STRATEGIES TO STRENGTHEN HEALTH MANAGEMENT INFORMATION SYSTEMS IN PUBLIC HEALTH CENTRES IN ADDIS ABABA, ETHIOPIA

by

BRHANU HAILESSLASSIE YOHANNES

submitted in accordance with the requirements for

the degree of

DOCTOR OF LITERATURE AND PHILOSOPHY

in the subject

PUBLIC HEALTH

at the

UNIVERSITY OF SOUTH AFRICA

SUPERVISOR: PROFESSOR MM RAMUKUMBA

NOVEMBER 2022

Student number: ***64084639***

DECLARATION

Name: **BRHANU HAILESSLASSIE YOHANNES**

Student number: **64084639**

Degree: **PHD IN PUBLIC HEALTH**

STRATEGIES TO STRENGTHEN HEALTH MANAGEMENT INFORMATION SYSTEMS IN PUBLIC HEALTH CENTRES IN ADDIS ABABA, ETHIOPIA

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I further declare that I have not previously submitted this work, or part of it, for examination at UNISA for another qualification or at any other higher education institution.

DATE: September 7, 2022

DEDICATION

I dedicate my work to my wife, Abeba Abrha, and lovely children, Fikirite-ab and Zenaze-ab, for their words of encouragement and push for persistence ringing in my ears and giving me the resilience to move forward. They have never left my side and are very special. Thank you, my family, for providing me with such wonderful encouragement, love, and understanding to become who I am today.

ACKNOWLEDGEMENTS

First and foremost, thanks to the Almighty God for giving me the strength and courage to pursue this study. A number of individuals made different contributions during this study period. It may be difficult to mention everybody by name as the list is limitless. However, I would like to offer my special thanks and gratitude to the following individuals:

- Above all, I must express my gratitude to my supervisor, Professor MM RAMUKUMBA, who supported and encouraged me from the inception of the topic and throughout, even when I was about to give up. I appreciate the time she devoted to guiding me to meet deadlines and her patience in assisting me. Her input and advice helped sharpen my critical thinking and research skills.
- The University of South Africa (UNISA), including the Ethiopian UNISA learning centre, for supporting me with tuition fees and research funds through its bursary scheme.
- Dr Girma Taye and Dr Dion Van Zyl, who provided me with invaluable guidance and comments on quantitative data analysis.
- My mother and my father for their love, prayers, and good wishes in my professional and personal life.
- My wife, S/r Abeba Abrha, and my children, Fikirite-ab Brhanu and Zenea-ab Brhanu, who sacrificed a lot to provide me with the space I needed to concentrate in and complete the doctoral degree. They showed great understanding when I missed some play times with them in order to make progress on my research.
- My colleague Aklilu Simanessew for his valuable support and encouragement. Without his support, this journey would have been impossible.
- All the study participants and data collectors who participated in this study.

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STUDENT NUMBER: 64084639

STUDENT: BRHANU HAILESSLASSIE YOHANNES

DEGREE: DOCTOR OF PUBLIC HEALTH

DEPARTMENT: HEALTH STUDIES, UNIVERSITY OF SOUTH AFRICA

SUPERVISOR: PROF MM RAMUKUMBA

ABSTRACT

A health management information system (HMIS) is the intersection between the business process of healthcare and information systems to deliver better healthcare services. A health information system is one of the health system's building blocks. The purpose of this study was to develop strategies to strengthen health management information systems in Ethiopia.

The study used the Performance of Routine Information System (PRISM). It adopted a quantitative research approach and implemented it over three phases. The first phase involved a retrospective document review of the quality of maternal health data across registers, tally sheets, DHIS2 databases, and data quality monitoring logbooks in ten randomly selected healthcare facilities using a standard quantitative checklist. The focus was on three data quality dimensions: accuracy, completeness and timeliness of specific maternal indicators and data elements. Maternal health programme was selected among different programmes which were found to have challenges with data quality. The second phase involved a descriptive cross-sectional survey using a close-ended questionnaire. The population for this phase included health professionals working in Addis Ababa public health centres who used the health management information system. These professionals were recruited from the ten public health centres used in Phase 1 through multistage stratified sampling techniques. The collected data were analysed using SPSS Version 26. The findings of the two phases were combined to derive meta-inferences. In the final phase, a Delphi technique was used to develop strategies that were validated by a team of experts to strengthen the data quality, data management and information use in public healthcare facilities.

The first phase of the document review revealed that the overall data quality was poor across the maternal data sources in terms of accuracy, completeness, and timeliness. Furthermore, key findings of the second phase indicated that the components of data management were not consistently practised, a large amount of data was shelved and unprocessed, and information was not used for decisions in accordance with standards in healthcare facilities due to a variety of factors. These issues were further linked to organisational, technical and behavioural factors.

In conclusion, combined key findings indicate that a large amount of data was not properly managed across data management processes, lacked data quality, and was not used satisfactorily at all levels. As a whole, the importance of data quality, data management and information needs was not recognised and practised, particularly at case teams level. Hence, HIS strategies were developed to address the identified gaps..

Key concepts: Culture of information use; Data quality; Data management processes; Health Information System; Health Management Information System; Maternal health data.

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LIST OF ABBREVIATIONS AND ACRONYMS

AHO	Africa health observatory
AIHW	Australian Institute of Health and Welfare
DHIS2	District Health Information System
FMOH	Federal Ministry of Health
FMOHE	Federal Ministry of Health of Ethiopia
HIS	Health Information System
HMIS	Health Management Information System
HMN	Health Metrics Network
LQAS	Lot Quality assurance sampling
NDMO	National Data Management Office
PRISM	Performance of Routine Information System Management
RDQA	Routine Data Quality Assessment
RHIS	Routine health information system
SDG	Sustainable Development Goals
UNISA	University of South Africa
USAID	United States Agency for International Development
WHO	World Health Organization

CERTIFICATE OF LANGUAGE EDITING

I, the undersigned, declare that I have edited the DLitt et Phil Thesis of Brhanu Hailesslassie Yohannes, titled: **STRATEGIES TO STRENGTHEN HEALTH MANAGEMENT INFORMATION SYSTEMS IN PUBLIC HEALTH CENTRES IN ADDIS ABABA, ETHIOPIA.**

Some sections of the thesis, such as certain figures and documents included in the annexures, could not be edited because they were supplied as complete images or were not corrected since they formed part of the research. Some of those items may contain errors.

I am also not responsible for the correctness of any changes made to the thesis before submission or after changes advised by the examiners have been implemented.

Signed:

Prof (emeritus) P.J. Botha

Date: 2 November 2022

CHAPTER ONE
OVERVIEW OF THE STUDY

1.1 INTRODUCTION

A health management information system (HMIS) is the intersection between the business process of healthcare and information systems to deliver better healthcare services. A health information system is one of the health system's building blocks. As a consequence, the value of information on health can be enhanced through easy access for policymakers and incentives for information users (Health Metrics Network [HMN] & World Health Orgaization [WHO] 2012:5). Accurate, complete and timely information on health is an essential foundation for strengthening public healthcare action and health systems. The healthcare industry, however, is influenced by technical, organizational and behavioural factors (Hlaing & Myint 2022:8). In response, a health information system is designed for multiple users and can be summed up as an information generation system that enables decision-makers at each level of the health system to identify problems and needs, make health policy decisions based on evidence and optimally allocate scarce resources. This information system can also be used for different purposes (Health Metrics Network [HMN] & WHO 2012:14).

The availability and accessibility of good data quality in the health system can contribute significantly to achieving maternal health targets in the sustainable development goals (SDGs). Thus, improved maternal health service is linked directly to an effective health information system, while poor data quality management practices lead to wrong and ineffective decision-making processes. For example, in many developing countries, the health information system has not been generating useful health information at all levels of the health system (Measure Evaluation 2012:13). Similarly, recent evidence shows that 24% of healthcare facilities in Ethiopia did not ensure the level of data accuracy for maternal data monthly before the data were processed for different purposes. This low level of data accuracy significantly contributed to unreliable information resulting in a lack of trust from information users (Solomon, Addise, Tassew, Balcha & Abebe 2021:6).

This chapter presents the research problem, purpose, and research questions of the study, as well as background information. The chapter also presents the core research concepts and the study's foundations and summarises the methodology followed.

1.2 RESEARCH PROBLEM

1.2.1 Background of the problem

In its most straightforward and direct sense, data could be described as raw facts of numbers and words that have yet to be organized, processed and analyzed. These are considered important ingredients that could be used as building blocks to process and use for evidence-based planning and decision-making processes (Baškarada & Koronios 2013:7). The standard practice of recording, collecting, compiling, analyzing and presenting data of public healthcare centres according to the expected national standard is called data management. Beyond this, the data that have been processed, analyzed and contextualized to produce something useful for decision purposes are called information (Stedman 2019:2). Data quality is often defined as "fitness for use" in relation to reasonable standards of completeness, accuracy, timeliness and accessibility for decision-makers and users (Nikiforova 2020:1).

The Federal Ministry of Health of Ethiopia (FMOHE) envisages fair and affordable access to all types of healthcare services for all its citizens. This vision involves robust health information systems by establishing an effective application cycle for data collection, compilation, analysis, reporting, and decision-making. This is the process of transforming data into knowledge of information and action (FMOHE 2016:7). Policy makers, managers and leaders are encouraged to make data-driven and evidence-based decisions. But, they are constantly confronted with various levels of difficulty in their quest to find consistent, accurate, complete and timely reported health information on which to base their decision undertakings, including maternal health data. The magnitude and effect of such problems may not be similar in all countries, but in less developed countries, the magnitude appears to be broader and more complicated. As a result of these deficiencies, especially in less developed countries, including Ethiopia, there is a pressing need to develop a culture of data management and information use at the level of public health centres (Ndabarora, Chipps & Uys

2013:16). Complete, accurate, and timely accessible healthcare data including the maternal health data form the basis for informing the development of health policy and the establishment of priority interventions to address health determinants (Lemma, Janson, Persson, Wickremasinghe & Källestål 2020:2). Such data could aid public healthcare policy development and the establishment of priorities for interventions to modify health determinants (Lemma et al. 2020:2).

However, the use of information in policy development, strategic planning, and decision-making is not widely established and practised in Ethiopia, particularly at the lower levels. In addition, the national health information system (HIS) is lagging in generating the information needed to measure and respond to health inequities and their key determinants (FMOHE 2016:7). All healthcare data, including maternal health data, are compiled from a variety of sources and are expected to be managed in terms of quality before being forwarded to the following report level to support and guide decision-making at all levels (Health Metrics Network [HMN] & WHO 2012:33).

In Ethiopia, several health programs have identified various challenges regarding data management processes. No study has focused on the quality of maternal and child health (MCH) data collected within the HMIS, even though high-quality maternal health data are essential for monitoring and managing the high morbidity and mortality burden on pregnant women, newborns, and children (Ouedraogo, Kurji, Abebe, Labonté, Morankar, Bedru et al. 2019:8).

High-quality information is required for monitoring healthcare indicators (including maternal healthcare) in order to provide alerts and early warnings, support public health management, stimulate research, and determine health-status trends (WHO 2010:44). This means that the three dimensions of data quality, completeness, accuracy, and timeliness, can be used to determine the health status of the general public or a specific group of patients (Chen, Hailey, Wang & Yu 2014:4). What is more, the lack of technical skills in data management and information use has not been addressed in pre-service and post-service health professional training (Measure Evaluation 2010:6). Generally, technical, behavioural, and organizational determinants are associated with the data management and information use practices in public health centres, thereby affecting the achievement of defined objectives, goals, and visions (Innocent, Onzima, Katongole & Govule 2016:11).

1.2.2 Statement of the research problem

Evidence-based decision making is a fundamental requirement for a highly reliable healthcare system (Tilahun, Teklu, Mancuso, Endehabtu, Gashu & Mekonnen 2021:2). Public health decision-making is dependent on well-managed, timely reported, high-quality data and information (Chanyalew, Yitayal, Atnafu & Tilahun 2021:2; Tilahun et al. 2021:2). At all levels of the healthcare system, data management processes are important for effective health service management and to assess the extent to which the health services are fulfilling the required targets (Measure Evaluation 2015:6; Davis, Morgans & Burgess 2016:1; Janati, Hasanpoor, Hajebrahimi, Sadeghi-Bazargani & Khezri 2018:2). However, in reality, data are frequently underutilized for advocacy, program and policy improvement, or strategic planning. Instead, the information frequently remains in reports and is kept on shelves and in databases (Nutley & Reynolds 2013:2).

A study conducted in southern Ethiopia revealed that overall data quality was lower than the national target; this means that significant indicators were observed to be under-reported in all healthcare facilities, which was associated with low supervision quality, training status, and individual confidence in performing HMIS activities (Solomon et al. 2021:2). As a result, only 37% of healthcare facilities engaged in discussion and made decisions based on routine health information; this was indicative of a limited culture of using information for decision-making in planning and management of implementing programs; and this could have had a significant impact on the health system's performance (Teklegiorgis, Tadesse, Mirutse & Terefe 2016:3). Generally, in Ethiopia, the effectiveness of data use for decision-making is insufficient. The quality of health data is an ongoing issue. This requires improving the relationship between data quality, data demand, and data use, which could create a cycle that may lead to improved health programs and policies to respond to priority health service needs (Tilahun et al. 2021:2).

In Ethiopia, data management and information use have not been given adequate attention, although they are important (Bogale 2021:2). Consequently, the majority of technical and leadership decisions and basic interventions are being made without tangible evidence; resulting in the failure of many healthcare programs (Chanyalew et al. 2021:9; Bogale 2021:7; Chen et al. 2014:15). This study used the maternal healthcare program to review data quality, as improving maternal health is a global, national, and local public health priority (Kruk, Gage, Arsenault, Jordan, Leslie, Roder-DeWan et al. 2018:3).

1.3 RESEARCH AIM/PURPOSE

The purpose of this study was to develop strategies to strengthen health management information systems in Ethiopia.

1.3.1 Research objectives

Phase 1: Retrospective quantitative document review

- To assess the accuracy, completeness and timeliness of maternal health data generated in the public healthcare centres in Addis Ababa.

Phase 2: Descriptive cross-sectional survey

- To investigate the influence of technical, behavioural and organizational factors on data management processes.
- To determine the extent of health information use in public healthcare centres.

Phase 3: Strategies development for data management & information use

- To develop strategies for data management and information use in public health centres.

1.3.2 Research questions/hypotheses

- What is the quality of maternal data produced in public healthcare centres in Addis Ababa?
- How do technical, behavioural and organizational factors influence data management processes?
- What is the extent of health information use in healthcare centres?
- Which strategies could be used for effective data management and information use in public healthcare centres?

1.4 SIGNIFICANCE OF THE STUDY

Healthcare is an information-intensive system that generates huge volumes of data every day. It is estimated that up to 15% of the overall health budget can be spent on data management and use of information in one way or another (Piatti-Fünfkirchen, Lindelow & Yoo 2018:3). Therefore, it is imperative that health information be managed as efficiently as possible to ensure that high quality and timely data are regularly reported in order to improve the safety and quality of care at the point of delivery of health services (Alwan, Ali, Aly, Badr, Doctor, Mandil et al. 2018:4). Safe and reliable healthcare depends on access to accurate, valid, consistent, timely and complete data and information. Data management and information use are two of the top priorities and transformation agendas of the government of Ethiopia and its development partners. Ethiopia is strongly committed to strengthening the national Health Information System (HIS) through HMIS. The policy has thus identified the HMIS as a key component for the successful implementation of the Strategic Plan of the Health Sector Transformation Program (HSTP) (Shagake 2014:12). Hence, it is important to transform the data management practices of public healthcare centres to make information available, accessible and utilized by viable and appropriate information communication technologies for decision-making processes as an essential component that ultimately affects the access, quality and equity of healthcare delivery at all levels of healthcare (FMOHE 2016:18).

For that reason, there are two primary driving forces to conduct this study in the area of data management and information use in public healthcare facilities: First, the existing data management and culture of information use in public healthcare facilities is significantly lagging behind when compared with the pre-defined national expected standards. This, in turn, could affect the availability, accessibility, and overall demand and culture of information use for decision-making at different levels of the health system in general and in public healthcare centres in particular. Second, the Ethiopian Federal Ministry of Health's (FMOHE) roadmap to the information revolution is motivating and creating an enabling environment for interested researchers in this area to think broadly and strategically about how best to achieve the Ethiopian healthcare system's long-term HIS strategy.

This study is significant in that it will make contributions to three critical areas of HIS: determining maternal health data based on three dimensions, namely completeness, accuracy, and timeliness; describing the components of data management processes currently used in healthcare facilities; and determining the use of information for evidence-based decisions in managing healthcare activities. The findings on data quality dimensions, the components of data management processes as well as various practices of information use, may benefit a variety of leaders, ranging from case teams to ministers of health, healthcare professionals at healthcare facilities, healthcare policymakers, and researchers, as well as the body of knowledge in general.

Moreover, these findings may inspire leaders at all levels, particularly policymakers, to think broadly and deeply about the technical, behavioural, and organizational factors that influence HIS implementation at all levels and consider current validated interventions as a solution to address challenges. Essentially, the current findings will assist administrative leaders at sub-city, regional and national levels in better understanding the practical and theoretical challenges of HIS implementation, allowing them to apply these evidence-based facts to address them.

Taking everything into account, the reviewed and expert-validated HIS strategies, along with the properly documented action plans that take into account all responsible bodies across different levels and measurable success indicators with specific timeframes for HIS evaluation, may contribute significantly to the improvement of the HMIS at all levels of the healthcare system. This means that high levels of data quality and optimal information use can be significantly improved if these validated interventions are accepted, properly implemented, and rigorously measured. Additionally, high data quality may significantly impact the quality of healthcare service, including maternal healthcare, optimal service utilization, and maximum client satisfaction.

1.5 DEFINITIONS OF KEY CONCEPTS

The purpose of defining key concepts is to present the abstract or theoretical significance of the concepts being studied (Khan 2018:4).

Data: A collection of facts in a formalized manner suitable for communication by human beings or by computer (WHO 2012:42). In this study, “data” is defined as numbers that have yet to be processed and analysed in health centres for maternal health data.

Data management: The development, application and monitoring of plans, policies and practices for controlling, protecting, providing and improving the value of data and information assets (Stedman 2019:2; National Data Management Office [NDMO] 2021:4). In this study, data management is defined as a practice in which data from public healthcare centres are collected, compiled, analyzed, displayed and documented according to the anticipated national standard.

Information: The data processed, analyzed and contextualized for decision-making is called information (Boell & Cecez-Kecmanovic 2015:2). In this study, information is defined as the data or indicators that have been processed, analyzed and contextualized at public health centres and lower levels for various decisions.

Information use: Information use at the healthcare facility level is primarily defined in three ways: (1) information repackaging and dissemination, (2) performance review and use of written feedback, and (3) evidence-based decision-making processes (FMOH 2015:157). In this study, information use is defined as the practice of information repackaging, information dissemination, shaping decisions and influencing others in public health centres.

A Health Management Information System (HMIS): It is a system for collecting, keeping, retrieving, and processing health data in order to enhance decision-making. It is one of the six major pillars or components of the health system. It helps to connect the other five healthcare system components (service delivery, the health workforce, access to necessary medications, financing, and leadership) with healthcare data (Endriyas, Alano, Mekonnen, Ayele, Kelaye, Shiferaw et al. 2019:1). In this study, HMIS is defined as a system that aids in the improvement of data quality, data management, and information use in public healthcare facilities in order to improve overall decision-making processes.

1.6 OPERATIONALIZATION OF CONCEPTS

Data quality: In this study, data quality refers to data accuracy, completeness and timeliness. Thus, data fit for purpose.

Accuracy: In this study, data accuracy is achieved if all the values of study data elements (n=8) and indicators (n=10) of maternal health data in registers, tally sheets, report forms and the DHIS2 database are found uniform and identical for all of the six consecutive reporting months.

Completeness: In this study, data completeness is defined as the presence of all the values of data elements and indicators in maternal registers, tally sheets, reporting forms and the DHIS2 database. In this case, 17 data elements were used as evaluation criteria to review the content completeness of four indicators: family planning visit, the ANC first visit, skilled birth attendance, and early postnatal care visit.

Timeliness: In this study, timeliness is defined as all the expected report types from case teams and public health centres being checked and reported to their following levels on stipulated times in the given time frame from April to September 2019.

Technical Determinants: In this study, technical determinants refer to computer literacy, the availability of different HMIS tools (registers, tally sheets, report formats, and HMIS manuals), knowledge of HMIS tools, and the perception of user-friendliness of HMIS tools to manage data and use information in public healthcare centres, and levels below that.

Organizational Determinants: In this study, organizational determinants refer to the availability of written data management and information use strategies; a culture of information use; the availability of HMIS resources; supervision; the motivation to strengthen the HMIS; staff empowerment; onsite training; accountability; and the budget allocation to strengthen the HMIS in the public health centres.

Behavioural Determinants: In this study, a behavioural determinant is defined in relation to knowledge to optimize information use and to manage data process activities; confidence in information use and in managing data processes; competence in information use and in managing data processes; motivation to optimize information use; and the level of involvement in data management tasks to optimize information use in public healthcare centres, and levels below that.

1.7 FOUNDATIONS OF THE STUDY

This section describes the positivist research paradigm and the Performance of the Routine Information System Management (PRISM) theoretical framework used and followed in this study.

1.7.1 Research paradigm

A research paradigm is a shared worldview representing a discipline's beliefs and values and guiding the solving of problems (Chilisa & Kawulich 2012:1). This research paradigm provides a framework for theory and research. It includes four assumptions, namely: epistemology (it defines and deals with the position of the researcher in relation to subjects being researched or the way of knowing), ontology (it defines the nature of reality), methodology (it deals with principles and procedures of how research should be conducted using an appropriate approach); and axiology (it defines, evaluates and understands the concepts of ethical issues) (Khatri 2020:1).

This study was approached from a positivist paradigm which states that a belief or fact can be tested empirically, verified or disconfirmed based on the concepts such as the data values, measured result, specific objective of the study, and tested theory. It also supports the possibility of identifying the strength of relationships between independent and dependent variables. Therefore, the researcher used the positivist paradigm to measure, quantify and examine the level of statistical significance association of organizational, behavioural and technical factors with the data management and information use practice in public healthcare centres (Chilisa & Kawulich 2012:8). The four paradigm assumptions are discussed below.

Ontology: Positivists argue that there is a single reality; this reality is objectively presentable and measurable using instruments that are independent of the researcher. In other words, knowledge is objective and quantifiable and can be broken into measurable and quantifiable study variables (Antwi & Hamza 2015:3; Khatri 2020:2). This implies that there is a specific objective reality governed by unchangeable natural cause-and-effect laws composed of stable preexisting patterns or an order that can be discovered, but it is neither time-bound nor context-bound in a way that allows for generalization (Aliyu & Adamu 2015:4). This concept was applied in this study as follows: In phase one, the quality of maternal data produced in public health centres was quantified and objectively measured across three data quality dimensions (accuracy, completeness, and timeliness) using the document review checklist. Also, in phase two, the effect of technical, behavioural, and organizational factors on data management and information use, as well as the use of healthcare information for decision-making processes, was quantified and measured using a quantitative questionnaire objectively.

