, Nigeria and Uganda to inform the development and strengthening of health strategies and policy guidelines pertaining to health management information systems, maternal and child health and non-communicable diseases.

EDUCATION

PhD	**2020**	**Johns Hopkins Bloomberg School of Public Health** Department of International Health Health Systems Program	Baltimore, MD
MSPH	**2013**	**Johns Hopkins Bloomberg School of Public Health** Department of International Health Global Disease Epidemiology and Control Program	Baltimore, MD
MS	**2011**	**Georgetown University** Biotechnology	Washington, DC
BS	**2009**	**University of California, Los Angeles** Anthropology	Los Angeles, CA

PROFESSIONAL & RESEARCH EXPERIENCE

Aug 2016 – Oct 2020 **Doctoral Researcher, Johns Hopkins Bloomberg School of Public Health**

<u>The Private Health Sector's Preparedness, Responsibility, and Response to COVID-19 in India</u>

- Provided technical support in the design and implementation of a qualitative research study examining the role of the formal and informal private health sector in responding to the health needs of the poor in rural and urban geographies of Delhi, Uttar Pradesh and Kerala in India
- Conducted key informant interviews with government officials and health providers, and completing a policy document analysis for Uttar Pradesh

<u>Pandemic Pulse Project on COVID-19 in the United States</u>

- Supported the manuscript writing and analysis of findings from a panel of cross-sectional phone surveys being implemented across the United States that examine adults' perceptions about COVID-19 vaccines, COVID-19 prevention and treatment, behavioral risk factors, views on school re-opening, and perceptions about COVID-19 related stigma

<u>Uttar Pradesh Health System Strengthening Support Project</u>

- Provided technical assistance to the Technical Support Unit of the Government of UP on strengthening existing policy guidelines for health management information system (HMIS) data quality and data use by clearly articulating underlying determinants affecting HMIS performance, and identifying levers for potential intervention
- Coordinated the Data Use workstream on the project and supporting workplan development, report writing, and developing and maintaining strong collaborations with technical counterparts in partner organizations
- Managed and oversaw all phases of a mixed methods research study examining the performance of HMIS performance in Uttar Pradesh, India, including the development of study protocols, instruments, and training materials; implementation of trainings, data collection and data management; analysis of data, writing and dissemination of findings

<u>Mobile Phone Surveys for NCD Risk Factors in Uganda</u>

- Provided technical and analytical support in the research design, including development of the study protocol and data collection processes for a cross-sectional, household survey measuring the prevalence of non-communicable disease risk factors in the Iganga-Mayuge Health & Demographic Surveillance Site, Uganda

- Programmed the household survey in an open-source mobile data collection software, including updating and deploying revised surveys
- Monitored the data quality during data collection through designing data validation checks, and monitoring data quality through weekly analysis and meetings with co-investigators
- Designed the qualitative component of a mixed methods study including: i) in-depth interviews with national level policymakers to examine public sector programs/policies for NCD management in Uganda; ii) focus group discussions to gauge perceptions of NCD risks among community members

Other research projects

- Synthesized scientific evidence and technical guidance from the WHO and the CDC on COVID-19 to develop a comprehensive guide released by the Centers for Communications Programs at JHU
- Supported the analysis and writing of a research project that examines survey participation of two mobile phone survey implementation modalities: computer-assisted telephone interview and interactive voice response in Bangladesh and Tanzania
- Prepared the evaluation protocol, tools, and quantitative data analysis for a program measuring the effectiveness of a new health worker training program implemented in Rivers, Bauchi, and Niger states in Nigeria
- Completed a situation analysis for the WHO on adult immunization policies and programs in LMICs and factors affecting national level policy actors to introduce new adult vaccines
- Supported a literature review, analysis and manuscript writing on multi-sectoral collaborations for health

Mar 2016 – Aug 2016 **Research Consultant, National University of Singapore**

- Guided and co-led qualitative data analysis of in-depth interview data examining the views of policy actors in Pakistan, China and Cambodia on the role of international development funders in setting health priorities

Jan 2015 – July 2016 **Research Fellow, Stanford University**

- Performed a literature reviews on (i) approaches to conducting large-scale public policy evaluations; and (ii) innovative international financing mechanisms for non-communicable diseases

Aug 2013 – Oct 2014 **Research Associate, Johns Hopkins International Vaccine Access Center**

- Provided Gavi, the Vaccine Alliance with technical assistance on improving immunization financing sub-nationally in Nigeria through a pooled funding mechanism known as the basket fund
- Designed, and implemented a qualitative assessment of Nigeria's recent state primary health care reform through one-on-one and group interviews with state policymakers and health workers in Lagos & Niger
- Provided technical assistance to partners supporting the India's National Technical Advisory Group on Vaccines by synthesizing evidence-based briefs on the introduction of new vaccines
- Prepared monthly project reports detailing program updates and key deliverables to donors

TEACHING

Jan 2017 – May 2019 **Teaching Assistant, Johns Hopkins Bloomberg School of Public Health**

- Assisted course faculty with course management, grading, content development and facilitation of discussion sections for the following courses: (i) Large Scale Effectiveness Evaluation of Health Programs; (ii) Health Policy Analysis in Low- and Middle- Income Countries; (iii) Applications in Managing Health Organizations in Low- and Middle- Income Countries

HONORS & AWARDS

2020	The Mary and Carl Taylor Fund, Johns Hopkins Bloomberg School of Public Health
2018	The Georgeda Buchbinder Award, Johns Hopkins Bloomberg School of Public Health
2018	Delta Omega, Policy & Practice Dissertation Award, Johns Hopkins Bloomberg School of Public Health
2017	The Mary and Carl Taylor Fund, Johns Hopkins Bloomberg School of Public Health
2017	Doctoral Research Award - Health Systems Program, Johns Hopkins Bloomberg School of Public Health
2013	Oak Ridge Institute for Science and Education (ORISE) Vaccine Policy Fellowship
2010	Merit Scholarship from the Graduate School of Arts and Sciences, Georgetown University
2009	Orders of Omega & Gamma Sigma Alpha (Honors Undergraduate Societies)