Epistemology is concerned with the validity, scope, and methods of acquiring knowledge. This section of the research paradigm addresses the following questions: a) what is a knowledge claim; b) how is knowledge acquired or produced; and c) how the extent of transferability is determined (Antwi & Hamza 2015:3; Khatri 2020:3). This paradigm also clarifies the nature of knowledge acquisition in the following ways: knowledge can be described in systematic ways; it consists of verified hypotheses that can be regarded as facts or laws; it is probabilistic in nature, holding true for large groups of people or occurring in a variety of situations; and it is accurate and certain (Aliyu & Adamu 2015:6). Positivists see knowledge as stable and generalizable statements of belief or facts that can be measured, confirmed, verified or disconfirmed. One fundamental assumption of this paradigm is to develop the most objective means of bringing reality closer together. Another basic assumption of this paradigm is to develop the most objective methods for the closest approximation of reality (Chilisa & Kawulich 2012:8). This philosophical viewpoint was centred on how this research was carried out and what established the knowledge obtained from the three phases (Jonker & Pennink 2010:61). This paradigm has been used to explain variable-to-variable causal relationships (Aliyu & Adamu 2015:9). In this regard, study variables were conceptually and operationally defined and classified, and the level of interactions/associations between the dependent and independent variables was quantified and justified.

Axiology refers to the nature of ethical behaviour in research and deals with the ethical issues and values of the research process. It involves defining, assessing and understanding the concepts of right and wrong behaviour related to the study research (Antwi & Hamza 2015:3 Khatri 2020:4). In this study, potential biases in recruitment, data collection, and analysis were avoided as follows: the UNISA Ethiopian Learning Centre and the Addis Ababa Health Bureau research and ethics committees provided ethical clearance and approval for the current study.

Methodology is a research strategy used to explain or define the principles and procedures for conducting research (Aliyu, Singhry, Adamu & Abubakar 2015:14). Thus, the positivist research paradigm supports quantitative research methodology and survey design. This paradigm calls for an objective methodology for measuring and testing variables related to general cause and effect (Antwi & Hamza 2015:4; Khatri 2020:3). The methodological paradigm also investigates issues such as the role of the researcher and the research method used (Aliyu & Adamu 2015:11). The researcher's role in this study was objective, value-free and unaffected by the subject. Structured quantifiable and objective methods were used in this study in line with the positivist paradigm.

In general, the positivist paradigm was instrumental in producing a specific and objective reality from quantitative data using a variety of structured techniques.

1.7.2 Theoretical framework of the study

The theoretical framework provides context, reflects the position of the researcher and highlights concepts and the relationships between them. This study adopted the Performance of Routine Information System Management (PRISM) (Aqil, Lippeveled & Hozumi 2009:12).

The theoretical framework provides a logical structure of connected concepts that helps guide and provide a picture or visual display of how ideas relate to each other. The PRISM theoretical framework (Aqil et al. 2009:12) guides and provides an overview of the effect of technical, behavioural, organizational and socio-demographical factors on data management and information use.

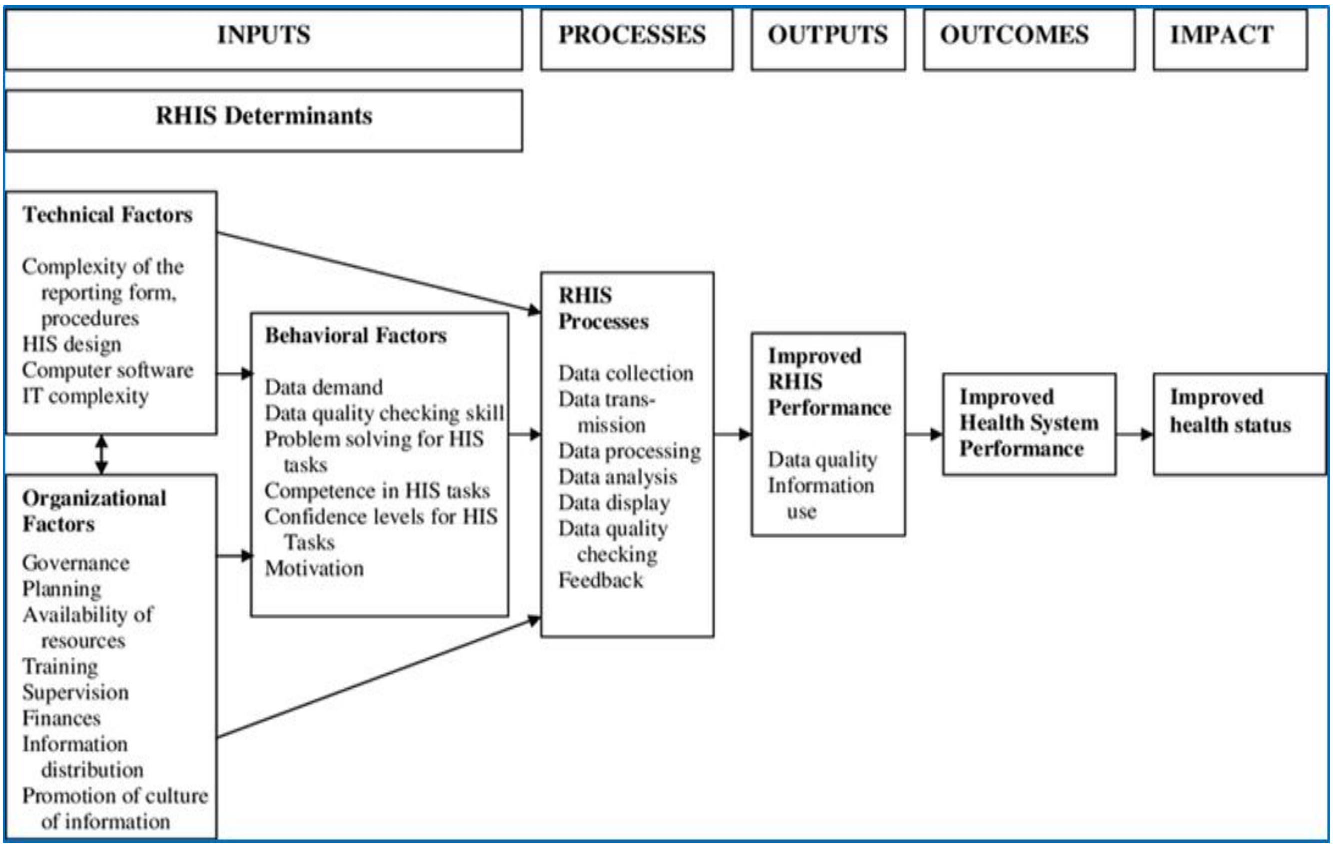

Figure1.1: PRISM (performance of routine information system management) Framework

Source: Adopted Performance of Routine Information System Management (PRISM) theoretical framework (Aqil, Lippeveled & Hozumi 2009:5).

Behavioural determinant is defined as the knowledge, skill, confidence and motivation to manage data and use information in public health centres (Measure Evaluation 2015:88). Thus, the level of confidence, motivation and competency of individuals are directly affecting the processes and performances of routine health information system (RHIS) tasks in the health facilities (Teklegiorgis et al. 2016:7). The PRISM theoretical framework assumes that, if people are aware of the benefits of RHIS tasks, they are confident and competent in performing these tasks and that the complexity of the task is not challenging and then they are able to continuously and sustainably perform data management and information use tasks in all health institutions (Saigí-Rubió, Pereyra-Rodríguez, Torrent-Sellens, Eguia, Azzopardi-Muscat & Novillo-Ortiz 2021:3). In this study, behavioural determinants are conceptualized in relation to knowledge to use information and manage data; the level of confidence in information use and to manage data; the motivation in information use and involvement in managing data.

Organizational determinants is defined as the state of management, governance, planning, training, supervision, finance, feedback and promotion to manage data and use information in health centres (Measure Evaluation 2015:88). Organizational factors such as a lack of regular rewards for good work, poor staff empowerment to make decisions, not being held accountable for poor performance, low management support of the health management information system, and lack of supervision and written feedback significantly affect the data management and information use practices (Teklegiorgis et al. 2016:7; Saigí-Rubió et al. 2021:3). In this study, organizational determinants are well articulated in relation to the availability of written data management and information use strategies; the culture of information use; the availability of an HMIS plan; the provision of internal supervision to strengthen the HMIS; the motivation to strengthen the HMIS; staff empowerment to make evidence-based decisions; onsite training to strengthen the HMIS; accountability to strengthen the HMIS; and budget allocation to strengthen the HMIS.

A technical determinant is defined as the related factors for the development, management and improvement of RHIS processes and performance with specialized know-how and technology (Teklegiorgis et al. 2016:6). These factors include indicator development, data collection and procedural manual design, information technology types, and data processing and analytical software developments, all of which have the potential to impact on the RHIS performance (Saig-Rubió et al. 2021:3). In this study, technical determinants are conceptualized in relation to computer literacy to manage data; the availability of HMIS tools (registers, tally sheets, report formats, and HMIS manuals) to strengthen HMIS; the knowledge of HMIS tools (manuals, indicators, registers, tallies and formats) to strengthen the HMIS; and the perceived user-friendliness of HMIS tools to strengthen the HMIS.

1.8 RESEARCH METHODOLOGY

1.8.1 Research approach

The investigation approach represents a plan and procedures for research that spans the wide-ranging approach to research design, data collection, analysis and data interpretation (Creswell & Creswell 2018:40). The positivist research paradigm underpins the methodology and design of quantitative research. This paradigm requires an objective or detached research methodology that focuses on measuring study variables and testing hypotheses associated with general causal explanations (Antwi & Hamza 2015:4; Khatri 2020:2). Therefore, the researcher applied a quantitative research approach (Creswell & Creswell 2018:40). Quantitative research entails formal objectives, research questions, the purpose of the study, systematic process of numeric data collection and statistical data analysis.

The study took place in three separate and interrelated phases. Phase I examined and reviewed maternal health documents, including registers, tally sheets, reporting forms, data quality monitoring logbooks, and DHIS2 databases retrospectively to measure the level of data accuracy, data completeness and report timeliness from April to September 2019, using a standard quantitative checklist. A descriptive cross-sectional survey was applied in Phase II, using a structured, close-ended and quantitative type of data collection tool to determine and quantify the effect of technical, behavioural and organizational factors on data management processes and the extent of the use of health information in public healthcare centres, core processes and case teams. Finally, the Delphi technique was conducted in Phase III to develop possible strategies to strengthen the processes of data management and information use at the level of the public healthcare centre. The three phases of the research methodology used in this study are summarized in Table 1.1. The research methodology is presented and discussed in detail in Chapter 3.

Table 1.1: Summary of the research methodology

Study phase	Study objectives	Target population	Sampling	Data collection	Data analysis
Phase I	To assess the accuracy, completeness and timeliness of maternal health data generated in the public health centres.	Maternal health documents, including registers, tally sheets, reporting forms, data quality monitoring logbooks, and DHIS2 database of the healthcare centres.	Purposive sampling technique.	Checklist-based retrospective quantitative document review.	Descriptive data analysis to summarize data quality (accuracy, completeness & timeliness).
Phase II	To investigate the influence of technical, behavioural and organizational factors on data management processes. To determine the extent of health information use in public health centres.	Healthcare providers who are working in public health centres and using health information data for more than a year.	Stratified sampling technique.	Quantitative cross-sectional survey to collect data from individuals at the ten randomly selected public health centres.	Descriptive and inferential data analysis to summarize the effect of determinant factors on data management and information use practices.
Phase III	To develop possible strategies for data management and information use in public health centres	Health information system experts with sufficient experience in data management. and information use practices.	Delphi method.	An expert review and validation approach was used to reach a consensus on the proposed strategies, action plans, responsible body, success indicator, and implementation time frame.	Descriptive data analysis to summarise expert review and validation strategies using percentage and mean.

1.9 SCOPE OF THE STUDY

The study was performed in Addis Ababa, Ethiopia, in ten public healthcare centres. It was limited to one city. However, by the nature of the approach used, the findings are generalizable. Among all other programs in Ethiopia that have been reported in the literature as experiencing data quality challenges, this study selected the maternal health program to assess maternal data quality as it was not feasible to include more than one programme. The data management and information use practices and the effects of technical, behavioural and organizational factors on the data management and information were not limited to maternal services, as this is a system-wide challenge.

1.10 THESIS STRUCTURE

The seven chapters and sub-sections comprise this thesis. In order to allow readers to understand discussions on issues, the illustrated descriptions of each of these chapters are given below.

Chapter 1: Overview of the study: It provides an introduction to the problem, the purpose, and the objective and research issue of the study and provides background information. The chapter also describes the main concepts and the foundation of the study, gives a summary of the methodology, and provides the scope of the study.

Chapter 2: Literature review: This chapter emphasizes the status of the healthcare information system from the global to the national levels. It also focuses on the data management processes, the magnitude of data quality in terms of accuracy, completeness, and timeliness, and the extent to which information is used in healthcare facilities. The effects of socio-demographic, technical, organizational and behavioural determinants on the processes of data management and information use are reviewed and documented.

Chapter 3: Research methodology: This research methodology chapter presents three stages: (1) a retrospective quantitative document review (Phase I); (2) a descriptive cross-sectional survey (Phase II); and (3) strategy development (Phase III). This chapter contains information on the research approach, design, and methods used throughout the three phases. It also discusses the validity, reliability, and ethical considerations.

Chapter 4: Analysis and presentation of findings: The study's key findings are presented in two phases. The results of the quantitative document review are summarized and detailed in Phase I. Findings from Phase II are elaborated upon.

Chapter 5: Integration and interpretation: Chapter 5 presents an integration, interpretation and discussion of combined findings of the quantitative document review and the descriptive cross-sectional survey. The PRISM theoretical framework is used to guide the integration and interpretation of results.

Chapter 6: Strategy development, validation and discussion: The development and validation of the strategies using the Delphi technique are covered in this chapter. Processes followed in the development and validation of strategies are organized, discussed & documented.

Chapter 7: Summary, contributions, recommendations, limitations and conclusions: This chapter summarizes the combined findings and the study's key contributions. It also acknowledges the limitations of the study and draws conclusions in relation to the research's specific study objectives.

1.11 SUMMARY

The first chapter covered the introduction, background, problem statement, research objectives, and research questions. This chapter also discussed the study's foundation, overall research approach, and scope. The thesis structure and organization were presented at the end of this chapter. The next chapter of this study reviews the literature which supports this study.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents a review of the literature pertinent to this study. A literature review gathers information from numerous sources as a basis to conduct scientific research (Schryen, Benlian, Rowe, Gregor, Larsen, Petter et al. 2017:6). Journals, books and articles were used as primary sources of this review. The review produced comprehensive, descriptive and relevant concepts linked to this particular research topic (Winchester & Salji 2016:2).

Thus, the current study is built on relevant previous findings related to the general health information system and the practices of data management and information use in public health centres in particular.

This chapter is organized and presented from the global (developed countries) to the low- and middle-income countries, including Ethiopia. This approach draws a complete picture across levels in highlighting the accomplishments and challenges of the health information system. It concentrates on the organization of Ethiopia's healthcare system, with a particular emphasis on the health-information system. This chapter also covers data management processes, key data quality dimensions, and information use in the healthcare system. Finally, it discusses factors influencing data management and information use in general, as well as key determinants of maternal data quality and use in particular.

2.2 HEALTH INFORMATION SYSTEM (HIS)

The Health Information System (HIS) is one of the components of the health system used to collect, store and convert data into information. Therefore, it is an efficient tool for increasing the quality of data on healthcare services through processing, analysing and providing information for decision-making processes (Alipour & Ahmadi 2017:1). As a result, the HIS has to be used by decision-makers at each point of the management spiral to influence the health service management optimally.

Dagnew, Woreta and Shiferaw (2018:2) highlight the importance of the HIS in improving the healthcare system through evidence-based decision-making processes. In addition, Measure Evaluation (2018:4) demonstrates the significant contribution of the HIS in ensuring the dimensions of high-level data quality and information use in the healthcare system. The HIS is identified as one of the building blocks of the healthcare system and it forms the foundation of the healthcare system because it supports decision-making processes across the building blocks of the healthcare system (Measure Evaluation 2018:1). It is therefore essential for this study to determine how the HIS influences decision-making processes, progress monitoring and feedback mechanisms within the healthcare system. Policymakers, healthcare managers, healthcare providers and other users need high-level quality data and information to improve the efficiency and effectiveness of the healthcare system, track progress towards specific targets, and measure health programs and data qualities using key indicators (Winchester & Salji 2016:2; Nutley & Li 2018:32). According to Fetene et al. (2019:7), the Ethiopian health information system has been instrumental in providing evidence to assess the effectiveness and relevance of key health indicators such as antenatal care, contraceptive acceptance rates, vaccination rates, and access to essential drugs in health facilities.

While the implementation of the HIS has demonstrated significant progress in data quality, data management processes and the use of health information in global healthcare decisions, some challenges have been identified. For example, a systematic review conducted in Pakistan has found that limited skills in managing, analysing and interpreting data have significant effects on decision-making processes in the healthcare system (Akhlaq, McKinstry & Muhammad 2016:8).

Healthcare workers are critical to the healthcare system's operation. The impact of the health workforce on health systems, on the other hand, is frequently overlooked, resulting in weak and inefficient healthcare systems (Muthuri, Senkubuge & Hongoro 2020:1). Furthermore, they have been found to falsely increase target populations to obtain more funds or falsify performance to meet targets and objectives tied to performance incentives in Sub-Saharan African countries (Muthuri et al. 2020:16). The quality of the health information is also influenced by weak technical training and unreliable support in data management processes so that healthcare providers feel overloaded and unable to perform their data related tasks routinely (Akhlaq et al. 2016:8). On the other hand, these studies did not explain the extent to which staff is empowered and encouraged to make evidence-based decisions, as well as significant strategies that are important for promoting and maximizing the sense of ownership in managing data and using the information in the healthcare system. Even though the HIS has made a significant contribution to improving the performance of the healthcare system through the processes of data management and information use, the HIS benefits are not always achieved at lower levels of the healthcare system due to the lack of effective and feasible strategies that are important in influencing the technical, behavioural and organizational determinants.

2.2.1 Health information system (HIS) in developed countries

Over the past decade, health information systems in healthcare have become increasingly advanced. Their ever-growing range of capabilities has led to widespread use of these systems across the healthcare system (Measure Evaluation 2018:10). In this regard, the World Health Organization has highlighted a need for well-designed health information systems to ensure that services are delivered in accordance with standards for use in patient care and healthcare strategic and annual planning (Tripathi, Sharma & Nagarajan 2018:5). This means that the HIS was designed to be more effective at capturing, analyzing, disseminating and using accurate, complete and timely data in the healthcare system at all levels (Tripathi et al. 2018:4). As a result, evidence-based health information has been used effectively in many situations in the developed world to design strategies and plans; to monitor performance progress against national priorities, and to respond to emergencies in public healthcare (Tripathi et al. 2018:6).

Research undertaken in South Africa demonstrates that many high-income countries like Australia, Canada, Spain, Sweden, and Denmark have e-Health strategies, policies, legislation, and governance in support of the National HIS (Witter, Hamza, Alazemi, Alluhidan, Alghaith & Herbst 2020:6). In addition, a study conducted in Australia shows that concerns about making better use of evidence in policy making are closely linked to widespread pressure to improve the effectiveness and accountability of health service delivery in democratic countries such as Australia (Mamdani, Kweka, Binyaruka, Ramesh, Kapologwe, Hutchinson et al. 2018:1). As a result, it is clear that professional standards have significantly improved in analysis and evaluation, with greater attention being paid to clear program goals and performance indicators, and greater investment in data collection and analytical skills (Mamdani et al. 2016:8).

Furthermore, a comparable study reported that 90% of healthcare system data were linked to the HIS in Finland, Iceland, England and Singapore to monitor the quality and performance of health services on a regular basis when producing further approved statistics and studies (OECD 2015:43). Additionally, a study from the Netherlands shows that data and information accessibility across data sources has increased in the healthcare system (Bozorgmehr, Goosen, Mohsenpour, Kuehne, Razum & Kunst 2017:7). According to a similar study, general practitioners in healthcare centres in Australia, the Netherlands, New Zealand, and the United Kingdom used electronic health records almost universally (> 90%), resulting in improved healthcare service delivery (Wu & LaRue 2017:6).

While developed countries show remarkable progress in data management processes and the use of health information in healthcare decisions, some challenges have been identified. For example, from a European perspective, utilizing real-world data is faced with operational challenges such as feasibility, governance, and sustainability issues, which complicate access to and the routine use of multiple national health data sources, many of which will have different legal and ethical requirements for sharing and using data (Cave, Kurz & Arlett. 2019:3). For many high-income countries, the implementation of the electronic health system remains uncertain due to the continuous change in the characteristics of the health system, politically driven relationships between health care providers, and the fact that local organizations have different starting points, goals and resources (Witter, Hamza et al. 2020:14).

According to a German study, in comparison to the Netherlands, the availability and accessibility of existing health data sources are relatively poorer, which accounts for poor data quality, and this influences various decisions (Bozorgmehr et al. 2017:7). In addition, a study in Australia in 2018 shows that around 11% of actual deaths were not recorded and reported by the national health management information system. However, this study does not mention how to improve the completeness of death registration from different local data sources, such as maternal, child and other registration books (Hong, Hoa, Walker, Hill & Rao 2018:12). Besides, a study in Portland indicated that data incompleteness and poor motivation of health workers were identified as the challenge of information sharing and access in healthcare systems in Austria, Finland, Denmark and the United States (Eden, Totten, Kassakian, Gorman, McDonagh, Devine et al. 2016:6). Additionally, a comparable study from Europe and the US shows that lack of data management standards and difficulties in demonstrating the value of health information have been documented as HIS implementation barriers (Eden et al. 2016:7).

2.2.2 Health information system (HIS) in low- and middle-income countries

Several low- and middle-income countries (LMICs) have started to reform their healthcare systems. This reform included the district health information system (DHIS2) software to improve the dimensions of data quality, data management, and information use throughout healthcare facilities (Mbau & Gilson 2018:6). This software is an open source and is more of a generic tool than a pre-configured database application. Also, this software includes an open metadata model and a flexible user interface, allowing different users to specify content without programming (Byrne & Saebø 2021:5). DHIS2 is frequently designed as an integral part of the national HIS, with the following core components: data management and analysis, mapping healthcare services and recording facilities, logistics management, and mobile tracking of pregnant mothers in rural areas (Byrne & Saebø 2021:5). As a result, it was successfully used to monitor Bangladesh's health sector development plans, key performance indicators and targets (Begum, Khan, Adamou, Ferdous, Parvez, Islam et al. 2020: 8). These findings were supported by another study, which found that DHIS2 was used effectively and frequently in Iran to correctly analyze data, provide various reports, and help to improve data quality dimensions such as timeliness and completeness (Dehnavieh, Haghdoost, Khosravi, Hoseinabadi, Rahimi, Poursheikhali et al. 2019:5).

The functionality of health information systems is rapidly rising and improving in many LMICs as a result of regular data quality assessment and data quality assurance practices in healthcare facilities (Wagenaar, Hirschhorn, Henley, Gremu, Sindano, Chilengi et al. 2017:6). A similar finding from Ghana research reveals that the HIS has made an important contribution to improving the completeness and timeliness of reports through periodic capacity building, technical support, and written feedback (Adokiya, Awoonor-Williams, Beiersmann & Müller 2016:5). In general, all of these documented facts indicate that DHIS2 has been used successfully to address several HIS barriers, including data fragmentation; poor data quality; insufficient data review and feedback; and inadequate use of information to monitor and improve health programs (Samal & Dehury 2016:2; Dehnavieh, Rahimi, Khajehpour & Mehrolhassani 2019:8). Additionally, Dehnavieh et al. (2019:8) argue that on the importance of DHIS2 supporting and improving management of patient care; in the controlling of clinical errors and wrong decisions in healthcare facilities. The administrative processes of routine data are relatively less expensive and significantly important for policy guidance and program review. As a result, DHIS2 has been used to support clinical analysis, annual updating of indicators, publishing key indicators, and data quality control in Burkina Faso, Ghana, Uganda, and South Africa, as part of their national HIS, respectively (Kiilu, Okero, Muiruri & Owuondo 2015:2).

The functional relationship between the HIS, HMIS, and DHIS2 can be seen in the following ways: The health information system (HIS) is one of the building blocks of a healthcare system that aids in the development of evidence-based health policy decisions (Chanyalew et al. 2021:2). This system serves two general purposes: (I) it is used to handle individual data records using electronic medical records, and (ii) it aids in the association of systems with data collection for decision-making and information management, which is known as health management information systems (Dehnavieh et al. 2019:3). This means that the HMIS is regularly used to generate and manage routine data from healthcare facilities as an integral part of the HIS (Chanyalew et al. 2021:2). The District Health Information System (DHIS) falls under the second purpose of the HIS (data collection for information management and decision-making), and it is used to document data that is routinely collected in all public healthcare facilities in a country that uses the system (Dehnavieh et al. 2019:3). Therefore, this documented evidence indicates that the healthcare system is highly reliant on the integral functionality of the main system (i.e., the HIS); and the sub-systems (i.e., the HMIS, and the DHIS2) to consistently support, link, and integrate individual and program-specific data from various systems at multiple levels.

2.2.2.1 Challenges with the HIS in low- and middle-income countries

Despite the fact that low- and middle-income countries have made significant progress in data management processes and information use for healthcare decisions, some key HIS challenges have been identified and documented. This means that several countries collect and submit health data on a monthly, quarterly, bi-annual and annual basis. However, these collected data were not managed and utilized to improve the HIS performance and healthcare service utilization in many LMICs (Mucee, Kaburi, Odhiambo-Otieno & Kinyamu 2016:8). According to a growing body of evidence, regularly collected data from healthcare services are frequently ignored in LMICs because they are deemed incomplete, do not report on time, or are inconsistent/inaccurate across data sources (O'Hagan, Marx, Finnegan, Naphini, Ng'ambi, Laija et al. 2017:2). This finding was supported further by Lippeveld (2017:2), who argued that routine health information systems are underutilized in several LMIC settings for strategic and annual planning, as well as improving the healthcare service quality. Adokiya et al. (2016:6) discovered that the majority of healthcare services in Ghana still rely on paper-based medical records systems, contributing to poor data quality across the country. Additionally, comparable research in Malawi shows that most healthcare facilities continue to use paper forms to obtain and report data at the county level (O'Hagan et al. 2017:3).

According to a World Health Organization study on LMICs in the Eastern Mediterranean region, there are a number of common gaps that impede the development and strengthening of a national HIS, such as a lack of political commitment and priority given to HIS activities, as well as an overall lack of capacity of healthcare facilities to collect, collate, validate, and disseminate data and information (Akhlaq et al. 2016:9). In response to these various identified and documented HIS implementation challenges, the World Health Organization and its development partners have strongly urged and suggested that all countries should invest adequately in health information systems by 2030 (O'Hagan et al. 2017:2).

As confirmed by several relevant pieces of evidence, the main barriers to strengthening a HIS in LMICs included technical factors such as fragmented and limited functionality of electronic health information systems, as well as behavioural factors such as a lack of knowledge and motivation among healthcare workers (Akhlaq et al. 2016:9; Dehnavieh et al. 2019:8). These facts were supported further by Dehnavieh et al. (2019:8), who claimed that low-and middle-income countries lacked financial resources to fully implement DHIS2 at different levels of the healthcare system. Also, a study conducted in Pakistan shows that the lack of a HIS infrastructure and electricity shortages were the two most prominent barriers to strengthening the HIS in LMICs (Akhlaq et al. 2016:9). This indicates that the majority of health data collected in LMICs were not adequately managed and processed, but were instead used for various decision-making processes without adequate justification, analysis, and interpretation (Mucee et al. 2016:7). Similarly, Nigerian healthcare workers reported that data and information were not shared, used and documented appropriately in their hospitals (Mbau & Gilson 2018:5). This lack of institutional ownership did not encourage and support collective decision-making between internal and external stakeholders. Also, there are insufficient skills to manage data quality in public healthcare centres of LMIC (Uneke, Sombie, Keita, Lokossou, Johnson & Ongolo-Zogo 2017:7).

Overall, the relevant studies reviewed in this section adequately confirmed that the performance and functionality of healthcare facilities within the healthcare information system are nearly unused, despite the fact that they are expected to achieve healthcare system objectives and goals. This means that healthcare managers were unable to obtain timely, complete and accurate healthcare data for decision-making processes, as was the case in Ghana, due to technical, organizational and behavioural determinants (Mbau & Gilson 2018:5). In general, healthcare providers, managers, and policymakers around the world, particularly in LMICs, are unable to make evidence-based decisions at all levels due to key challenges in data quality (accuracy, completeness, and timeliness) and data management processes caused by a variety of technical, organizational, and behavioural determinants.

2.3 ORGANIZATION OF THE HEALTHCARE SYSTEM IN ETHIOPIA

Ethiopia is a federal parliamentary republic, with the Prime Minister serving as head of government. The Ethiopian constitution, introduced in 1995, created a federal government structure composed of nine regional states and two city administration councils, namely Dire Dawa and Addis Ababa. The regional states and city administrations are divided into districts and sub-districts (FMOH 2015:18).

The Ethiopian healthcare system aims to reduce morbidity, mortality and disability. It is decentralized to improve the health status of Ethiopians in collaboration with all stakeholders by providing a comprehensive package of preventive, promotive, rehabilitative and basic healthcare services (Measure Evaluation 2010:10). For that reason, the Ethiopian Federal Health Minister (FMOH) intends for communities to have equal and fair access to healthcare services. The services should be affordable and acceptable to all. This vision entails achieving effective data collection, analysis, and reporting on the HIS (Kefyalew, Kebede, Getachew, Mukanga, Awano, Tekalegne et al. 2016:6).

The Ethiopian healthcare system is structured into a three-tier system (Figure 2.1): primary, secondary and tertiary level of care. The primary level of care includes a primary hospital, health centre and health post. A health centre has an inpatient capacity of 5 beds and is staffed by 20 professionals on average. The health centre provides preventive and curative services. It also serves as a referral and training centre for health posts. A primary hospital provides inpatient, ambulatory, emergency surgical and blood transfusion services. The primary hospital is a referral and training centre for health centres. Additionally, a primary hospital has an inpatient capacity of 25-50 beds and is staffed by 53 professionals on average. The second tier is the general hospital that provides inpatient and ambulatory services. It is staffed by an average of 234 health workers. It is a referral centre for primary hospitals; and a training centre for health officers, nurses and emergency surgeons. The third tier is a specialized hospital that is staffed with 440 professionals on average, and it is a referral centre for general hospitals (FMOH 2015:142).

Ethiopian healthcare coverage and utilization is improved through the rapid expansion of private for-profit and non-governmental organizations in the country. The Federal Ministry Of Health (FMOH), regional health bureaus (RHBs) and district health offices have shared decision-making processes, decision powers, duties and responsibilities.

Consequently, the FMOH and the RHBs focus more on policy matters and technical support, while district health offices have the basic roles of managing and coordinating the operation of the district's healthcare system under their jurisdiction. The decentralization of power to regional governments has resulted in the shifting of decision-making for public service deliveries from the centre to largely under the authority of the regions and down to the district level (FMOH 2010:5).

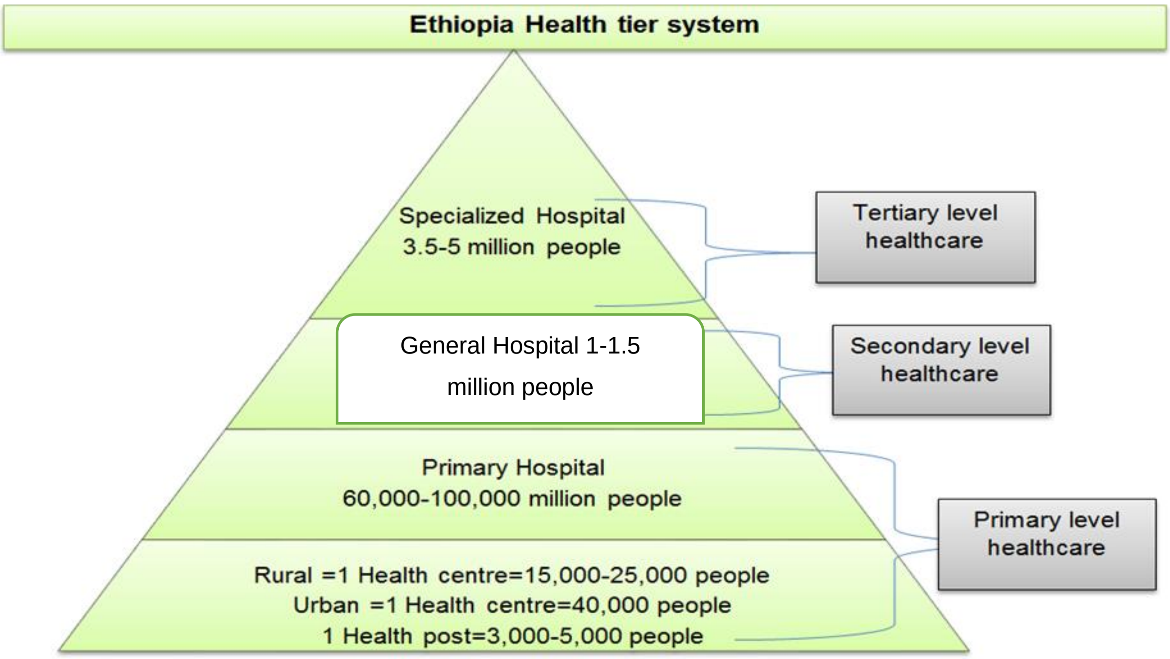

Figure 2.1: Source: Ethiopia health sector transformation plan (2015:142)

2.3.1 Health information system in Ethiopia

The Health Information System cannot exist on its own but is a functional entity within a comprehensive healthcare system that delivers integrated healthcare services, including curative care, rehabilitative care, disease prevention, and healthcare promotion. An effective HIS provides various kinds of information support to the decision-making process at all levels of the healthcare system (Measure Evaluation 2019:8). Thus health information systems should fit into the overall management structure of the healthcare system (Measure Evaluation 2019:12). This means that the structure of the HIS is significant and fundamental for producing better quality data and information to support all levels of management functions of the health system.

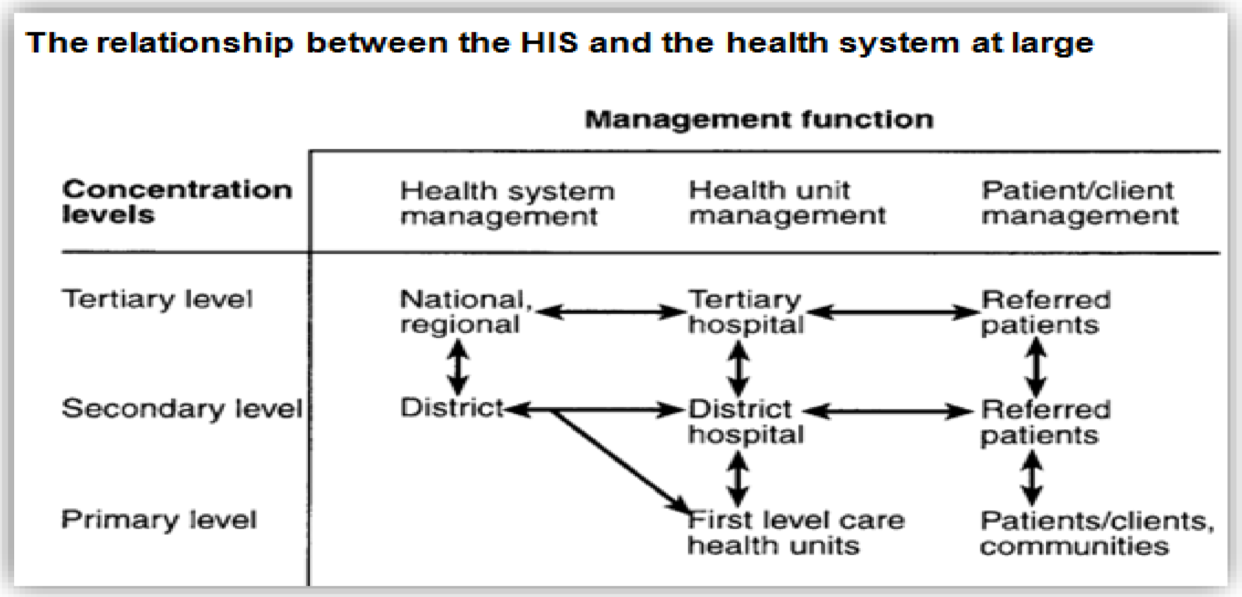

Figure 2.2: Source: Design and implementation of his (WHO 2000:28)

Currently, in Ethiopia, a national health information system strategic plan is developed and decision-making processes are more decentralized at the level of healthcare facilities. The Federal Ministry of Health (FMOH) is also more concerned with policy issues and technical support (WHO 2017:4). Moreover, the HIS in Ethiopia is operated by different authorities including the Central Statistics Agency of Ethiopia, the Ethiopian Health and Nutrition Research Institute, the Ministry of Health, and the Ministry of Justice. Therefore, in line with their mandates, these organizations have official internal structures dealing with the HIS (African Health Organization & WHO African Region online, s.a.). For example, the healthcare system collects and manages the HIS routinely, while population data is primarily acquired from the Central Statistical Agency (Sirintrapun & Artz 2015:4).

Currently, in Ethiopia, 131 healthcare service indicators are used to monitor, review and guide the performance of the Health Sector Transformation Plan (HSTP). These indicators are classified into four areas based on the HSTP's strategic point of view, including community health ownership (100 indicators); internal process (15 indicators); financial stewardship (7 indicators); and capacity building or learning and growth (9 indicators) (FMOH 2017:10). The District Health Information Software (DHIS-2) is open source software for data collection, validation, analysis, and presentation that is specifically designed to manage integrated health information. Around 47 countries worldwide, including Ethiopia, have adopted the DHIS-2 for national and program-specific HIS (Thangasamy, Gebremichael, Kebede, Sileshi, Elias & Tesfaye 2016:2). This software helps to disaggregate indicators in age, sex, region and other performance measurements to monitor healthcare programs; and it is also tailored to allow data entry, exchange and reporting via the internet (DHIS2 Documentation Team 2020:223).

The flow of data is based on the healthcare system's hierarchy from public health centres to the FMOH (FMOH 2013:11). In Ethiopia, the ultimate goal of the HIS is to inform decision-making for action; and this is measured in relation to the quality of the data produced and the evidence used for various decision-making processes to improve the functions of healthcare systems at all levels (FMOH 2015:56). As a result, special emphasis has been put on maintaining the HIS at the top-level of the health system to ensure evidence-based decision-making processes (Muhindo & Joloba 2016:4).

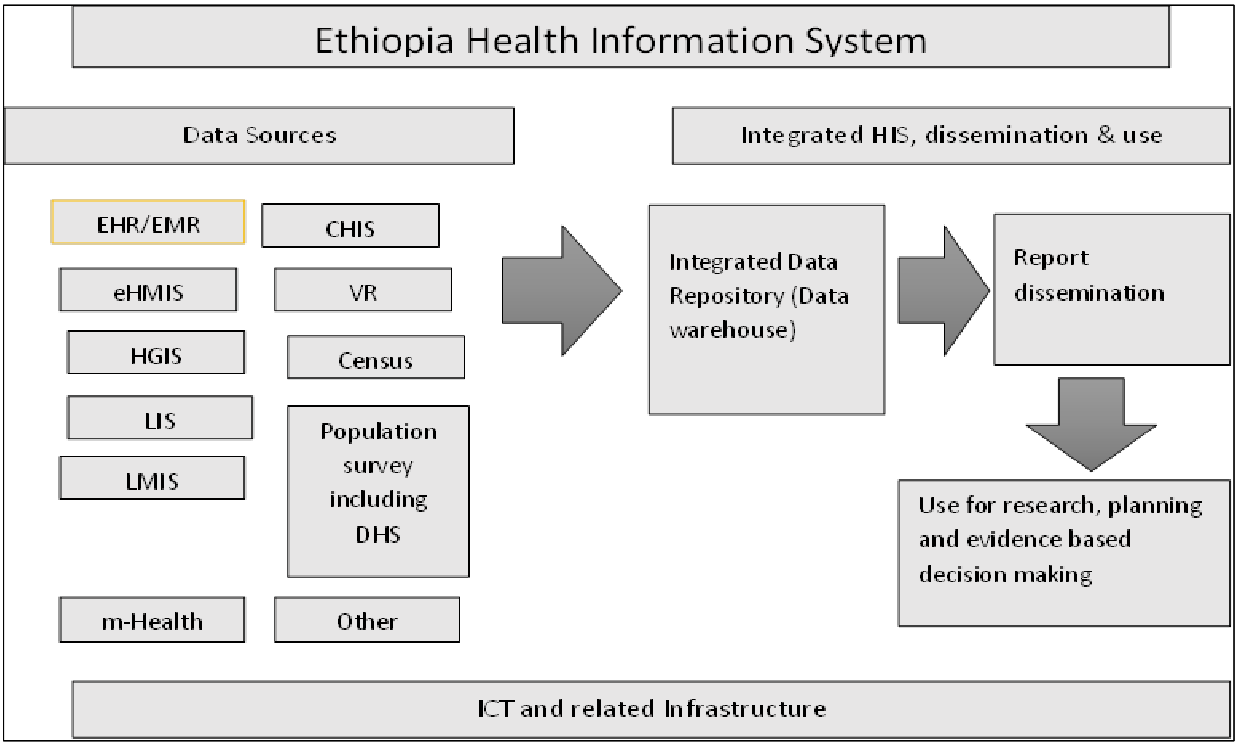

Figure 2.3: Source: Ethiopia health sector transformation plan (2015:15)

Even though there has been evidence of use and understanding of the importance of the HIS, there are practical gaps in the low level of the healthcare system to effectively meet the HIS demands of the country in Ethiopia. For instance, healthcare data is poorly managed and healthcare workers of the public healthcare institutions have low confidence in their skill to produce, analyze, and use data and information (Muhindo & Joloba 2016:6). In addition, the role of routine health data in tracking performance of healthcare and trends is missed by health system managers and clinicians (Dagnew et al. 2018:3). Consequently, many healthcare systems in Ethiopia do not fully link evidence to decision-making, they do not respond to priority health requirements, and different reports show that the quality and use of the data are still not improving as intended (Teklegiorgis et al. 2016:6; Tilahun et al. 2021:2). For these reasons, the regular practice on the component of data management and information use remains weak and unsatisfactory, most decisions and interventions are developed without concrete evidence, and the question on the failure of many healthcare programs in public healthcare centres remains unanswered (Trant 2015:7-9). Consistently, more than 400 data items are recorded from healthcare centres each month, but data have been observed inconsistently across the nine regions and the two city administrations of the country. Routine health data have thus not been used for multiple health requirements (Measure Evaluation 2015:23).

2.3.2 Maternal health data in Ethiopia

Globally, maternal and child health (MCH) services have been a public health priority in reducing morbidity and mortality among mothers and newborns. However, inadequate maternal data quality and use limit the trust and value that decision-makers place on data, thereby affecting future demand for data in decision-making processes (WHO 2021:5). Hence, improving maternal and newborn health outcomes requires more than just increased access and utilization of services. Along with increasing service coverage, improving data quality will support evidence-based care during critical periods, which will have a positive impact on the survival of the mother and newborn (Biadgo et al. 2021:2). Many Ethiopian healthcare facilities did not submit accurate, complete and timely monthly maternal and child health (MCH) data to higher levels (Ouedraogo et al. 2019:8). In this case, failure to submit standard quality MCH data to the next reporting levels may result in an incomplete and partial representation of MCH service provision at the lower reporting levels (Ouedraogo et al. 2019:8).

A similar study in Ethiopia found that the completeness of data in registers and reports was measured using four maternal health indicators (i.e., skilled birth attendance, family planning use, Penta 3 vaccination, and pneumonia under five-year-old children). As a result, the overall register and report completeness rates were found to be 53.5% and 56.3%, respectively, due to a lack of understanding of the data elements and indicators, as well as a lack of user-friendliness of the tools (Gebreslassie, Below, Ashebir, Gezae & Chekole 2020:2). The same can be said for the consistency of registers versus reports, which was found to be 38.9% overall due to data entry and arithmetic errors, as well as a lack of emphasis on data accuracy (Gebreslassie et al. 2020:2). This is justified by the fact that there is a significant lack of understanding at all levels of the maternal data elements and indicators. This is especially important when putting together a comprehensive picture of the quality of maternal health data in registers, tally sheets, reporting forms, and databases to guide effective strategies and decision-making processes throughout the healthcare system, especially at the lower levels. Furthermore, informed maternal healthcare decision-making contributes to a culture of transparency and accountability at all levels of the healthcare system.

Hence, strengthening the HMIS with a selected, reviewed and validated HIS strategy is essential to predict the information needs of the healthcare system at different levels, including maternal healthcare services (Kiilu et al. 2015:4). For instance, capacity building has contributed to improving skills of healthcare workers in data management by 20% in Ethiopia (Measure Evaluation 2018:7). Even though management of data quality including the maternal health data has improved and the value of information use for decision-making and patient care monitoring is raised significantly (Homer, Bhatia, Stout & Baldwin 2016:6), more needs to be done to significantly improve the data management process and information use through feasible and validated strategies at case team, core process and public health centre levels.

2.4 DATA MANAGEMENT PROCESSES

The HIS is used to convert raw data (inputs) into useful information that can be used to make evidence-based decisions (outputs) (Measure Evaluation 2019:21-22). In this study, data management is defined as a practice of collecting, collating, analysing, and presenting data from healthcare centres according to the expected and predefined national standard (Stedman 2019:2; National Data Management Office [NDMO] 2021:4). The concept of the data management processing is important in producing a standard quality of data at all levels of the healthcare system. As a result, data-informed decisions, HIS strategies, and client satisfaction are associated with the quality of data management in the healthcare system (Dagnew et al. 2018:4). For that reason, an integrated HIS is designed to pull and manage health data from a range of sources; and it is accessible for users in different locations in Ethiopia (FMOH 2015:155). For example, at the local level, decision support systems and simple data analysis tools have been established and implemented. Also, at regional and federal levels, progress tracking, estimation, and in-depth data analysis tools have been implemented and used accordingly (FMOH 2015:154). In general, a pyramid shape of data use is strengthened to utilize more key indicators at a lower level and less at the Minister Of Health level (FMOH 2015:156).