PRESENTATIONS

Nov 2020	Global Health Policy Research Forum (Online). Oral presentation on "Understanding when, how and why administrative data are manipulated in Uttar Pradesh, India" and panel discussion titled: "Using health policy analysis theory to analyze the politics of health systems governance."
Nov 2020	6th Global Symposium on Health Systems Research – HSR2020 (Online). Oral Presentation on "Understanding when, how and why administrative data are manipulated in Uttar Pradesh, India."
Mar 2019	Symposium at Consortium of Universities of Global Health (Chicago, USA). ePoster Presentation on "Curbing the rise of NCDs: Perspectives of national policy actors on how to manage and control NCDs in Uganda."
Oct 2018	Symposium on Health Policy Process Research (Liverpool, United Kingdom). Oral presentation on "Unpacking the complexities of state- and district-level decision-making for health in Uttar Pradesh & understanding the role of data."
Oct 2018	5th Global Symposium on Health Systems Research – HSR2018 (Liverpool, United Kingdom). Poster Presentation on "Examining outcomes of mobile phone surveys measuring NCD risk factors in LMICs: a collaboration between researchers and the private sector."
May 2018	Information and Communications Technologies for Development - ICT4Ds 2018 (Lusaka, Zambia). Panel Presentation titled "No Silver Bullet: Shifting cooperation, completion, and refusal rates for mobile phone surveys."
Apr 2016	Symposium at Consortium of Universities of Global Health (San Francisco, USA). Panel presentation titled: "No Longer Out in the Cold: Financing NCDs to Achieve the SDGs."
Sept 2015	Health Affairs Briefing on Non-Communicable Diseases: The Growing Burden (Washington DC, USA). Oral presentation on "Innovative Financing Strategies for NCDs" and panel discussion on "Economics and Finance."

PUBLICATIONS

Manuscripts under peer-review

Meghani A, McMahon S, Ddaaki W, Kennedy C. Elite interviewing in cross-cultural contexts. Under review. *Qualitative Research*.

Meghani A, Ssemugabo C, Pariyo G, Hyder A, Rutebemberwa E, Gibson D. Curbing the rise of noncommunicable diseases in Uganda: Perspectives of policy actors. Under review. *Global Health Science and Practice*.

Sauer M, Vasudevan P, **Meghani A**, Luthra K, Garcia C, Delora-Knoll M, Privor-Dumm L. Situational assessment of adult vaccine preventable disease and the potential for immunization advocacy and policy in low- and middle-income countries. Under review. *Vaccine*

Peer-reviewed journal articles

Bennett S, Jessani N, Glandon D, Qiu M, Scott K, **Meghani A**, El-Jardali F, Maceira D, Javadi D, Ghaffar A. Understanding the implications of the Sustainable Development Goals for health policy and systems research: results of a research priority setting exercise. *Globalization and Health.* 2020

Khan MS, Roychowdhury I†, **Meghani A†**, Hashmani F, Borghi J, Liverani M. Should performance-based incentives be used to motivate health care providers? Views of health sector managers in Cambodia, China and Pakistan. *Health Economics, Policy and Law.* 2019.

Glandon D, **Meghani A**, Jessani N, Qiu M, Bennett S. Identifying health policy and systems research priorities on multisectoral collaboration for health in low-income and middle-income countries. *BMJ Global Health.* 2018.

Basu S, **Meghani A**, Siddiqi A. Evaluating the Health Impact of Large-Scale Public Policy Changes: Classical and Novel Approaches. *Annu Rev Public Health.* 2017.

Khan MS, **Meghani A**, Liverani M, Roychowdhury I, Parkhurst J. How do external donors influence national health policy processes? Experiences of domestic policy actors in Cambodia and Pakistan. *Health Policy Plan.* 2017.

Ginsburg AS, **Meghani A**, Halstead SB, Yaich M. Use of the live attenuated Japanese Encephalitis vaccine SA 14–14–2 in children: A review of safety and tolerability studies. *Hum Vaccines Immunother*. 2017.

Meghani A, Basu S. Innovative financing mechanisms to address the global burden of non-communicable diseases: a review. *Health Aff*. 2015.

Santibanez TA, Lu PJ, O'Halloran A, **Meghani A**, Grabowsky M, Singleton JA. Trends in Childhood Influenza Vaccination Coverage from 2004 to 2012, United States. *Public Health Rep*. 2014.

Lu PJ, O'Halloran A, Bryan L, Kennedy ED, Ding H, Graitcer SB, Santibanez TA, **Meghani A**, Singleton JA. Trends and racial/ethnic disparities in influenza vaccination coverage among adults during the 2007-08 to 2011-12 season. *Am J Infect Control*. 2014.

White papers, and blogs

Meghani A, Abdulwahab A, Privor-Dumm L, and Wonodi CB. Basket Funds: A pooled arrangement to finance primary health care delivery and address the funding flow in Nigeria. Johns Hopkins International Vaccine Access Center. February 2015.

Meghani A, Jessani N. A panoply of voices, a plethora of ideas – Four key takeaways for translating evidence to action. Health Systems Global. December 2018.

SKILLS

Languages: English: native fluency; Hindi: native fluency; Spanish: conversational

Country research experiences: India, Nigeria, Uganda, and United States

Data analysis: Atlas.ti, STATA, Vensim (systems models), Microsoft Office (Word, Excel, PowerPoint)

E-data collection: KoBo Toolbox