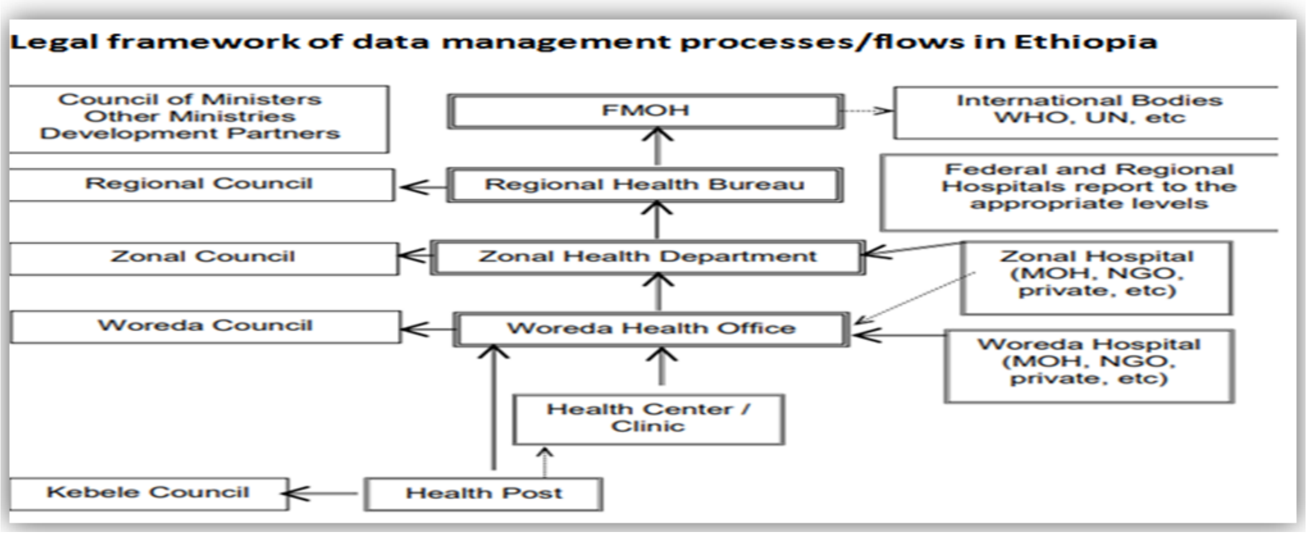

Figure 2.4: Source: Facilitator's guide for training of trainers (2010:91)

In general, well-designed and documented data sources, various HIS guidelines, and skilled staff are critical components of data management processes for tracking data quality and key performance indicators, identifying healthcare system bottlenecks, and improving evidence-based decision-making at all levels (EFMOH 2016:16). This means that high-quality data is especially important for populations with high disease and mortality rates, such as pregnant women and children (Ouedraogo et al. 2019:1).

While the HIS in Ethiopia shows remarkable progress in data management processes and data-driven healthcare decisions, some challenges have been identified and documented. For example, in 2016, a study in Eastern Ethiopia showed that 32.2 % of public healthcare facilities did not collate and perform data analysis monthly (Teklegiorgis et al. 2016:6).

A similar study in Ethiopia found that the overall quality of maternal health data was inaccurate, incomplete, and untimely (EPHI, FMOH & WHO 2016:68; Ouedraogo et al. 2019:10) due to a lack of effective interventions to ensure the effectiveness of HMIS in managing maternal health data on a regular basis. Also, the data of key performance indicators were not evaluated and reviewed in 39.3 % of healthcare facilities every month; and 42.3 % of these facilities did not document and manage their internal and external written feedback on the HIS timely. Moreover, 25% of public healthcare centres did not track and follow the quality of health data, which in turn impacted the quality of the healthcare system (Teklegiorgis et al. 2016:7). In summary, within the HIS, the data management processing is divided into four key functions (Sirintrapun & Artz 2015:4) as follows:

2.4.1 The data collection process

Data collection is the first and most important step in data management processes. It involves identifying data to be collected, selecting data collection methods, and collecting data. This step is instrumental in the management of data quality (Taylor 2019:4). Most LMICs collect data on paper; however, this practice has encountered a number of challenges due to technical, organizational, and behavioural factors (Berrueta, Ciapponi, Bardach, Cairoli, Castellano, Xiong et al. 2021:10).

Similarly, in Ethiopia, poor skills and a lack of support for collecting maternal health data at the health facility level have been identified as determinants. health centres have collected and reported more than 50 maternal and child health data items every month without maintaining its quality (FMOH 2017:11). In response, the HMIS was implemented to support the healthcare system and to address emerging healthcare data management needs, with a particular emphasis on maternal health data (Asemahagn 2017:3). This tool was assumed to be useful in healthcare facilities that are overburdened with data and have several parallel data collection and reporting systems, such as is the case with maternal health data (Measure Evaluation 2015:11), currently a high priority for the Ethiopian government (Asemahagn 2017:3).

Data in the healthcare centres are collected routinely in medical registers, and the quality of collected data is significant for planning, daily patient care management, proper resource allocation, disease prioritization, and informed decision-making (Dagnew et al. 2018:2). This would be accomplished if standard data collection techniques and processes are used to provide evidence that ultimately leads to improvements in the healthcare system at all levels (Muhindo & Joloba 2016:4).

However, according to a study conducted in Nigeria, a large portion of data management processes are paper-based, and client data were collected by healthcare workers using registers (Adejumo 2017:56), a system which is vulnerable to various errors in data collection.

Similarly, a Malawi study discovered that healthcare facilities used manual data collection processes, which imposed additional burdens on healthcare providers in terms of recording, extracting, and using data (Measure Evaluation 2018:14). In Tanzania, for example, family planning data were collected daily in paper registers, creating a burden for healthcare providers (Anasel, Swai & Masue 2019:13). In general, healthcare workers responsible for data collection require basic skills in gathering and summarizing data to support decision-makers (Measure Evaluation 2018:7). Such skills could be ensured by providing standard data management training to data producers. Additionally, decision-makers require training to develop data identification, leadership, and advocacy skills in order to secure funding and buy-in to put data-informed recommendations into action (Measure Evaluation 2018:8).

While there has been increasing evidence from regional and local studies that careful system design and innovation through the HIS can provide feasible solutions to data-related issues, the data collection process in most LMICs is poor in quality (Akhlaq et al. 2016:6). Therefore, healthcare workers in the LMICs have spent a significant proportion of their time in collecting large amounts of data. These collected data are rarely analyzed and used, especially at the point of data collection, to support various decision-making processes (Measure Evaluation 2018:9). This finding was supported by findings from Kenya that, due to high workload and lack of knowledge, healthcare workers face challenges in collecting accurate, complete and timely data as 40% their time is spent on collecting data (Mucee et al. 2016:1). Additionally, staff members feel overburdened and unable to properly complete their data-related tasks due to a lack of motivation and competence to produce and collect reliable health data, which has a negative impact on data quality (Akhlaq et al. 2016:6). Also, the level of health workers' perception of the routine data collection processes is directly associated with the quality of collected data (Berrueta et al. 2021:10). Most healthcare providers have faced a difficulty to understand the value of data collection in contributing to data quality in healthcare facilities (Akhlaq et al. 2016:2). The frequency and quality of supervisory visits in the healthcare system are related to the quality of data collection processes. The more supervisory visits with high quality to the public healthcare facility, the more efficient the data collection processes were (Nicol, Bradshaw, Uwimana-Nicol & Dudley 2017:10). This was supported by a similar study in Nigeria, which discovered a link between data collection processes, data quality, and the competency of healthcare workers (Bhattacharya, Umar, Audu, Allen, Schellenberg & Marchant 2019:14).

2.4.2 The data collation process

Data collation is the second step in the process of data management. This stage involves aggregating data elements and indicators from the healthcare register into summary sheet/tally sheets and reporting formats respectively (Nicol et al 2017:10). Thus, the essence of extracting and integrating data from the sources to summary sheets and reporting formats may include aggregation, calculation, cleaning, and rearranging values, with the goal of making reporting easier (Health Metrics Network [HMN] & WHO 2012:39). Accordingly, data can then be delivered in integrated data formats and summary sheets that allow generating tangible outputs that HIS users can use the aggregated data to inform their decisions at all levels (Health Metrics Network [HMN] & WHO 2012:39). As a result, the whole process of data compilation adds significant value to the data source by removing mistakes and correcting missing data; providing documented measures of degree of confidence in data; adjusting data from multiple sources to allow them to be used together; structuring data to be usable by end-user tools; and tracking all the above actions to tangibly support data-quality assessments (Health Metrics Network [HMN] & WHO 2012:39).

However, findings from Tanzania show that data compilation processes at the facility level are often rushed when reporting deadlines arrive, resulting in data backlogs and limited time spent on data compilation (Bhatia, Stout, Baldwin & Homer 2016:5). Also, research in South Africa in 2017 showed that most health professionals were unable to compile data at the level of health facilities due to lack of understanding of indicators, data elements and reporting formats, as well as lack of confidence, competency and institutional motivation (Nicol et al. 2017:10). Similarly, healthcare providers in Rwanda did not compile/summarize data in reporting forms and databases; still 27.3% of public healthcare centres showed data deviation from reporting forms to client registries, as well as data deviation from electronic databases to healthcare registries in 31.3% of health centres due to lack of data compilation skills and poor motivation of healthcare workers (Innocent et al. 2016:6).

2.4.3 Data analysis

Data analysis is the third, and crucial, step in the process of data management. Data from different sources are collected, collated and then analysed in order to form some conclusion and justification (Wagenaar et al. 2017:2). The process of data evaluation is called data analysis, using analytical and logical reasoning to examine each component of the data provided (Wagenaar et al. 2017:2). As a result, the HIS is an important building block in connecting the collected and compiled data to its being useful through data analysis. This means that analyzed and justified data are essential to national and local health priority decision-making processes to respond to basic community demand through the healthcare system (Health Metrics Network [HMN] & WHO 2012:46). In this regard, the DHIS2 was designed and implemented as a vehicle for conducting a detailed statistical analysis to investigate the magnitude of data quality, including completeness and report timeliness, in the healthcare system (Nasir, Gurupur & Liu 2016:4). A similar study conducted in the United States in 2019 found that practical data review meetings are likely to be an effective tool for improving data analysis skills and motivating healthcare workers in healthcare facilities (PAHO & WHO 2019:44).

Even though the development of the HIS to address data analysis gaps in LMICs has received significant and critical attention in recent years, there is a shortage of skilled healthcare providers to perform data analysis and support evidence and interventions in healthcare facilities (Wagenaar et al. 2017:2). This finding is supported by a study conducted in North-West Ethiopia, which found that only 24% of healthcare workers had received data analysis training, while the vast majority had not (Dagnew et al. 2018:5). There is frequently fragmentation among healthcare facilities, healthcare workers, and decision-makers at all levels, with a lack of clarity about roles and responsibilities for crucial data analysis functions. As a result, lower-level health personnel frequently see themselves as data collectors and aggregators, and they believe that data analysis and interpretation are the responsibility of others (Measure Evaluation 2018:17). Inadequately standardized processes and a lack of guidelines for supporting data use activities also impede data analysis in the healthcare system (Wagenaar et al. 2017:8). Additionally, a study from Kenya found a lack of motivation and confidence in analyzing and disseminating data, which does not help to improve the functioning of the healthcare system at the level of the health facilities (Mucee et al. 2016:8). Similarly, a South African study found that a lack of understanding and ability to analyze, interpret, and use data for decision-making processes has been documented in health centres due to a lack of training and support (Nicol et al. 2017:7). This was confirmed by Dagnew et al. (2018:4), who discovered that in Ethiopia, HIS challenges are not adequately analyzed and justified, and the use of quality data for decision-making processes in the healthcare system is still low and unsatisfactory.

In summary, the analysis of data is vital for reducing patients' administrative and healthcare costs. This means that analytical output can facilitate a clinical decision and assess the effectiveness and workload of healthcare facilities. Moreover, patient status can be checked and monitored using evidence. Healthcare facilities can use analyzed evidence to learn more about their performance, see where they are missing, and improve their services. Hence, analyzed data can help generate evidence and improve the quality of services and customer and staff satisfaction in healthcare facilities.

2.4.4 Data presentation and dissemination

Data presentation refers to the organization of data into tables, graphs or charts so that logical, statistical and subject-matter conclusions can be drawn from the measurements collected. On the other hand, data dissemination refers to the distribution or transmission of statistical data to end users (In & Lee 2017:8). Data presentation is the fourth and essential phase in the processes of data management. Thus, the analysed data/information should be well-presented in an effective format regardless of the amount of data and information; otherwise, it would be a significant loss for both users and readers (In & Lee 2017:8). Text, tables and graphs are effective for data and information presentation. Written and summarized reports, dashboards, special interest papers, and policy briefs are important user-dissemination media (In & Lee 2017:8). In this regard, healthcare managers are in charge of developing and disseminating a wide range of information products to end users. The products are then evaluated and interpreted in collaboration with the individuals who generate the data and those who use the data to achieve program outcomes (Measure Evaluation 2019:31). For example, Liberian health facilities have used charts and tables to demonstrate their performance (Republic of Liberia Ministry of Health and Social Welfare 2016:29).

Every day, approximately 800 women worldwide die from preventable causes related to pregnancy and childbirth, which could be reduced by improving maternal health data quality at all levels, particularly in healthcare facilities (Tarekegn, Lieberman & Giedraitis 2014:2). Antenatal care visits, skilled birth attendance, and postnatal care visits have been displayed and communicated in some Ethiopian healthcare facilities with the goal of improving maternal healthcare quality and service utilization (Tarekegn et al. 2014:6). In a similar Ethiopian study, healthcare facilities tracked and displayed maternal health indicators such as the ANC first and fourth visits, skilled birth attendance coverage, and post-natal care visits using charts and graphs (Wilunda, Tanaka, Putoto, Tsegaye & Kawakami 2016:6).

Findings from Western Ethiopia, on the other hand, show that only 7.2% of public healthcare centres used charts and tables to display data, with the vast majority not displaying any data at all (Asemahagn 2017:9). Similarly, a study conducted in North-West Ethiopia discovered that only 24% of healthcare facilities used charts to present their data (Dagnew et al. 2018:5). The above-mentioned findings show that data presentation was 44% higher in Liberia than in Ethiopia. Despite the fact that there has been a slight improvement in the practice of data presentation in Ethiopia in 2018 (24%) compared to 2017 (7.2%), this is still 61% lower compared with ≥85% national standards.

The quality of data presentation and dissemination are linked to understanding indicators, data elements, and reporting formats. It is evident from the above literature that the value of data collection and collation is not adequately established; data are not sufficiently analysed, justified and presented at the level of healthcare facilities. Hence, the use of quality data for decision-making is still low in LMICs. Overall, the four components of the data management process are essential for evaluating and monitoring various healthcare programs and patient care management. Figure 2.5 below shows the links between data management processes and key data quality dimensions.

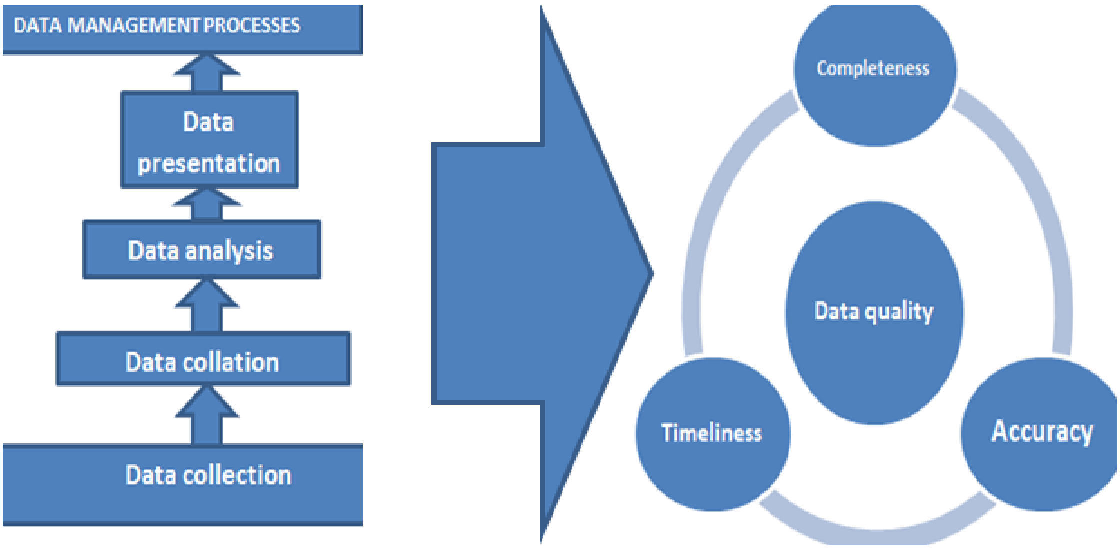

Figure 2.5: Summary of data management processes and data quality dimensions

2.5 DATA QUALITY

Data quality is defined as data suitable for use and which meet specified healthcare system data quality standards. This definition states that data quality is dependent on the purpose of data use (Measure Evaluation 2018:3). Thus, data quality is a contextual and multi-dimensional concept; and this is expressed in different dimensions; the selection and definition of the dimensions depend on the data types and field purpose (Gimbel, Mwanza, Nisingizwe, Michel, Hirschhorn, Hingora et al. 2017:6). The dimensions of data quality are articulated and measured by completeness, relevance, consistency, timeliness, accuracy, and accessibility (Yu, Liu, Wang & Cao 2014:3). Hence, these data quality dimensions are useful to define and examine the performance of the HIS in relation to data management processes and information use practices in a given healthcare system (Yu et al. 2014:3). Essentially, to ensure high data quality, a wide range of policies, strategies and data management processes are necessary. The management of data quality, including regular local data quality controls; data checking prior to use; up-to-date training and frequent written feedback to data collectors and users, is significantly essential to measure and improve the healthcare system performance at all levels (Health Metrics Network [HMN] & WHO 2012:45).

In this perspective, accessibility is defined as data elements and indicators that are easily available and legally permissible for various users in the healthcare system. This dimension of data quality is used to evaluate the degree of data accessibility in the healthcare system. Consistency is defined as how the value of data elements and indicators are the same across registers, tallies, reporting forms and databases to evaluate the data reliability. Simultaneously, data relevance is defined as how data are meaningful to and useful for the performance of the process or application for which they are collected (Hovenga & Grain 2013:14).

The current study focuses primarily on three dimensions of data quality: completeness, timeliness, and accuracy. Completeness is applied to quantify the percentage of data elements and indicators fully recorded in the registers of public healthcare facilities. Completeness is also used to measure the percentage of public health centres reporting to the next level of the health system on a regular basis (Gabr et al. 2021:11). Timeliness refers to the submission of all types of reports to the next level based on the pre-defined national and standard reporting time (Gabr et al. 2021:16). Accuracy is important to compare data in registers with tally sheets, reporting forms and DHIS2 databases of the public health facilities in a given study month, while it is also important to compare the value of data elements and indicators between the HMIS tools including register, tally sheets, reporting formats, and DHIS2 databases (Yu et al. 2014:3).

Thus, data quality management at the healthcare facility level is a backbone for planning, performance measurement, policy formulation and healthcare system clinical decision-making (EFMOH 2016:9). Healthcare workers at lower levels of the healthcare system frequently lack time to cross-check data quality and regard data-related tasks as of low priority in health facilities due to competing demands, resulting in poor data quality and limited use for various decision-making processes (Yarinbab & Assefa 2018:7).

2.5.1 Data accuracy

Accuracy of data refers to data measurement against a referenced source and is found to be correct and consistent (Gabr et al. 2021:3). This was supported by the Measure Evaluation (2018:9), which found that consistent data quality audits and data review meetings improved the accuracy of routine data in Mozambique and Zambia. As a result, in Malawi, the value of an antenatal care visit (ANC) was found to be accurate across all the HMIS data sources, including registers, reports, and the DHIS2 software (O'Hagan et al. 2017:10). Likewise, a 2016 Rwanda study confirmed that 73.3% of healthcare facilities reported accurate data to the next reporting levels to support various decision-making processes (Innocent et al. 2016:5). Furthermore, in Uganda, 65% of healthcare facilities have reported accurate immunization data to the next level (Nsubuga, Luzze, Ampeire, Kasasa, Toliva & Riolexus 2018:4). A similar study published in Ethiopia found that 48% of healthcare centres reported accurate data to the next level (Yarinbab & Assefa 2018:7). These could be strengthened further if selected and measurable data quality assurance interventions are well-identified, documented, and used in conjunction with feedback loops, supporting supervision, mentoring, and training to be most effective in improving data accuracy (PAHO & WHO 2019:44). In this case, basic data quality training has been identified as one of the effective interventions in ensuring data accuracy; for example, 58% of trained healthcare workers in Malawi have been involved in ensuring the accuracy of routinely collected data at the service delivery unit (O'Hagan et al. 2017:8).

While data accuracy shows significant progress in managing data quality to support healthcare decisions, some challenges to data accuracy have been identified. This means that inaccurate data have resulted from data recording, collection, compilation and entry due to a lack of competency, motivation and commitment. It is, therefore, essential to compare data with the real world in order to justify and evaluate data accuracy (Anasel et al. 2019:17). A recent study from Tanzania showed that data from the outpatient department of healthcare facilities were inaccurate between registers and reporting formats and the data in tally sheets were often inconsistent with the data in the registers, which therefore did not match the data in the summary report (Anasel et al. 2019:18).

In Ethiopia, data accuracy in health facilities remained less than 85% of national standards. This means that, for example, 52% of public healthcare centres in western Ethiopia did not regularly check the accuracy of data elements and indicators against the national standards. As a result, a lack of data accuracy in health facilities has impacted the quality of standard health service use (Yarinbab & Assefa 2018:7). For that reason, these identified gaps are glaringly evident at a moment when the accuracy of healthcare data becomes a basic pillar of multiple decision-making processes at all levels (Alipour & Ahmadi 2017:2). Furthermore, these studies would have been more substantive when workable strategies for addressing data accuracy determinants had been reviewed, validated, and justified concerning the Ethiopian context.

2.5.2 Data timeliness

Timeliness refers to the extent to which the data age represents reality from the time required. Thus, timeliness is very important as the most current data has more potential to be considered high-quality data (Health Metrics Network [HMN] & WHO 2012:38). It is a fundamental aspect of data quality to ensure various decision-making processes. Also, well-organized and timely accessible data drives better evidence-based decisions and understanding of what to expect in the future of the healthcare system (Tripathi et al. 2018:8). A study conducted in Rwanda shows that 93.8% of health facilities reported data on time to the next reporting level to support decision-making processes (Innocent et al. 2016:5). A similar study conducted in Nigeria in 2019 showed that 84% of reports were submitted on time to the next reporting level (Bhattacharya et al. 2019:7). Evidence of reporting timeliness from studies conducted in Ethiopia showed 59.6%, but two years later, in 2018, there was a slight improvement with 70% in public healthcare centres (Abera, Daniel, Letta & Tsegaw 2016:10; Yarinbab & Assefa 2018:4). In comparison with Rwanda, Ethiopia scored 33.5% lower in reporting timeliness. Two years later, timeliness was 23.8% less than that found in Rwanda and 20% lower than the Ethiopian national standard. This means that the health system was not responding to the community demand for high-quality healthcare services on time due to the accessibility of poor data quality (Yarinbab & Assefa 2018:7). Thus, this evidence provides a basic clue to how the current study is relevant in assessing the magnitude and factors associated with timeliness of data generated in the healthcare centres as well as in developing validated and effective strategies to strengthen the HIS in Ethiopia.

2.5.3 Data completeness

Completeness is achieved when all data elements and indicators are recorded on registers, summary sheets, reporting formats and the DHIS2. This dimension of data quality is used to determine which data are missing and whether omissions are acceptable. It is also used to compare the proportion of recorded data elements and indicators against the required standards (Gabr et al. 2021:11). Data completeness is one of the most important dimensions of data quality and has been measured in terms of the percentage of expected data values present across various data sources including register, tally sheet, reporting form, and database (Adejumo 2017:38). According to Nsubuga et al. (2018:4), more than 90% of Ugandan health centres reported complete data on immunization to the following levels. This could have resulted from a number of well-targeted interventions that improved data quality. For example, a study conducted in Nigeria found that after providing basic data quality training to healthcare providers, facility reporting completeness increased significantly from 54.5% to 90.9% at the end of three months (Nwankwo & Sambo 2018:4). In Western Ethiopia, 42% of health facilities sent complete data to the next level, creating an opportunity for information to be more likely to be used when making decisions than was the case with those who did not send a complete report (Fikru & Dereje 2018:5).

Even though data completeness has improved significantly, in Nigeria, 22.7% of healthcare facilities did not send complete data to the next level (Adejumo 2017:38). In Ethiopia, data incompleteness was three times higher than in Nigeria, with 71% of healthcare centres failing to fill out data in tally sheets and reporting forms completely, thereby influencing various decisions at all levels (Teklegiorgis et al. 2016:7-8). This is further supported by the fact that, on a monthly basis, 22% of data elements and indicators in Ethiopia are reported incompletely (Yarinbab & Assefa 2018:7). Generally, if data is complete, accurate, and readily available on time, it can influence various decision-making processes to help managers, policymakers, and patient care providers both theoretically and practically. The goal of the HIS is to generate high-quality data that can be used in evidence-based decision-making processes.

2.6 INFORMATION USE IN HEALTHCARE

Information use at the healthcare facility level is primarily defined in three ways: (1) information repackaging and dissemination, (2) performance review and use of written feedback, and (3) evidence-based decision-making processes (FMOH 2015:157). The use of data and information is critical and important across various health system activities to promote and maintain the quality of primary, secondary, and tertiary healthcare systems (FMOH 2015:114). This is possible if there is a significant and powerful health information system that supports the generation and management of complete, accurate, and timely data to ensure the effective utilization of healthcare information, including maternal health data, at all levels of the healthcare system (Muhindo & Joloba 2016:4).

Significant practice and adequate experiences in information-use culture have the potential to improve and create a cycle that leads to improved patient care management, health programs and policies, as well as improved effectiveness and sustainability of health systems at all levels (Mucee et al. 2016:2). This is supported and confirmed by a study conducted in Malawi, which found that data and information were used for performance tracking and improving healthcare service utilization in healthcare facilities (O’Hagan et al. 2017:9). Similarly, in Rwanda, 24% of healthcare facilities used information to make decisions about health service coverage, disease trends, medicine consumption, vaccine wastage, monthly income and expenditure (Innocent et al. 2016:9). A similar finding from Ethiopia in 2016 indicated that health centres that have tracked their effectiveness are more likely than others to use data on decision-making processes (Abera et al. 2016:12). In this case, data was used to make decisions in only 51.3% of Ethiopian healthcare facilities including the maternal healthcare services (Shiferaw, Zegeye, Assefa & Yenit 2017:4).

According to an Ethiopian study, healthcare facilities planned to discuss and make decisions on important public health indicators, including maternal health indicators such as skilled birth attendance, family planning use, Penta 3 vaccination, and pneumonia in children under the age of five, but only 42.9% of the selected health indicators received decisions compared to the plan (Gebreslassie et al. 2020:3). When maternal health data from facilities are of sufficient quality, the data can be used for effective clinical care and management at the facility level, as well as to review policies and resource allocation at the regional and national levels. This means that high-quality facility-maternal healthcare data can be used to produce accurate estimates of service delivery coverage at all levels of the health system, allowing communities to determine whether they are getting the services they need, such as the proportion of facility births attended by a skilled health worker (Bhattacharya et al. 2019:2).

However, according to a study conducted in three parts of Ethiopia, only 32.1% of health workers in Gondar, 32.9% in Jimma, and 45.8% in East Gojam use data for decision-making to assess maternal healthcare service utilization, service quality and coverage (Gebreslassie et al. 2020:4).

It is reasonable that in a well-functioning healthcare information system with well-trained people, well-defined standards, and adequate support, the information needed to make evidence-based decisions could be produced (Muhindo & Joloba 2016:4). In practice, HIS-related supporting supervision and written feedback from higher levels were insufficient and unsatisfactory for improving service quality and the use of data to make appropriate decisions (Akhlaq et al. 2016:13). A Benin study confirmed this reality, revealing that data dissemination and use in healthcare facilities or departments remain insufficient due to technical, organizational, and behavioural factors (Ahanhanzo, Kpozehouen, Sopoh, Sossa-Jérôme, Ouedraogo & Wilmet-Dramaix 2016:5). In Ethiopia, data quality, accessibility, and utilization remain low throughout the healthcare system, particularly in healthcare facilities. In this case, policymakers, program managers, and healthcare leaders use healthcare information less than they should in making evidence-based decisions about healthcare programs and policies (EFMOH 2016:9).

2.6.1 Information repackaging and dissemination

Information repackaging is a way to organize analysed data or information in a form that is more appropriate and usable to users. This systematic process is important for adding value to the information services in order to save time and costs for each user (Dongardive 2013:1). This is important to interpret and convert information into a form that can be easily understood by the different target users to improve healthcare services utilization (Radhakrishnan & Francis 2018:1). The steps involved in repackaging information include: identifying user knowledge about how to use information; identifying the type of information needs; selecting the appropriate format for repackaging information; and choosing the appropriate channel for distributing information (Radhakrishnan & Francis 2018:4).

Many health information technology innovations were developed in the preparation of comprehensive information and evidence in formats that are capable of capturing the attention of users and policymakers; also, with the re-packaging of information in great detail, a health information system can be used to draw readers with evidence and the healthcare system can be progressively improved (Health Metrics Network [HMN] & WHO 2012:46). Thus, some new computerized analytic tools generate standardized reports which are helpful for information repackaging. Also, standardised reporting formats, profiles and briefs are highly effective in repackaging information (Chen et al. 2014:15). In Tanzania, for example, health organizations generate much information in the form of guidelines, technical reports, journals, manuals, leaflets, brochures and booklets (Chipungahelo, Haruna & Ndege 2015:3). As a result, it is critical to receive written feedback from a wide range of users to identify problems, reflect new needs, and add features that could be improved during the next cycle of information re-packaging (Mucee et al. 2016:3).

The repackaged information should be disseminated to users. Thus, the new and relevant information is used to share information for various purposes such as better performance management, strategic and annual planning, advocacy, and policy development (Health Metrics Network [HMN] & WHO 2012:46). In this case, three key elements of dissemination need to be well-defined and addressed: first, the content of the message to be transmitted; second, the layout or format for communicating information; and third, the route of communication with users. As a result, information produced in public healthcare centres, where staff and the communities can access it, should be disseminated adequately and regularly (Chen et al. 2014:15). Besides, to address the link between request, supply and quality of healthcare data, a culture in which information is needed should be promoted. Hence, different types of information at diverse levels of the medical system are now obtained and used by several stakeholders. For example, healthcare providers use patient care data; managers require that information for improving efficiency and efficiency; planners rely on operational decision statistics; and policy-makers use healthcare information to prioritize and allocate resources (Health Metrics Network [HMN] & WHO 2012:46).

Even though repackaging and disseminating information is a critical component of using health information, most developing countries have been limited in this within the health system due to insufficient staff training, poor health information infrastructure, and irregular electricity supply (Ugwuogu 2015:6). This is supported by research from South Africa, which revealed that information was not repackaged and disseminated at the level of healthcare facilities due to a lack of basic skills in how to repackage and disseminate information in a simple, easy-to-understand, and usable format (Nicol et al. 2017:7).

2.6.2 Performance review and feedback utilisation

The Measure Evaluation has developed a Performance of Routine Information System Management (PRISM) framework to assess and evaluate the routine health information system (RHIS) (Muhindo & Joloba 2016:4). This approach mainly focuses on improving data quality and information utilization across the healthcare system. Furthermore, for standard performance evaluation techniques at the healthcare facility level, facility records such as patient-based and aggregated data and administrative data are required for health managers and healthcare workers to determine resource requirements, healthcare service quality and utilization (Chen et al. 2014:8).

The aforementioned facts were reinforced by O'Hagan et al. (2017:11), who stated that health facilities with complete routine data were more likely to analyze performance and service utilization regularly than those without complete data. Targeted and effective interventions could accomplish this at all levels. For example, peer learning networks have been a useful strategy in health institutions for sharing health information and discussing written feedback. Feedback must involve a two-way flow of information between supervisors and health professionals in order to be effective in problem-solving (PAHO & WHO 2019:48). This was demonstrated further in Kenya, where productive and effective written feedback provided to healthcare practitioners had a positive impact on the process and quality of healthcare service utilization (Mucee et al. 2016:41). Similarly, an Ethiopian study found that the quality of data was 3.5 times better in healthcare centres that received written feedback regularly following a post-review meeting compared to those that did not (Teklegiorgis et al. 2016:6). This was confirmed by O'Hagan et al. (2017:11), who argued that effective written feedback, along with other interventions such as the availability of data management standards, could significantly improve the overall data quality and information use expectations at all levels of the health care system.

Feedback is conceptually and practically an essential component of the cycle of the use of healthcare information, facilitating open communication and encouraging discussion and problem-solving. However, healthcare facilities and their health workers in developing countries rarely receive written and inclusive feedback on the HIS. Where feedback is provided, it tends to be unconstructive, outdated, and unproductive (Dehnavieh et al. 2019:2). As a result, the practice of performance review and measurement based on evidence is generally insufficient to address different decision-making processes in healthcare facilities. For example, 51% of healthcare facilities in Liberia did not receive regular and written feedback from higher levels on data management and information use (USAID 2012:8). Similarly, 40% of public healthcare facilities in Ethiopia did not hold a monthly performance review meeting, and there was no dissemination of written feedback at the health centre level (Teklegiorgis et al. 2016:7).

2.6.3 Data-driven decision making

Decision-making is an important part of the management cycle because it allows many users to make evidence-based decisions at different levels in the healthcare system (Measure Evaluation 2018:8). Healthcare facility managers frequently want high-quality data for decision-making processes to increase human resource availability, to determine disease trends and decide healthcare service coverages (Measure Evaluation 2015:6). These findings were verified by studies conducted in Tanzania and Morocco, which demonstrated that data-driven evidence was used to assess and evaluate healthcare system performance and harmonize priorities at multiple levels (Anasel et al. 2019:28; Le-pape, Suarez, Mhayi, Haazen & Ozaltin 2017:9). Similarly, 46 per cent of South African health facilities used data to make decisions on planning, budgeting, and progress tracking (Nicol et al. 2017:4), compared to 38.4 per cent of Ethiopian healthcare facilities (Asemahagn 2017:8).

Despite tremendous improvements, data-driven decision-making processes have lagged far behind expectations, particularly in healthcare contexts. Evidence-based decision-making in low- and middle-income countries' healthcare facilities is frequently influenced by donor policy and demand (Measure Evaluation 2018:14). This could be exacerbated by frequent fragmentation across levels among healthcare facilities, healthcare workers, and decision-makers, as well as a lack of clarity on roles and responsibilities for essential functions in data administration and information use, resulting in data that are frequently not used to make data-driven decisions such as budget allocation processes (Measure Evaluation 2018:15). Furthermore, some HIS interventions were identified to be less likely to ensure continuous information use if they are not accompanied by leadership support and follow-up at all levels (PAHO & WHO 2019:36). The facts stated above are consistent with the Tanzanian study which found that data utilization for policy and decision-making is very limited, particularly in lower-level healthcare facilities, due to a lack of a forum in the healthcare system for policymakers, researchers, and healthcare workers to share and discuss data issues (Somi, Matee, Wengaa, Darcy & Perera 2017:6). Similarly, policymaking decisions in Ethiopia are fragmented and disorganized due to competing interests of various users and agencies, resulting in significant and considerable health data remaining underused to improve organizational effectiveness and community need (Dagnew et al. 2018: 5; Yarinbab & Assefa 2018:7; Abera et al. 2016:10). For that reason, data-driven decision-making barriers will be used as a guide in this study to investigate verified HIS interventions in depth.

2.7 DETERMINANTS OF DATA MANAGEMENT AND INFORMATION USE

The Performance of Routine Information System Management (PRISM) framework consists of tools for assessing HIS performance and identifying technical, behavioural and organizational factors influencing HIS; assisting in designing priority actions to improve performance; and improving the quality and use of health data (Measure Evaluation 2018:12). Consequently, it could be used in research to assess the effectiveness of HIS interventions that include: improving data interpretation and using problem-solving skills, improving computer use; promoting information use; strengthening governance and financial resources to sustain RHIS activity (Anasel et al. 2019:27). In addition, this framework can be used to assess routine health information system (RHIS) performance, processes, and its major organizational, technical, and behavioural determinants. These tools can be used to monitor changes in RHIS data quality and use of information; RHIS processes and task skills; and the promotion of information culture (Measure Evaluation 2019:8). In this regard, the theoretical framework of PRISM is significant to manage data and information that can be used to plan, monitor and evaluate the effectiveness of health services against the predefined objectives. In this study, data management and information use determinants are classified as technical, organizational, and behavioural.

2.7.1 Technical determinants

Technical determinants are defined as the specialized know-how and technology required in developing, managing, and improving routine health information system processes and performance (Measure Evaluation 2015:88). The main focus is on the competency of users to work on a computer, interpret HMIS manuals, and understand how to manage data processes. For example, if indicators are irrelevant, data collection forms are complex to fill in, and if computer software is not user-friendly, the confidence level and motivation of routine users of the HIS will be affected. In this regard, computer literacy continues to be a challenge in LMICs, for example, a study in Kenya showed that only 63.5% of health workers had computer skills to manage electronic medical records in health facilities (Nandikove, Mwaura-Tenambergen & Njuguna 2017:6). Furthermore, the availability of standard reporting tools as well as the user-friendliness of routine HIS tasks were significantly linked to improving the quality of data management and information use practices in Kenya at the level of healthcare facilities (Kirimi 2017:36). At the same time, at healthcare facilities in Kenya, 51.2% and 23.1% of healthcare providers had computer knowledge and competency to check data accuracy, respectively (Kiilu et al. 2015:3). Similarly, a study from Ethiopia indicates that healthcare facilities with skilled manpower on the use of computer for data management and information use were three times more likely to manage data and use information than health facilities without such attributes (Teklegiorgis et al. 2016:6).

In 2017 a South African study indicated that most clinicians lack numerical analytical skills to manage and analyse data and have a lack of understanding of the definitions of certain data elements and indicators in the healthcare system (Nicol et al. 2017:10). A similar study reveals that lack of competence in data collection, compilation, and analysis as well as multiple HIS tools that consume time in filing, and a lack of computers to handle data, were identified as technical factors that adversely affected the use of health management information in Kenya's healthcare facilities (Mucee et al. 2016:8). Another study confirmed that 75% of healthcare workers in Ethiopia did not know the details of national health indicators, and 70% of these healthcare workers could not manage, analyse and present data at the level of public healthcare facilities.

As a consequence, technical and leadership decisions regularly had limited support from evidence (Dagnew et al. 2018:5). Briefly, from global to national perspectives, the effects of technical determinants as obstacles and facilitators on HIS in healthcare facilities are well-articulated and documented. As a result, this study intends to link these findings to current research to guide feasible and applicable strategies to strengthen the health management information system in Ethiopian healthcare facilities.

2.7.2 Behavioural determinants

A behavioural determinant is defined as knowledge, skills, confidence and motivation to manage data and use information in healthcare facilities (Measure Evaluation 2015:88). RHIS processes and performance are directly linked to the level of confidence, motivation and competence of data producers and users to perform HIS tasks. Specifically, limited knowledge of the usefulness of RHIS data has been found to be an important factor in low data quality and use of information. The PRISM framework suggests that if people understand the utility of RHIS tasks, and feel confident and competent to perform the RHIS task, then they will complete their tasks properly. For example, a study conducted in Kenya shows that the ability to check data quality, level of motivation, confidence and competence to perform health information system tasks has been identified as significant factors in improving the quality of data management and information use practices (Kirimi 2017:40). In addition, an Ethiopian study shows that an average level of confidence of health professionals in checking the dimensions of HMIS data quality in healthcare facilities was 60% (Dufera, Lamenew, Demissie & Guda 2018:5).

South African research shows that the lack of motivation of healthcare workers towards tasks related to the HIS was highlighted as a factor that hinders the quality of data collection. Some staff, for instance, either did not carefully fill in the registers or did not collect data properly (Nicol et al. 2017:9). Furthermore, a Ugandan study shows that most healthcare workers view data collection activities separately from clinical care. As a result, they did not feel motivated towards simultaneous participation in data collection and clinical care tasks (Muhindo & Joloba 2016:3). Another study in Ethiopia shows that 86% of healthcare workers were unable to compile, analyse and interpret routine data to identify and prioritize gaps, and thus to set targets in healthcare facilities due to a lack of basic skills in data management processes (Dufera et al. 2018:5). Most health workers were poorly trained and unable even to manage, interpret and use data. And then, the level of confidence, motivation and competency towards data management processes and information use was unsatisfactory at the level of healthcare facilities due to a lack of incentives and feasible strategies to strengthen the health information system in the healthcare facilities.

2.7.3 Organizational determinants

An organizational determinant is defined as the availability of strategies, a plan, a culture of information use, internal supervision, motivation, staff empowerment, training, accountability, and budget allocation to manage data and use information in health centres (Measure Evaluation 2015:88). The availability of the RHIS planning and data management; the provision of supportive supervision and written feedback; and the promotion of data management and information use culture are all important to the development, management and improvement of RHIS processes and performance. In the public healthcare facilities of the LMIC settings, organizational factors continue to be more influential. A study in Kenya, for example, shows that supportive supervision, promoting of an information use culture and staff training have been identified as statistically significant in improving the quality of data management and information use practices in the healthcare system (Kirimi 2017:40). A systematic review of data quality and information use of low- and middle income countries conducted in Pakistan reveals that providing training to staff and healthcare professionals has been found to be the most significant facilitator for the management and use of health data and information in the healthcare facilities (Akhlaq et al. 2017:13). Similarly, 45.5% and 28.9% of healthcare workers in healthcare centres in Ethiopia received regular feedback on data quality and use of information as well as basic training, respectively (Shiferaw et al. 2017:4). Also, in Ethiopia, healthcare centres that had trained healthcare workers to compile reporting formats and summary sheets were 2.53 times more likely than those without qualified healthcare workers to manage data and use information (Teklegiorgis et al. 2016: 6).

While remarkable progress in improving data management and information use can result from positive changes in organizational determinants, many studies have identified a negative impact caused by organizational determinants. For example, the lack of a written HMIS plan and feedback, limited internal supervision, and work overload were identified as major factors impeding data quality tasks, with uncollected data sometimes left for months in healthcare facilities in South Africa (Nicol et al. 2017:9). A systematic review carried out in Pakistan reveals that lack of written feedback, supporting supervision, and basic training was recognized as the greatest barrier to effective data management and use in the health care systems of low- and middle income countries (Akhlaq et al. 2017:13). In addition, 58% and 46% of public healthcare centres in Ethiopia did not receive internal supportive supervision and regular written feedback (Dagnew et al. 2018: 5). In summary, regular rewards for good data management and information use work were not provided, staff were not empowered and motivated to make decisions, and accountability was not practised for good or poor performance in data management and information use practices. In addition, there was no practice-based training on recording, compiling, analysing, interpreting and presenting information at the health facility level (Davidescu, Apostu, Paul & Casuneanu 2020:24).

2.8 KEY DETERMINANTS OF MATERNAL DATA QUALITY AND USE

Maternal healthcare is an important program among public healthcare programs at all levels, from global to local, and it requires special attention by identifying and addressing key determinants of data quality and use at all levels, especially in healthcare facilities (Bhattacharya et al. 2019:3). Technical factors like the number and complexity of maternal health reporting forms, and a lack of guidelines and protocols, added to the system's burdens and contributed to poor maternal data quality and use (Ismail, Alshmari, Latif & Ahmad 2017:6). In addition to that, organizational factors like a lack of routine feedback and supervision at all levels, especially in healthcare facilities, have hampered the quality of maternal health data and the consistent use of information in Nigeria (Bhattacharya et al. 2019:16). Similarly, Lemma et al. (2020:9) identified determinants for improving maternal data quality and use at all levels, particularly in healthcare facilities, such as annual data quality assessments, feedback using a summary data quality ranking tool, targeted supportive supervision for service units with poor data quality and use, and data quality and use-related training.

Additionally, peer review of performance on common maternal data quality issues after healthcare facilities presented their status, as well as a lack of knowledge, skills, and training, have all been identified as determinants of maternal data quality and use (Ismail et al. 2017:6). The findings summarized in this section confirmed that technical, organizational, and behavioural factors had been identified as determinants of maternal health data quality and use at all levels of the healthcare system, particularly in healthcare facilities.

2.9 SUMMARY

This chapter presented and described a global, African and Ethiopian view of the health information system achievements and challenges. It has documented and elaborated on the key improvements and gaps in data quality dimensions, focusing on data accuracy, timelines and completeness. Additionally, it has reviewed the status of four components of data management processes: data collection, data compilation, data analysis, and data presentation. Moreover, the three key dimensions of information use practices, including information repackaging and dissemination, performance review and feedback utilisation, and evidence-based decision-making, were discussed and documented. Finally, the factors that influence the data management processes and information use practices, including maternal data quality (technical, organizational and behavioural), were described. The next chapter focuses on the research methodology of the study.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter describes the methodology that guided this study. It argues that the research pyramid approach and the theoretical framework present a logical flow. The purpose of this study was to develop strategies to strengthen health management information systems in Ethiopia. The chapter thus discusses the research approach, research design, and research methods throughout the three phases. The last section presents considerations regarding validity, reliability and ethics.

3.2 RESEARCH APPROACH

The research approach is a research plan and procedures that outline the steps from the broad assumption of research design, data collection method, data analysis, and data interpretation (Creswell & Creswell 2018:40). The researcher used a quantitative research approach because the nature of the collected data from the study variables was quantified as categorical or numerical values that could be used to describe the relationship between variables. Quantitative studies, according to Gray, Grove & Sutherland (2017:54), are intended to describe and investigate the relationship between quantifiable and measurable variables. These variables are numbers and are used to measure relationships between them. Data are collected from structured surveys in quantitative studies and can be summarized numerically. Thus, the justification for this quantitative investigation is that it seeks to produce principles and propositions that describe the study variables, in this case, data management and information use, which can be described using independent variables such as socio-demographic, technical, organizational, and behavioural factors that allow generalization to other similar situations (Gray, Grove & Sutherland 2017:109).

The research pyramid shown in Figure 3.1 below guided this study. The pyramid's primary function is to assist the researcher in learning to structure research processes consciously (Jonker & Pennink 2010:25). The research paradigm discussed in chapter one of this study focused on the basic assumptions of positivism. Methodology is the way in which a researcher conducts research, and it assumes that there is a logical order that the researcher must follow in order to achieve certain purposes and objectives, whereas the research method deals with specific steps of action that must be carried out in a specific order (Leavy 2017:16; Rajasekar, Philominathan & Chinnathambi 2013:5). The final component of the research pyramid is research techniques, which are focused on practical instruments or tools for data collection and analysis (Jonker & Pennink 2010:25).

Figure 3.1: The research pyramid (Jonker & Pennink 2010:23).

3.3 RESEARCH DESIGN

A research design is a set of formal procedures for data collection, analysis, and interpretation, such as those found in a quantitative, qualitative, or mixed study (Creswell & Creswell 2018:309; Gray, Grove & Sutherland 2017:195). In this study, a non-experimental quantitative descriptive design was used.

3.3.1 Quantitative research

A quantitative approach defines the relationships between dependent and independent variables and generates numerical outputs that can be descriptive, inferential, or both (Bordens & Abbott 2011:38). This study used a quantitative research approach. This approach is frequently regarded as purely scientific, justifiable and founded on facts that are frequently reflected in exact figures (Jonker &

Pennink 2010:38). According to Kothari (2004:3), this approach is appropriate for research questions that can be expressed and determined in terms of quantity or numerical descriptions. This approach entails both detailed statistical descriptions and generalizability (Leavy 2017:87).

This methodological approach is based on logical designs that aim to gather evidence in support of specific theories and hypotheses (Leavy 2017:87). This method is most commonly used to investigate the causal relationships or associations between dependent variables such as data management and information use, and independent variables such as socio-demographic, technical, behavioural and organizational factors (Pruzan 2017:87). Its goal is to answer defined research questions. In this study, this was the best method for determining and quantifying the quality of maternal data produced in public health centres, as well as for measuring how technical, behavioural, and organizational factors influenced data management and information use. It was also appropriate for quantifying how much information in healthcare centres was used in decision-making.

Quantitative data are expressed in either descriptive, inferential, or both ways, and this was used to compute study variables in percentages, averages, and variations (minimum and maximum). It was specifically used to assess the accuracy, completeness, and timeliness of data generated, as well as to determine the extent to which health information is used and the level of expert consensus on proposed HMIS strategies on an average and single score. Also, inferential data analysis was used to compute the associations between dependent and independent variables as positive, negative, or neutral. Therefore, this research was conducted in three phases as follows:

Phase I: In this phase, a retrospective quantitative documentary review was applied to evaluate the maternal health documents, including registers, tallies, reporting forms, data quality monitoring logooks, and databases. The documents included: family planning (FP), antenatal care (ANC), delivery services, postnatal care (PNC), and abortion care services. A standard checklist was developed to review the quality of the data generated from healthcare centres, with a special focus on the accuracy, completeness and timeliness of maternal health data elements and indicators. The insights from the data quality review were linked to organizational, technical and behavioural determinants of the second phase of this study. Therefore, this document review approach was an appropriate foundation for the second phase.

Phase II: This phase involved a descriptive cross-sectional survey to investigate the influence of technical, behavioural, and organizational factors on data management and to determine the extent of health information use in public health centres. A close-ended structured questionnaire was developed and pretested. Descriptive analysis was used to determine the magnitude of data management practices and the level of information use; inferential statistics was used to determine the strength and direction of the relationship and the levels of significance. Key findings from phases one and two that were integrated to arrive at new meanings in Phase II were used as a baseline for strategy development, indicating concrete evidence from two data sets.

Phase III: This phase involved the development of strategies for use in public healthcare centres in Addis Ababa. The rationale for this phase was to confirm strategies that could be used to improve data management and information use. This phase had three stages: preparation, implementation, and finalization. Potential experts were identified and defined as individuals with sufficient knowledge of the healthcare information system. The implementation phase was divided into two rounds. The level of expert consensus for each strategy, as well as the overall strategy, were determined. Five key validation criteria were established in the second round, and the same experts who participated in the first round validated the final HIS strategies.

3.3.2 Theoretical framework of the study variables, study phases and objectives

The theoretical framework that guided this study's variables, study phases, and study objectives are depicted in Figure 3.4 below. This figure also indicates the relationship and integration of the processes in phases one and two. Furthermore, the relationship between the independent variables and the alignment of each specific objective across the phases are demonstrated.

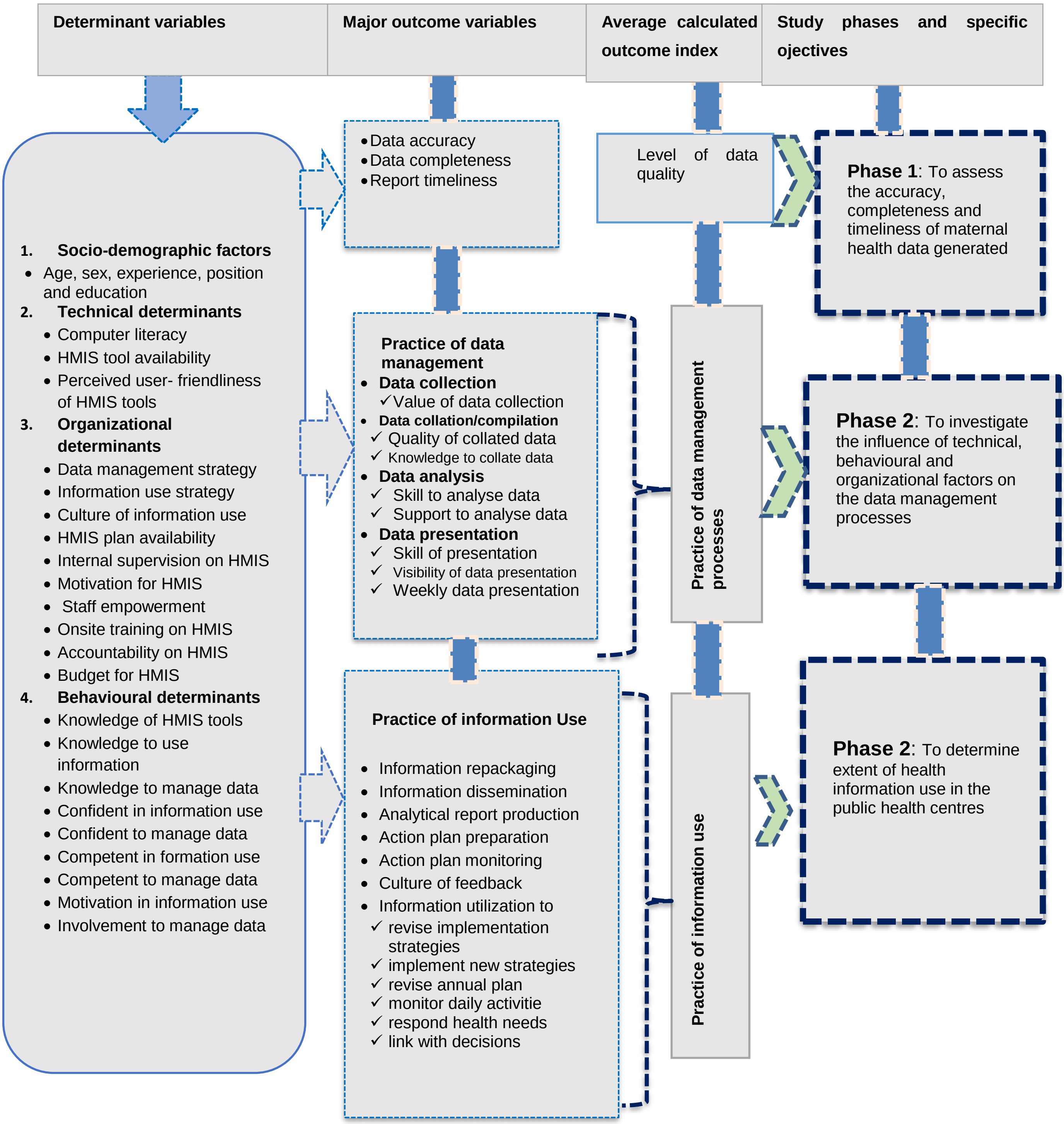

Figure 3.2: Theoretical framework of variables, study phases and objectives

3.4 RESEARCH METHODS

3.4.1 Study setting and period

This research was carried out in the Addis Ababa city administration, which consists of ten sub-cities and 117 districts. There are 110 public healthcare facilities in total, spread across ten sub-cities. Each healthcare centre has a three-tiered structure that includes the healthcare centre at the top, core processes in the middle, and case teams at the bottom. On average, 7800 health workers work in the city's public healthcare centres. The locations of the ten randomly selected healthcare facilities, as well as the pilot site, are indicated on a map in Figure 3.3 below.

Study period: In Phase I, the quantitative data was collected retrospectively from maternal healthcare documents of ten healthcare centres in December 2019. In Phase II, quantitative data were collected using a cross-sectional survey in May 2020. The modified Delphi technique was used in the third phase to develop and validate strategies from April 2021 to June 2021.

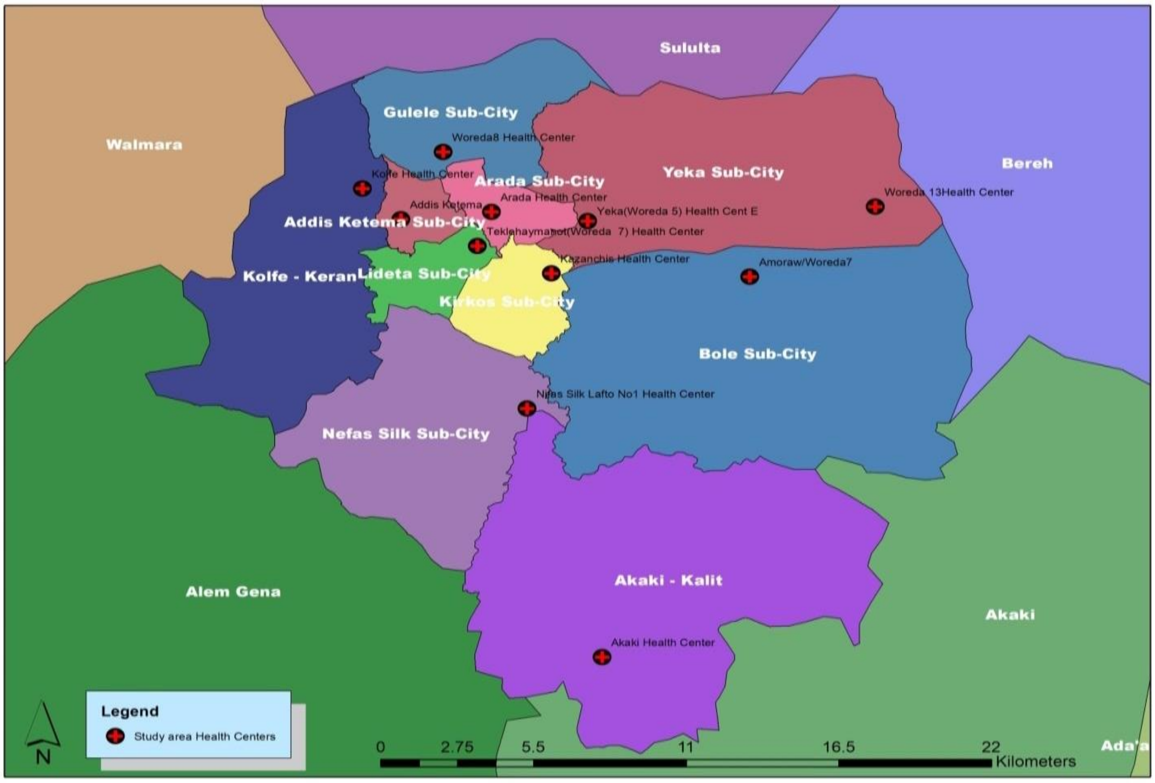

Figure 3.3: Map of Addis Ababa city and location of study public healthcare centres

3.5 METHODS FOR PHASE I

3.5.1 Retrospective document review

This study used a retrospective document review to assess the accuracy, completeness, and timeliness of maternal data. This type of document review is carried out after an event or data value that needs to be reviewed occurred in the past at a specific location, in this case, healthcare facilities (Laake, Benestad & Olsen 2007:255). This can also be used as a medical record review, which is a type of research design that uses a variety of data sources to answer one or more research questions, such as registers, electronic databases, diagnostic test results, and notes from health-care providers (Vassar & Matthew 2013:1).

In this study, this was defined as systematically collecting quantifiable data retrospectively based on the selected data elements and indicators from maternal health documents (registers, reporting forms, tallies, and DHIS2) across the selected healthcare centres; and then organizing and analyzing the collected data in relation to the defined data quality dimension such as accuracy, completeness, and timeliness. This design was chosen to evaluate maternal healthcare documents by identifying countable errors, omissions, or inconsistencies in order to measure the required data quality dimension (accuracy, completeness, and timeliness).

The quantitative retrospective method was chosen for this study because it has a clear beginning and end point and is used to quantify numerical data. It is based on a firm methodological approach that can be used to determine whether the researcher has operated correctly or not. It is further concerned with facts and verifiable information; it can capture vast amounts of data far faster than other research activities, and it is verifiable and can be used to duplicate results (Jonker & Pennink 2010:74).

Maano and Lindiwe (2017:2) used the quantitative retrospective review approach to assess and quantify the magnitude of reported occupational accidents, injuries, and diseases by reviewing all construction industry-related documents, such as notification forms and injury and accident registers. Also, Daz-Méndez and Adams (2021:3) applied a quantitative retrospective document review followed by descriptive data analysis in their study to quantify the magnitude of obesity related to diet and physical activity (Daz-Méndez and Adams 2021:3). A similar study was conducted, which used a retrospective quantitative document review at a large psychiatric hospital in Toronto, Ontario, to assess the quality of mental health data using five data quality indicators (Urbanoski, Benoit, Mulsant, Willett, Sahar & Rush 2012:3).

As a result, this study technique was deemed appropriate in determining the quality of maternal data produced in public health centres in Addis Ababa. It was also used to quantify and triangulate findings across multiple months, healthcare facilities, and HMIS data sources.

This review added value by obtaining key findings and linking those findings across the second and third phases of the study, allowing for conclusions in relation to the study questions and objectives. This means that value was added as a supplement to the second phase, which combined and interpreted findings as meta-inferences, and it was also used to support and lay the groundwork for the development of HMIS strategies to address the goal of this research.

3.5.2 Indicators and data elements used to review data quality

In this study, a total of 13 indicators and 25 data elements were reviewed across data sources that had been preplanned in advance. This translated to:

- Ten indicators and eight data elements were used to review data accuracy.
- Of the ten indicators, four of them, including family planning visit, the ANC first visit, skilled birth attendance (SBA) and early postnatal care visit (EPNC), as well as 17 data elements were used to review content completeness, as shown below in Tables 3.1 and 3.2.
- Finally, three indicators were used to review timeliness, as indicated below in Table 3.3.

The majority of technical and leadership decisions and basic interventions are being made without tangible evidence, resulting in the failure of many healthcare programs

(Chanyalew et al. 2021:9; Bogale 2021:7; Chen et al. 2014:15). This study focused on maternal health data.

The main reason for focusing on these indicators is their importance in monitoring and reporting at national, regional, and local levels. This means that maternal health in general, and specifically these selected indicators, constitute a top priority for Ethiopian health programs at all levels in order to determine the scope of the gaps to improve data quality.

Table 3.1: Indicators and data elements used to review data accuracy

SN	Indictors used to review accuracy	Data elements used to review accuracy
1	Family planning visit	1. New contraceptive users by age category
		2. Repeat contraceptive users by age category
2	ANC 1st visit	It is a count indicator that does not have a direct data element
3	ANC 4th visit	It is a count indicator that does not have a direct data element
4	Syphilis total tested	1. Test result-Reactive
		2. Test Result-Non-Reactive
5	Hepatitis total tested	1. Test result-Reactive
		2. Test Result-Non-Reactive
6	Skilled Birth Attendance (SBA)	It is a count indicator that does not have a direct data element
7	Live birth	It is a count indicator that does not have a direct data element
8	Maternal deaths	It is a count indicator that does not have a direct data element
9	Early postnatal Care (EPNC) visit within 7days	It is a count indicator that does not have a direct data element
10	Abortion care services	1. Safe abortion care performed
		2. Post-abortion care performed
	Total indicators=10	Total data elements=8

Table 3.2: Indicators and data elements used to review content completeness

SN	Indicators used to review content completeness	Questions used to review content completeness	Other data elements used to review content completeness
1	Family planning visit	Are the two data elements completely filled in under Counselling and testing?	1) HIV Test performed
			2) Target population code filled
2	ANC 1st visit	Are all the data elements completely filled in under personal information?	1) Serial number;
			2) Name of the client
			3) Medical record number
			4) Age
			5) Last Menstruation Period (DD/MM/YY)
			6) Expected data of delivery (DD/MM/YY)
		Are all the data elements completely filled in under HIV Assessment?	1) HIV Test accepted
			2) Target population code filled
		Are all the data elements completely filled in in under Counselling?	1) Infant feeding
			2) Identified and counselled on danger signs
			3) Family planning methods
			4) Maternal Nutrition
3	Skilled Birth Attendance (SBA)	Are all the data elements completely filled in under immediate postpartum family planning (IPPFP)	1) Type of contraceptive acceptance filled (New or repeat)
4	Early postnatal Care visit (EPNC)	Are all the data elements completely filled in under HIV Assessment?	1) HIV test performed
			2) Target population code filled
	Total indicators=4		Total data elements=17

Table 3.3: Indicators used to review report timeliness from the data quality monitoring logbook

SN	Reviewed indicators	Questions used to review report timeliness
1	Monthly report received date from case teams	Is the report received date from case teams documented in the data quality monitoring logbook (check logbook)?
2	Monthly written feedback on timeliness to case teams	Is written feedback about the reporting timeliness provided from the HMIS unit for case teams? (check written feedback)
3	Monthly report sending to next level via DHIS2	Has the Health Centre been reporting its service reports to the next level on a timely basis? (Check timeliness on DHIS2)
4	Total indicators=3	Total Questions on report timeliness=3

3.5.3 Data sources used to review data quality

Data sources: A total of five data sources, including registers, tallies, reporting forms, DHIS2, and a data quality monitoring logbook, were used to review maternal healthcare data quality.

Sampling: Healthcare centre selection: There are ten administrative sub-cities within the study area. In this study, one health centre per sub-city was chosen at random using a simple random sampling technique to review the data quality of selected maternal indicators. The maternal healthcare documents (registers, tallies, and reporting forms), as well as the data quality monitoring logbook, were identified, organized, and prepared at each randomly selected healthcare centre.

3.5.4 Data collection

The systematic gathering and measurement of quantitative values based on variables of interest in order to answer stated research questions and objectives are referred to as data collection. The primary goal of data collection is to collect adequate and reliable data for statistical analysis (Bairagi & Munot 2019:131; Abawi 2013:2). In this study, quantitative data were gathered through a retrospective document review.

3.5.4.1 Development and testing of the data collection instrument

A checklist was developed, pretested and used to review data completeness, accuracy and timeliness of the maternal health documents. This instrument was structured and closed-ended, as required in quantitative research. Maano and Lindiwe (2017:2), for example, used a checklist to conduct a retrospective review of quantitative data from notification forms and registers to assess the magnitude of reported occupational accidents, injuries, and diseases in Namibia. In this study, the checklist was designed to review registers, tally sheets, reporting formats, and DHIS2 data-bases. The checklist was appropriate to summarize, compare, and generalize the results of the document review easily. The following steps were followed:

- **First**, the type of documents to be reviewed (registers, tally sheets, reporting formats, DHIS2 bases and data quality monitoring logbook) was identified and prepared.
- **Second**, key data quality dimensions were identified, labelled and formatted into three sections such as accuracy, completeness and timeliness.
- **Third**, the numbers and type of responses per question were fixed; and clear instructions were written.
- **Finally**, the checklist was pretested, the result of the pre-test was discussed, and refinement was made to the instrument.

Pre-testing the instrument was important to maintain the quality of the research. In this case, the checklist was pre-tested in a single healthcare facility. The facility was not chosen as part of the main study facilities. This pretesting healthcare facility has met the study criteria. This means that the organisational structure, standards, working methods, and processes are identical among the Addis Abeba city's health centres. This shows that the public healthcare facilities managed by the city are held to the same standards and utilized similar workforces. Moreover, HMIS is a standard practise in every health centre within the city adminstration. The objective of the pre-test was to ensure the instrument's consistency and logical flow, as well as the language, structure, and design.

Findings of the pre-test of the instrument: Key findings from the pre-test were used to organize and order the flow and content of the checklist about data completeness. For example, during the pre-test, four levels of questions were used to review each of the following maternal indicators: family planning users, the ANC first visits, skilled birth attendance, and early postnatal care visits, whereas, after the pre-test, this was reduced to three levels of questions: (1) total cases documented in registers, (II) total cases completely filled in, and (III) total cases not completely filled in at least with one data element. Additionally, the definitions of data accuracy, data completeness, and report timeliness were added and labelled at the top of each page of the checklist after the pre-test to improve the quality of the review. The number of days required to review one healthcare centre was determined to be three days after the pretest.

3.5.5 Data collection processes

The data collection process or procedure is defined as the process of determining the type of data to be collected, establishing a timeframe for data collection, determining the type of data collection method, and collecting the data using the appropriate instrument (Chen, Yu, Hailey & Cui 2020:2). The following steps of data collection process were used: Permission letter and ethical clearance: As a first step, each head of a randomly selected healthcare facility received a permission letter and ethical clearance (Annexure 2 & 3). A pre-study site visit was held to discuss the study and review processes with administrative units at the facility. A pre-study discussion is a meeting with healthcare facility management and responsible bodies to establish a conducive and supportive environment based on review scheduling that allows familiarization with target documents and working conditions at each facility before starting the review (Gyanchandani, Mahatme & Motwani 2016:2).

Training of research assistants: Two research assistants with a bachelor of science (BSc) in health informatics and more than five years of experience in HMIS tasks in healthcare facilities were trained for two days on how to retrospectively review maternal healthcare documents (registers, tallies, reporting forms, DHIS2 and data quality monitoring logbook), one day during and one day after the pre-test. The assistants signed a confidentiality agreement. The researcher assistants assisted the investigator during the document review at the site level on a daily basis. The daily review feedback from each healthcare facility was shared among the investigator and research assistants to be used as a lesson for the next facility reviews. Maternal health registers, tallies, and report formats for family planning (FP), antenatal care (ANC), delivery service, postnatal care (PNC), and abortion care services, as well as the data quality monitoring logbook, were identified in collaboration with each healthcare centre's management team and responsible bodies; the research team then reviewed the documents. Finally, each facility HMIS officer logged into the DHIS2 database and generated the required data, which the research team then accessed and reviewed.

The extraction process was performed as follows: Each data source was identified, organized and prepared to allow for smooth data extraction. The checklist was printed, and the review began with accuracy, then completeness, and finally timeliness. This means that once a section was completed, it was cross-checked, cleaned, and any data errors or faulty data corrected across the reviewed months, indicators, and data elements before moving on to the next section.

3.5.6 Data preparation and statistical data analysis

Data preparation for analysis: The primary goal of data preparation was to ensure that raw data were accurately prepared for processing and analysis by identifying and correcting errors in order to validate data quality (Hameed & Naumann 2020:1; Abdallah, Du & Webb 2017:2). Preparing data has several benefits: it aids in the detection of errors, improves data quality, and saves time for data analysis processes; otherwise, errors become more difficult to understand and correct (Hameed & Naumann 2020:1). As a result, an Excel format for data entry was created first, followed by data entry. Microsoft Excel is a powerful tool for managing various types of data (Begum & Ahmed 2015:7). The data in the Excel spreadsheet were cleaned and maintained their original quality by comparing them to the original data source. It was cross-checked to identify missing values and arithmetic errors across the reviewed months, healthcare facilities, selected indicators, and data elements to ensure smooth data analysis.

Statistical data analysis is the process of converting raw data into a meaningful pattern using statistical tools. This means that data analysis contributes to the generation of meaningful information, which can then be interpreted to produce comprehensive field knowledge (Lengauer 2020:1). Data analysis is useful for describing and summarizing data, understanding the current situation based on the data, assisting in the interpretation of findings, and drawing conclusions and recommendations (Alem 2020:18). In this study, the primary goal of data analysis was to transform, evaluate, and understand the maternal healthcare data quality. The data from the retrospective document review was analyzed in Microsoft Excel, and key findings were presented in tables and graphs, followed by textual justifications (recommendations and conclusions). In particular, descriptive data analysis was used to assess measures of frequency distribution, central tendency, and variations, as listed below.

Descriptive data analysis: enable meaningful, understandable, and interpretable data visualization. Descriptive statistics are classified into three types:

1. **Frequency of distributions:** This type of analysis helps in counting the number of occurrences of a category, which is typically expressed as a percentage (Manikandan 2011:1). The frequency distribution was used to present the frequency of selected indicators and data elements of data accuracy, completeness, and timeliness across the HMIS data sources. Furthermore, the percentage of total cases that were completely filled in as well as those that were not completely filled in indicated. Also, the documentation status of data elements in the data quality monitoring logbook was cross-tabulated in months and healthcare facilities.
2. **Measures of central tendency:** It represents the sample with a single value, such as mean/average. In this particular study, it was used to compute the average accuracy, completeness, and timeliness.
3. **Measures of dispersion,** such as score/value range as minimum and maximum. This means that it tries to show how evenly distributed individual scores are and how they differ from one another (Pruzan 2017:111). In this case, it was used to measure the minimum and maximum variations of data elements and indicators across the HMIS tools, healthcare facilities and study months.

In general, this type of analysis was one of the simplest methods of summarizing research data via tabulation and graphical displays that provided very effective descriptions. As a result, such analyses are critical for identifying patterns in descriptive and summarizing ways (Alem 2020:18). Tables and charts were used to compare data accuracy, completeness and timeliness among public health centres. Data were quantified and measured descriptively in percentages. A comparison was made among registers, tallies, report formats, and DHIS2 data-bases. Moreover, cross-tabulation was tested to compare the level of data accuracy, data completeness and report timeliness over six months. Key findings were also cross-tabulated and statistically compared across time, location, and HMIS data sources.

3.6 METHODS FOR PHASE II

3.6.1 Descriptive cross-sectional survey

This study employed a descriptive cross-sectional survey to collect quantitative data at a fixed point in time. These data were essential for describing and investigating the relationships between the dependent and independent variables (Leavy 2017:269; Zangirolami-Raimundo, Echeimberg & Leone 2018:2; Laake et al. 2007:258). The most important aspect of this technique is that it uses a representative sample of the population to generalize the results to the entire study population, and it allows the researcher to calculate the magnitude of the dependent and independent variables (Omair 2015:3). This means that the technique was useful in collecting appropriate data for assessing the statistical association of socio-demographic, technical, organizational, and behavioural factors with data management and information use in randomly selected healthcare facilities (Omair 2015:3; Sreedharan, Chandrasekaran & Gopakumar 2019:2). Furthermore, this study technique has the following additional advantages: it allows the researcher to look for a meaningful result from the descriptive cross-sectional survey. This means that descriptive analysis was used to calculate the magnitudes of the study variables, while inferential findings were used to indicate the level of statistical associations, strength, and direction of the effects by appropriately answering the research questions and objectives. It is also a more cost-effective way to conduct research using this design when compared to other research designs (Zangirolami-Raimundo et al. 2018:5; Sedgwick 2014:3).). In this study, data was collected from all participants within one month and analyzed immediately; this data collection period was relatively short and cost-effective. The approach provides control over the measurement process because everything obtained during this phase was quickly and easily measured and analyzed. This allowed immediate entering; analyzing data (Zangirolami-Raimundo et al. 2018:2).

3.6.2 Target population

The entire set of units for which survey data are used to draw conclusions is referred to as the target population (Bairagi & Munot 2019:90). The target population for this study was 746 healthcare providers working in Addis Ababa's public healthcare centres who used the health management information system (HMIS) for data management and information use in their respective healthcare units, including the maternal healthcare service units. In this case, individual healthcare providers, healthcare facility management team members, core process heads, case team heads, and HIT/HMIS officers.

3.6.3 Sampling and sample

Sampling is the process by which a researcher selects a few individual cases from a larger population. The researcher must first identify the element of the study. An element is a type of person, group, or a nonliving object that the researcher is interested in (Leavy 2017:76). In this study, a sample was drawn using a multistage random sampling technique. In the first stage, one healthcare centre was chosen randomly; in the second stage, study participants were divided into five strata; in the final stage, participants were chosen from each stratum. This is based on probability theory, in which samples are chosen in such a way that each element in the population has a known chance of being chosen (Daniels & Minot 2020:19; Leavy 2017:79). The rationale or multistage random sampling technique was to generate principles and propositions that describe the selected healthcare providers and are represented proportionally from each stratum, and this enabled the researcher to enhance the precision and representativeness of the final sample (Taherdoost 2020:5). Furthermore, Daniels & Minot (2020:19), Leavy (2017:79) and Sharma (2017:2) indicate the following scientific benefits and justifications for using multistage sampling following with stratification:

- It has the potential to reduce human bias in the selection of cases through proportional representations of each stratum of the population being studied. In this study, study subjects were stratified as individual healthcare providers, case team heads, core process heads, healthcare centre heads, and HMIS officers. The use of a stratified procedure to select units is superior because it increases the likelihood of the units being evenly distributed across the population and provides valid precision.

- This increases the representation of specific strata (groups) within the population while also ensuring that these strata are not over-represented.
- Since the study units used to make up the sample were selected using probabilistic methods, statistical conclusions could be drawn from the collected data.
- This enabled the researcher to compare strata and make more valid inferences from the sample to the population to determine how technical, behavioural, and organizational factors influenced data management and information use, as well as how health data from health centres were used in decision-making, using evidence from multiple dimensions of each stratum.

Sampling frame: It is a list of all the study elements that a researcher can identify in a study population when able to do so (Kumar 2011:398). As a result, the electronic human resource system (eHRIS) of each selected public healthcare centre was used as a sampling frame to identify and categorize the study population into five relevant strata, as shown in Figure 3.4 below. These selected healthcare centres were used to review the document in Phase I.

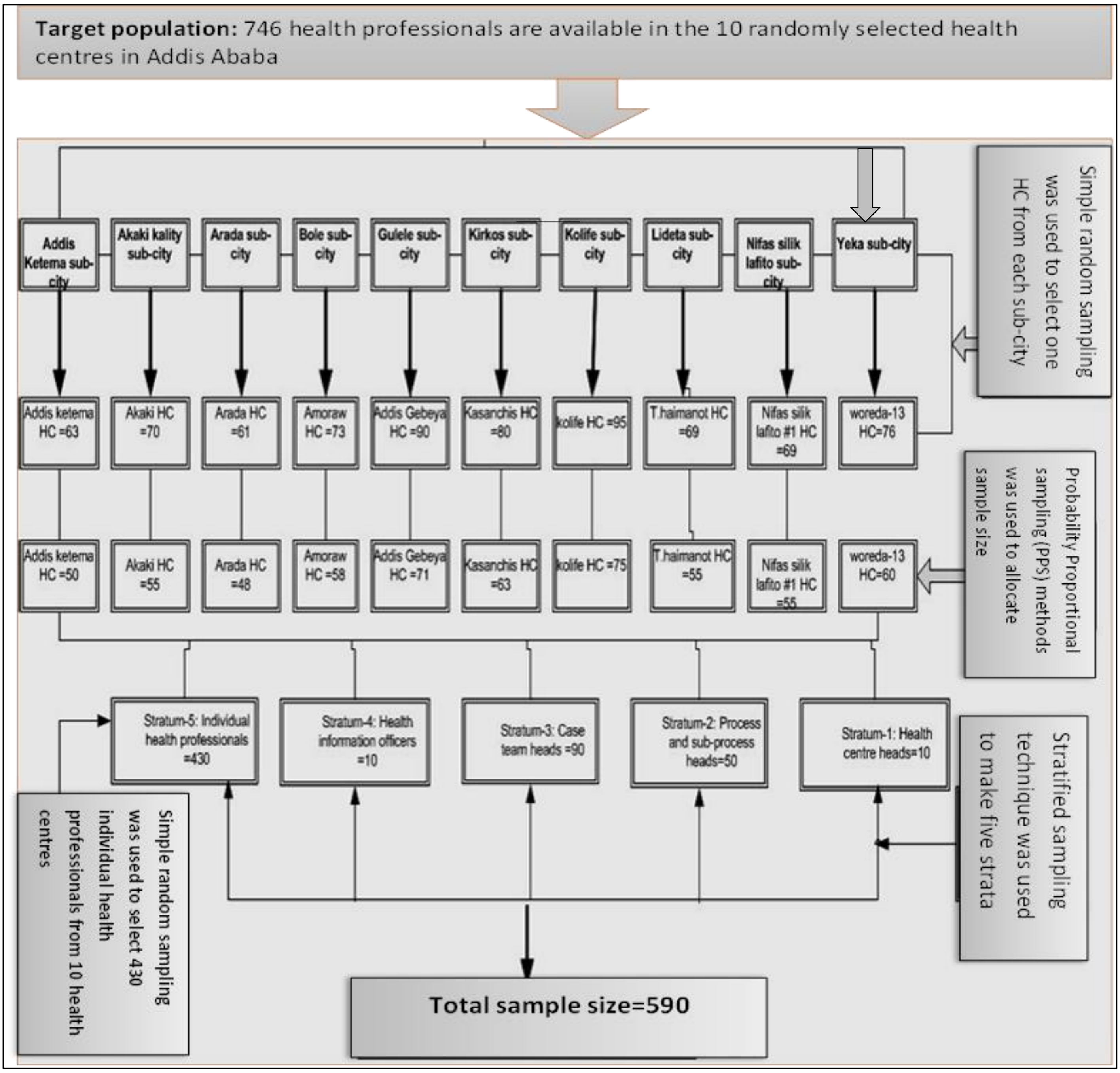

Figure 3.4: Pictorial description of the research sampling procedure

- **Sample size determination:** According to Pruzan (2017:243), sample size determination refers to the process of determining how many observations or study participants to include in a statistical sample; he also adds the following points to be considered:

- Desired confidence level: This value, expressed as a percentage, tells us how confident the researcher is in the results. It is common practice to use 95%.
- Acceptable margin of error or confidence interval: All surveys contain error, and this figure, expressed as a percentage, indicates the amount of error that is acceptable. It is common practice to use 5%, which means that the survey results will be accurate to within a margin of error of 5%.
- The non-response rate is the failure to obtain information from a designated individual for any reason, and in this study, 5% (0.05) was used.
- Hence the sample size was calculated as follows: Where:
    - ✓ n = sample size,
    - ✓ Z=1.96 for 95%confidence level, i.e. Type I (α=0.05);
    - ✓ The proportion (p=57.9%) is used from a similar study design and study population in Ethiopia (Yarinbab & Assefa 2018:4).
    - ✓ The desire precision (margin of error) is ε=0.05;
    - ✓ 5% (0.05) non-response rate; and
    - ✓ Design effect (i.e., d=1.5).
    - ✓ Based on the above assumptions, the sample size was calculated using the below formula.

$$n = \frac{Z^{2}{}_{\alpha/2\,tabu}\; p(1-p)*d}{E^{2}}$$

$$\frac{(1.96 * 1.96) * 0.579\ (1 - 0.579) * 1.5}{(0.05 * 0.05)\ = 0.0025}$$

$$\frac{(3.8416)*(0,3656)=1.4045}{(0.05*0.05)\ =0.0025} = \underline{\underline{561.8 \approx 562}}$$

$$Non\ response\ rate = 562 * 0.05 = \underline{\underline{28}}$$

$$Total\ sample\ size\ (n) = 562 + 28 = 590$$

3.6.4 Inclusion and exclusion criteria

Inclusion criteria:

- Healthcare providers who have been working in the selected healthcare facilities for more than a year.
- Healthcare providers who are working in the public healthcare centres as well as management members of health centres, health information officers, core process heads and case team heads.

Exclusion criteria:

- Healthcare providers who had less than one year of experience working in healthcare centres.

3.6.5 Development and testing of the data collection instrument

The development of a survey instrument should be guided by research questions and a theoretical framework to improve reliability (Parsons, Hutchison, Hall, Parsons, Ives & Leggett 2019:3). Similarly, in this study, the study objectives, variables, theoretical framework and a literature guided the development of the data collection instrument. This means that the questionnaire was developed to investigate the influence of technical, behavioural, and organizational factors on data management, as well as the extent of health information use in Addis Ababa's public health centres; this tool was also refined using literature. Saris and Gallhofer (2014:178) agreed that carefully developing and pilot testing data collection instruments is critical. The questions in the tool were divided into six sections based on the operationalized variables. The first four sections covered the independent variables (socio-demographic, technical, organizational, and behavioural determinants), while the last two covered the dependent variables (data management and information use).

The second, third, and fourth sections of the tool were designed using a five-point Likert scale, with strongly disagree=1, disagree=2, Neither agree nor disagree=3, agree=4, and strongly agree=5. A clear instruction was written at the top of these sections to indicate respondent level of agreement or disagreement using the Likert scale. The final two sections (fifth and sixth) were designed with three response levels to express each respondent's response in the provided empty space using Yes=1, No=2, and Not sure=3.

Pre-testing is essential in research, and it is recommended that the sample size for pre-testing be at least 5% of the total sample size (Perneger, Courvoisier, Hudelson & Gayet-Ageron 2015:2). The purpose of pre-testing a research instrument is to improve questionnaire reliability by reducing errors and ambiguity. This means it can assist in identifying issues with language clarity, question flow, and design (Zimba & Likando 2014:4). Kumar (2011:393) also discussed the significance of pre-testing in quantitative research, where the researcher expects to test the tool prior to data collection. This means that each question should be evaluated for clarity, understanding, wording, and meaning, with the goal of removing or correcting any potential problems. The questionnaire was pre-tested in 5% (n=30) of the study participants who were not part of the study population to ensure internal consistency or reliability of the tool. This stage was done to clarify language and concepts; to categorize appropriate response; to ensure logical the flow of the information.

The sequence and consistency of the questions were optimized by beginning with non-sensitive questions. An appropriate response scale has been assigned to each question. Clear instructions were labeled at the top of each page of each section, assuming to help study participants understand how to respond to each question based on the self-administered questionnaire.

The final and approved questionnaire was originally prepared in English, and it was translated by academics from the University of Mekelle into Amharic language version and then back to English to ensure consistency, as shown in Figure 3.5 below.

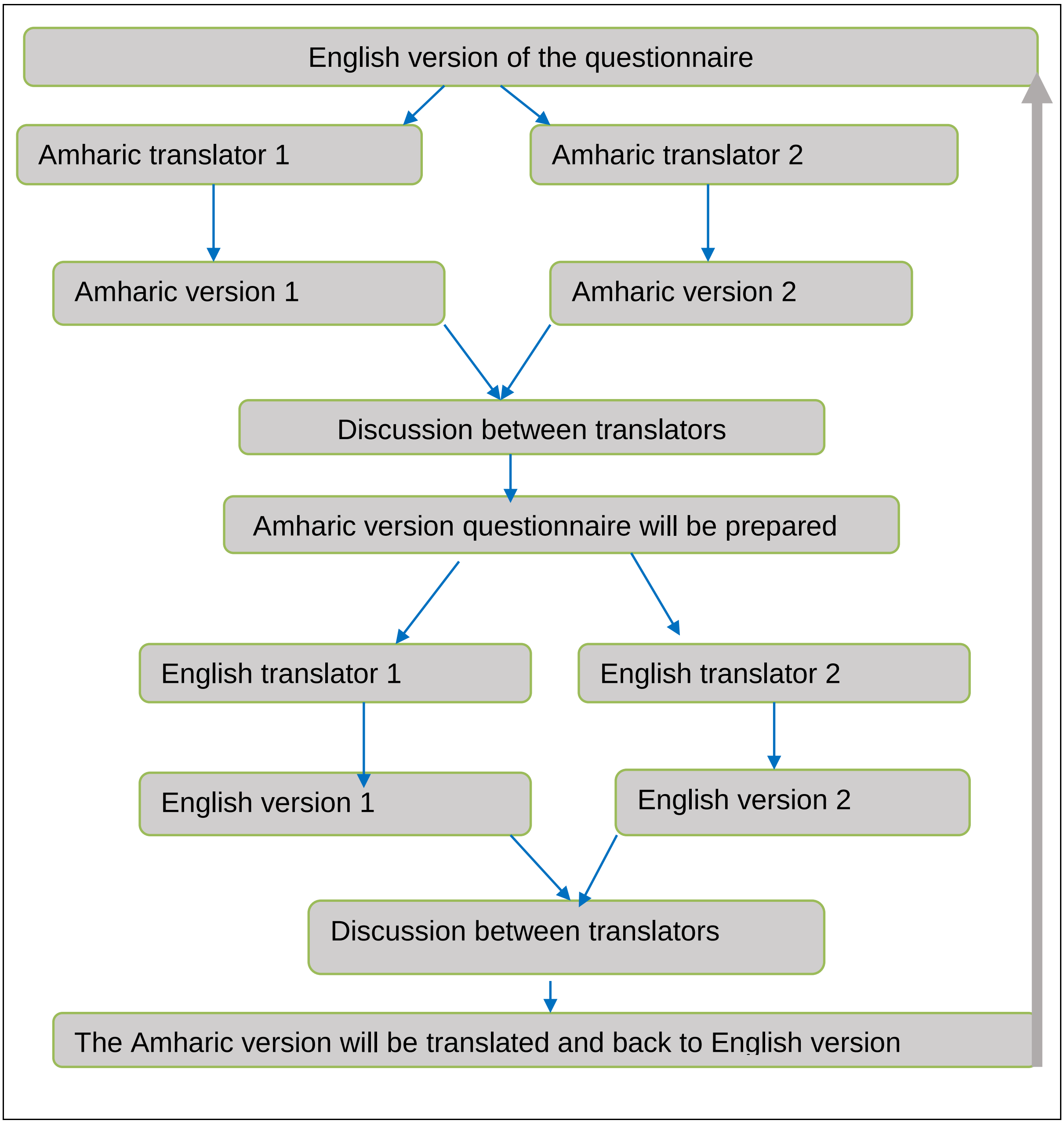

Figure 3. 5: Translation process of the questionnaire

3.6.6 Data collection process

First, the researcher used the letter of permission from the regional health bureau research ethics committee (Annexure 3) as evidence and the ethical clearance obtained from the University of South Africa, Department of Public Health, and Research Ethics Committee (Annexure 1). Second, the information sheet (Annexure 8) with the consent form were provided to each study participant, and those who agreed and signed the consent form participated and filled out the questionnaire.

Third, the two research assistants who participated in phase I assisted with distributing self-administered questionnaires and the subsequent collection for 20 working days in the ten randomly selected healthcare facilities, implying that distribution and collection took two days per healthcare facility. Fially, data were collected from heads of health centres, heads of core processes, heads of case teams, HMIS officers, and healthcare providers accordingly.

3.6.7 Data management and statistical data analysis

Data management: Paper-based records were kept on a separated and locked shelf and were accessible to the researcher and assistants only. Similarly, a softcopy of collected data was accessed only by the researcher. A strong password was set for both the folder that stored the data and the computer. The data collected were checked for completeness before being entered into SPSS software for analysis. And then, data were entered into SPSS Version 26 primarily to code, to recheck missing data, and to make it ready for analysis.

Statistical data analysis is the body of mathematical techniques or processes for describing, organizing, and interpreting quantitative data. There are two types of statistical analyses: descriptive and inferential (Alem 2020:8). Both descriptive and inferential data analysis were conducted.

Descriptive data analysis is a type of statistical analysis that measures the central tendency in mean or average, frequency in percentages, and distribution to determine maximum and minimum variations, and it also provides a knowledge base that can be used as a foundation for more quantitative analysis (George & Mallery 2019:112). This means that descriptive analysis was appropriate for describing, displaying, and summarizing key findings. This provides a baseline that supports the next step of inferential data analysis. It provided a broader picture of an event or phenomenon in simple and descriptive ways (Baha 2016:8). As a result, this analysis was used to calculate and present frequency distributions in percentages; a measure of central tendency, for example, to calculate respondents' mean age and years of experience in their current position; and dispersion was used, for example, to calculate the standard deviation of respondents' age and years of experience.

Recoding is a technique that allows combining or re-grouping numbers of responses to a new small number. The main reason recordings have become important is that they are used to simplify the process of analysis because in logistic regression, as the number of categories increases, the level of statistical prediction decreases. Henceforth, it is recommended to minimize the number of categories to improve the accuracy of estimations as well as to ensure simplification, summarization and visualization of the findings (Dey 2003:209). For that reason, the numbers of responses listed in the Likert scales were regrouped or recoded into three levels, including (1) level of disagreement, which is a negative dimension, was recoded as “strongly disagree or disagree”; (2) level of the neutral category was kept as it is “neither agree nor disagree”; and (3) level of agreement, which is a positive dimension, was recoded as “strongly agree or agree”. Furthermore, age and years of experience in the present position are continuous variables. As a result, these two variables are categorized into meaningful categories to make statistical analysis and interpretation easy.

Analytical/inferential data analysis: Logistic regression is frequently used when there are multiple independent variables and binary dependent variables (Boateng & Abaye 2019:4; Garson 2014:12; Rao 2008:187). Bivariate logistic regression analysis is a statistical method used to predict the relationship between a dependent variable and an independent variable (Nayebi 2020:97). Bivariate logistic regression analysis was used to determine the effect of each independent variable on the practices of data management processing and practices of information use. Bivariate analysis is one of the simplest forms of statistical analysis. It is used to find out whether there is an effect or association between two variables or not (i.e., between the dependent and independent variable) without considering the contributions or effects of the other independent variables (Garson 2014:13). The bivariate logistic regression analysis was used to identify the level of significance and strength of association between each selected independent variable (demographic, organizational, technical and behavioural factors) with the data management and information use separately.

Multivariate logistic regression: Tesfaw and Fenta (2021:3) define multivariate logistic regression as a statistical model used to estimate the effect of factors on the dichotomous dependent variable/s; in this case, the effect of socio-demographic, technical, organizational, and behavioural factors on data management and information use. This statistical procedure is used to estimate the effect of one or more independent variables on the dichotomous dependent variable/s in order to summarize the relationship between the dependent and independent variables. The regression analysis is ideal because the dependent variables, data management and information use, are binary.

The logistic regression assumptions were tested to demonstrate the average and single effect of independent variables (technical, organizational, and behavioural) on the dependent variables (data management and information use) based on the value of the odds-ratio. In other words, the levels of effect, the direction of effect, and the statistical significance of the independent variables on the dependent variables were statistically estimated (Korkmaz, Güney & Yiğîter 2012: 5 & 8). Logistic regression analysis requires one or more sets of explanatory variables (socio-demographic, technical, organizational and behavioural) to determine a dependent variable (data management and information use) (Berger 2017:2). It can be either continuous (i.e., interval or ratio variables) or categorical (i.e., ordinal or nominal variables) (Hassan 2020:5). In this study, 27 independent variables were identified and studied including 22 ordinal variables (technical=4, organizational=10, and behavioural=8); 3 nominal variables (sex, current position, and education); and two continuous variables (age, and work experience).

This was applied and interpreted to mean that if the odds-ratio was less than one, there was a negative association, and it was interpreted as the independent variable was less likely statistically associated with the dependent variable; if the odds-ratio was greater than one, it had a positive association, and it was interpreted as the independent variable was more likely to be statistically associated with the dependent variable. This analysis was also used to calculate the magnitude of the effect using the odds-ratio value. This means that socio-demographic, technical, organizational, and behavioural factors were tested, and their effect on the dependent variables. The level of statistical significance of each independent variable was measured using the P-value. This means that if an independent variable has a P-value less than 0.05, it was determined to be statistically significant in predicting data management and or information use.

3.6.8 Logistic regression assumptions

In this study, key logistic regression assumptions, such as detecting multicollinearity, looking for significant outliers, and employing a large sample size, were tested and found to be valid. These are defined, justified, and presented as follows:

Multicollinearity refers to a high correlation between two or more independent variables in a multiple regression analysis (Nayebi 2020: 22 & 24). In this case, a standard error greater than 2.0 indicates numerical problems, such as multicollinearity among the independent variables (Islam 2018:4; Adeboye, Fagoyinbo & Olatayo 2014:2). In response to this, each independent variable in this study was tested and measured using the standard errors of each independent variable to determine the presence of multicollinearity. This means that the value of standard error 2.0 was used as a cut point for determining the presence of multicollinearity. As a result, there was no evidence of multi-co-linearity. The standard error of each independent variable was found to be less than one, and each has a chance of predicting the outcome variable of data management and information use.

Table 3.4: Standard errors of independent variables from multicollinearity analysis

Determinants of data management in multivariate logistic regression (n=561)			Determinants of information use in multivariate logistic regression (n=561)	
SN	Variables in the Equation	Standard error (S.E.)	Variables in the Equation	Standard error (S.E.)
1	Age	1.08	Age	1.06
2	Sex	0.48	Sex	0.48
3	Years of experience	0.85	Years of experience	0.79
4	Work position	1.49	Work position	1.58
5	Level of Education	1.04	Level of Education	1.21
6	Computer skills to manage data	0.61	Computer skills to manage data	0.71
7	Average availability of HMIS tools	1.19	Average availability of HMIS tools	1.19
8	Average Knowledge on HMIS tools	0.88	Average knowledge of HMIS tools	0.9
9	Average User-friendliness on HMIS tools	0.81	Average user-friendliness on HMIS tools	0.8
10	Availability of data management strategy	1.25	Availability of information use strategy	1.36
11	Availability of information use strategy	1.24	Culture of information use	0.82
12	Culture of information use	0.84	Availability of separate HMIS plan	1.2
13	Availability of separate HMIS plan	1.12	Monthly internal supervision	1.33
14	Monthly internal supervision	1.29	Motivation to strengthen HMIS	0.94
15	Motivation to strengthen HMIS	0.98	Staff makes decisions	1.21
16	Staff is make decisions	0.74	Accountability to strengthen HMIS	0.62
17	Accountability to strengthen HMIS	1.2	Adequate budget	1.11
18	Adequate budget	1.4	knowledge to optimize information use	1.73
19	Involvement in data management tasks	0.61	Confident in information use	1.62
20	Knowledge of managing data	1.34	Competent in information use	1.25
21	Confident in managing data	0.32	Motivation to optimize information use	1.55
22	Competent in data process	0.71	Behavioural determinants of information use	0.91
23	Behavioural determinants of data management	1.22	Behavioural determinants of information use	1.17

No significant outliers: Outliers are scores or observations that deviate significantly from the rest of the data in a given data set, and a single outlier can cause reality to be distorted by influencing the mean and standard deviation. For example, if an outlier affects a standard deviation, the statistical power of a given study may be severely reduced (Field 2018:321). In this study, Cook's distance and standardized residual tests were used to identify outliers that were assumed that if it is greater than one, it is cause for concern (Field 2018:511). In this case, the value of cook's distance less than 1.0 was used as a cut points for determining the absence of outliers in each of the study participant. Hence, all the 590 cases were checked using the cook's distance. Consequently, all the cases were free from outliers. Also, standardized residual was tested to check potential outliers; and if the value of standardized residual of each case is 3 and close to 3, it is a concern for outliers (Field 2018:538). In this case, all the 590 cases were checked and found less than three, which is evidence for free from outlier of each case in this study.

Table 3.5A and B: Cook's distance and standardized residual tests to check significant outliers

cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual
1	0.42	0.36	**40**	0.00	0.00	**79**	0.00	0.00	**118**	0.00	0.00	**157**	0.00	0.00	**196**	0.00	0.00	**235**	0.00	0.00	**274**	0.00	0.00
2	0.00	0.00	**41**	0.00	0.00	**80**	0.00	0.00	**119**	0.00	0.00	**158**	0.00	0.00	**197**	0.00	0.00	**236**	0.02	-0.12	**275**	0.00	0.00
3	0.00	0.00	**42**	0.00	0.00	**81**	0.00	0.00	**120**	0.00	0.00	**159**	0.00	0.00	**198**	0.00	0.00	**237**	0.00	0.00	**276**	0.00	0.00
4	0.00	0.00	**43**	0.00	0.00	**82**	0.00	0.00	**121**	0.00	0.00	**160**	0.00	0.00	**199**	0.00	0.01	**238**	0.00	0.00	**277**	0.00	0.00
5	0.00	0.00	**44**	0.00	0.00	**83**	0.00	0.00	**122**	0.00	0.00	**161**	0.00	0.00	**200**	0.00	0.00	**239**	0.00	0.00	**278**	0.00	0.00
6	0.00	0.00	**45**	0.00	0.00	**84**	0.00	0.00	**123**	0.00	0.00	**162**	0.00	0.00	**201**	0.00	0.00	**240**	0.00	0.00	**279**	0.00	0.00
7	0.00	0.00	**46**	0.00	0.00	**85**	0.00	0.00	**124**	0.32	0.22	**163**	0.00	0.00	**202**	0.00	0.00	**241**	0.00	0.00	**280**	0.00	0.00
8	0.02	0.10	**47**	0.00	0.00	**86**	0.00	0.00	**125**	0.00	0.00	**164**	0.00	-0.05	**203**	0.00	0.00	**242**	0.00	-0.02	**281**	0.00	0.00
9	0.00	0.00	**48**	0.00	0.00	**87**	0.00	0.00	**126**	0.00	0.00	**165**	0.00	0.00	**204**	0.00	-0.01	**243**	0.00	0.00	**282**	0.00	0.00
10	0.00	0.00	**49**	0.40	-0.31	**88**	0.00	0.00	**127**	0.00	0.00	**166**	0.00	0.00	**205**	0.00	0.00	**244**	0.00	0.00	**283**	0.00	-0.04
11	0.00	0.05	**50**	0.00	0.00	**89**	0.00	0.00	**128**	0.00	0.00	**167**	0.00	-0.01	**206**	0.00	0.00	**245**	0.00	0.00	**284**	0.00	0.00
12	0.82	1.07	**51**	0.00	-0.06	**90**	0.00	0.00	**129**	0.00	0.00	**168**	0.00	0.00	**207**	0.00	0.00	**246**	0.00	0.00	**285**	0.00	0.00
13	0.00	0.01	**52**	0.00	-0.13	**91**	0.00	0.00	**130**	0.00	0.00	**169**	0.00	0.00	**208**	0.00	0.00	**247**	0.00	0.00	**286**	0.00	0.00
14	0.00	0.00	**53**	0.00	0.00	**92**	0.00	0.00	**131**	0.00	0.00	**170**	0.00	0.00	**209**	0.00	0.00	**248**	0.00	0.00	**287**	0.00	0.00
15	0.02	0.10	**54**	0.00	0.00	**93**	0.00	0.00	**132**	0.00	0.00	**171**	0.00	0.00	**210**	0.00	0.00	**249**	0.00	0.00	**288**	0.00	0.00
16	0.05	0.68	**55**	0.00	0.00	**94**	0.00	0.00	**133**	0.84	0.98	**172**	0.00	0.00	**211**	0.00	0.00	**250**	0.00	0.00	**289**	0.00	0.00
17	0.00	0.00	**56**	0.00	0.00	**95**	0.00	0.00	**134**	0.00	0.00	**173**	0.00	0.00	**212**	0.00	-0.01	**251**	0.00	0.00	**290**	0.00	0.00
18	0.71	0.33	**57**	0.00	-0.04	**96**	0.00	0.00	**135**	0.00	0.00	**174**	0.00	0.00	**213**	0.00	0.00	**252**	0.00	0.00	**291**	0.00	0.00
19	0.00	0.00	**58**	0.00	0.00	**97**	0.00	0.00	**136**	0.00	0.00	**175**	0.00	0.00	**214**	0.00	0.00	**253**	0.00	0.00	**292**	0.00	0.00
20	0.01	0.41	**59**	0.00	0.00	**98**	0.00	0.00	**137**	0.00	0.00	**176**	0.00	0.00	**215**	0.00	0.00	**254**	0.00	0.00	**293**	0.00	0.00
21	0.00	0.00	**60**	0.00	0.00	**99**	0.00	0.00	**138**	0.00	0.00	**177**	0.00	0.00	**216**	0.00	-0.02	**255**	0.00	0.00	**294**	0.00	0.00
22	0.59	0.71	**61**	6.65	-0.40	**100**	0.00	0.00	**139**	0.00	0.00	**178**	0.00	0.00	**217**	0.00	0.00	**256**	0.00	0.00	**295**	0.00	0.00
23	0.00	0.00	**62**	0.00	0.00	**101**	0.00	0.00	**140**	0.00	0.00	**179**	0.03	0.14	**218**	0.00	0.00	**257**	0.00	0.00	**296**	0.00	0.00
24	0.00	0.00	**63**	0.00	0.00	**102**	0.00	0.00	**141**	0.00	0.00	**180**	0.34	0.42	**219**	0.00	0.00	**258**	0.00	0.00	**297**	0.00	0.00
25	0.00	0.01	**64**	0.00	0.00	**103**	0.00	0.02	**142**	0.00	0.00	**181**	0.00	0.00	**220**	0.00	0.00	**259**	0.00	0.00	**298**	0.00	0.00
26	0.00	0.00	**65**	0.00	0.00	**104**	0.00	0.00	**143**	0.00	0.00	**182**	0.00	0.00	**221**	0.00	0.00	**260**	0.00	0.00	**299**	0.00	0.00
27	0.18	0.52	**66**	0.00	0.00	**105**	0.00	0.00	**144**	0.00	-0.01	**183**	0.00	0.00	**222**	0.00	0.00	**261**	0.00	0.00	**300**	0.00	0.00
28	0.24	0.59	**67**	0.00	0.00	**106**	0.00	0.00	**145**	0.00	0.00	**184**	0.01	0.11	**223**	0.00	0.00	**262**	0.00	0.00	**301**	0.00	0.00
29	0.00	0.00	**68**	0.00	0.00	**107**	0.00	0.00	**146**	0.00	0.00	**185**	0.00	0.00	**224**	0.00	0.00	**263**	0.00	0.00	**302**	0.00	0.00
30	0.39	0.50	**69**	0.00	0.00	**108**	0.17	0.20	**147**	0.00	0.00	**186**	0.00	0.01	**225**	0.00	0.00	**264**	0.00	0.00	**303**	0.00	0.00
31	0.53	1.18	**70**	0.00	0.00	**109**	0.02	0.10	**148**	0.00	0.00	**187**	0.00	0.00	**226**	0.00	0.00	**265**	0.00	0.00	**304**	0.00	0.00
32	0.00	0.00	**71**	0.00	0.00	**110**	0.00	0.00	**149**	0.00	0.00	**188**	0.00	0.00	**227**	0.00	0.00	**266**	0.00	0.00	**305**	0.00	0.00
33	0.00	0.00	**72**	0.00	0.00	**111**	0.00	0.00	**150**	0.00	0.00	**189**	0.00	0.01	**228**	0.00	0.00	**267**	0.00	0.00	**306**	0.00	0.00
34	0.00	0.00	**73**	0.00	0.00	**112**	0.00	0.00	**151**	0.00	0.00	**190**	0.00	0.00	**229**	0.00	0.00	**268**	0.07	-0.17	**307**	0.00	0.00
35	0.00	0.00	**74**	0.00	0.00	**113**	0.00	0.00	**152**	0.00	0.00	**191**	0.00	0.00	**230**	0.00	0.00	**269**	0.00	0.00	**308**	0.00	0.00
36	0.00	0.00	**75**	0.00	0.00	**114**	0.87	0.49	**153**	0.00	0.00	**192**	0.07	0.17	**231**	0.00	0.00	**270**	0.00	0.00	**309**	0.00	0.00
37	0.00	0.00	**76**	0.00	0.00	**115**	0.00	0.00	**154**	0.00	0.00	**193**	0.53	0.29	**232**	0.00	0.00	**271**	0.00	0.00	**310**	0.00	0.00
38	0.00	0.00	**77**	0.00	0.00	**116**	0.00	0.00	**155**	0.00	0.00	**194**	0.53	0.37	**233**	0.00	0.00	**272**	0.00	0.00	**311**	0.00	0.00
39	0.00	0.00	**78**	0.00	0.00	**117**	0.00	0.00	**156**	0.00	0.00	**195**	0.00	0.00	**234**	0.02	-0.11	**273**	0.00	0.00	**312**	0.00	0.00

cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual	cases checked outliers	Cook's distance	standardized residual
313	0.00	0.00	**352**	0.74	0.62	**391**	0.30	0.38	**430**	0.00	0.06	**469**	0.00	0.00	**508**	0.00	0.00	**547**	0.51	0.45	**586**	0.00	0.00
314	0.00	0.00	**353**	0.00	-0.04	**392**	0.00	0.00	**431**	0.00	0.01	**470**	0.09	0.26	**509**	0.45	0.65	**548**	0.04	-0.34	**587**	0.00	0.00
315	0.00	0.00	**354**	0.00	-0.03	**393**	0.00	0.00	**432**	0.06	-0.28	**471**	0.33	0.50	**510**	0.00	0.00	**549**	0.04	0.34	**588**	0.00	0.00
316	0.00	0.00	**355**	0.81	-0.39	**394**	0.00	0.04	**433**	0.00	0.00	**472**	0.27	0.42	**511**	0.00	0.00	**550**	0.01	0.12	**589**	0.00	0.00
317	0.00	0.00	**356**	0.00	0.00	**395**	0.00	-0.01	**434**	0.00	0.00	**473**	0.00	0.08	**512**	0.00	0.00	**551**	0.00	0.03	**590**	0.00	0.00
318	0.00	0.00	**357**	0.00	0.00	**396**	0.01	0.13	**435**	0.31	0.78	**474**	0.15	0.37	**513**	0.00	0.00	**552**	0.00	0.00			
319	0.00	0.00	**358**	0.48	0.64	**397**	0.00	0.03	**436**	0.00	0.00	**475**	0.00	0.00	**514**	0.00	0.01	**553**	0.46	0.99			
320	0.00	0.00	**359**	0.11	0.34	**398**	0.08	0.24	**437**	0.34	1.05	**476**	0.00	0.00	**515**	0.00	0.01	**554**	0.59	1.69			
321	0.00	0.00	**360**	0.47	0.98	**399**	0.00	0.05	**438**	0.94	0.74	**477**	0.00	0.00	**516**	0.00	0.00	**555**	0.17	1.92			
322	0.00	0.00	**361**	0.10	0.21	**400**	0.87	-0.38	**439**	0.09	0.32	**478**	0.00	0.00	**517**	0.54	0.78	**556**	0.78	0.98			
323	0.00	0.00	**362**	0.10	0.21	**401**	0.00	0.00	**440**	0.00	0.06	**479**	0.00	0.00	**518**	0.00	0.08	**557**	0.65	0.78			
324	0.00	0.00	**363**	0.08	0.75	**402**	0.00	0.00	**441**	0.00	0.04	**480**	0.00	-0.02	**519**	0.00	0.00	**558**	0.00	0.02			
325	0.14	-0.98	**364**	0.00	0.00	**403**	0.00	0.02	**442**	0.90	0.75	**481**	0.00	0.00	**520**	0.07	0.46	**559**	0.01	0.02			
326	0.00	0.00	**365**	0.00	0.00	**404**	0.00	0.01	**443**	0.34	0.64	**482**	0.00	0.00	**521**	0.00	0.00	**560**	0.02	0.66			
327	0.00	0.00	**366**	0.00	0.00	**405**	0.06	0.20	**444**	0.00	-0.01	**483**	0.00	-0.09	**522**	0.00	0.00	**561**	0.00	0.04			
328	0.15	0.76	**367**	0.00	0.00	**406**	0.00	0.00	**445**	0.00	-0.02	**484**	0.00	0.00	**523**	0.00	0.01	**562**	0.00	0.00			
329	0.00	0.00	**368**	0.61	-0.05	**407**	0.14	0.59	**446**	0.00	0.00	**485**	0.00	0.00	**524**	0.00	0.00	**563**	0.00	0.00			
330	0.00	0.00	**369**	0.00	0.00	**408**	0.00	0.00	**447**	0.00	0.00	**486**	0.00	0.00	**525**	0.00	-0.03	**564**	0.00	0.00			
331	0.01	0.12	**370**	0.47	0.76	**409**	0.00	0.00	**448**	0.00	0.00	**487**	0.00	0.00	**526**	0.00	0.00	**565**	0.40	0.33			
332	0.00	0.00	**371**	0.92	0.55	**410**	0.27	0.42	**449**	0.00	0.00	**488**	0.00	0.00	**527**	0.00	0.00	**566**	0.00	0.00			
333	0.00	0.00	**372**	0.50	0.20	**411**	0.22	0.39	**450**	0.00	-0.02	**489**	0.00	0.00	**528**	0.02	-0.13	**567**	0.00	0.00			
334	0.00	0.00	**373**	0.00	-0.04	**412**	0.00	0.00	**451**	0.03	-1.49	**490**	0.00	0.00	**529**	0.00	0.00	**568**	0.00	0.00			
335	0.00	0.00	**374**	0.00	0.00	**413**	0.02	0.19	**452**	0.00	0.00	**491**	0.00	0.00	**530**	0.00	0.00	**569**	0.00	0.00			
336	0.00	0.00	**375**	0.00	-0.01	**414**	0.00	0.07	**453**	0.00	0.00	**492**	0.00	0.00	**531**	0.00	-0.01	**570**	0.00	0.07			
337	0.00	0.00	**376**	0.00	-0.10	**415**	0.00	-0.02	**454**	0.00	0.00	**493**	0.00	0.00	**532**	0.01	-0.14	**571**	0.00	0.00			
338	0.00	0.00	**377**	0.01	-0.14	**416**	0.00	0.07	**455**	0.00	0.00	**494**	0.00	0.00	**533**	0.00	0.00	**572**	0.00	0.00			
339	0.00	0.00	**378**	0.76	0.87	**417**	0.87	0.52	**456**	0.00	0.00	**495**	0.00	0.00	**534**	0.00	0.00	**573**	0.00	0.00			
340	0.00	0.00	**379**	0.29	0.20	**418**	0.00	-0.01	**457**	0.00	-0.04	**496**	0.00	0.00	**535**	0.00	0.00	**574**	0.00	0.00			
341	0.00	0.00	**380**	0.82	0.01	**419**	0.00	0.01	**458**	0.00	0.00	**497**	0.00	0.00	**536**	0.00	-0.02	**575**	0.00	0.03			
342	0.00	0.00	**381**	0.13	-0.27	**420**	0.02	-0.20	**459**	0.00	0.00	**498**	0.53	-0.41	**537**	0.23	-0.30	**576**	0.00	0.00			
343	0.81	0.42	**382**	0.67	0.01	**421**	0.00	-0.04	**460**	0.00	0.00	**499**	0.00	0.00	**538**	0.01	-0.11	**577**	0.00	0.00			
344	0.00	0.00	**383**	0.01	0.19	**422**	0.17	1.73	**461**	0.87	-0.95	**500**	0.00	0.00	**539**	0.26	-0.30	**578**	0.00	0.00			
345	0.00	0.00	**384**	0.00	-0.01	**423**	0.00	0.00	**462**	0.00	0.00	**501**	0.00	0.00	**540**	0.23	-0.35	**579**	0.00	0.00			
346	0.00	0.00	**385**	0.00	0.00	**424**	0.54	1.11	**463**	0.00	0.00	**502**	0.10	0.26	**541**	0.98	-0.45	**580**	0.00	0.00			
347	0.00	0.00	**386**	0.07	0.31	**425**	0.33	-0.88	**464**	0.00	0.00	**503**	0.00	0.01	**542**	0.77	-0.65	**581**	0.00	0.00			
348	0.00	0.01	**387**	0.09	0.62	**426**	0.01	0.16	**465**	0.00	0.00	**504**	0.02	0.14	**543**	0.00	-0.01	**582**	0.00	0.00			
349	0.00	0.00	**388**	0.01	0.16	**427**	0.00	-0.08	**466**	0.00	-0.02	**505**	0.00	0.00	**544**	0.24	0.45	**583**	0.00	0.00			
350	0.01	0.12	**389**	0.00	0.01	**428**	0.00	0.00	**467**	0.00	0.00	**506**	0.00	0.00	**545**	0.47	-0.90	**584**	0.00	0.00			
351	0.00	0.02	**390**	0.00	0.00	**429**	6.82	-1.02	**468**	0.00	0.00	**507**	0.00	0.00	**546**	0.00	-0.02	**585**	0.00	0.00			

Large sample size: A minimum of 20 cases/events per predictor is required to check the adequacy of the sample size in logistic regression (Ogundimu, Altman & Collins 2016:2; Bujang, SaAt, Sidik & Joo 2018:2). In this study, 27 key predictors were identified (five socio-demographic factors, four technical determinants, ten organizational determinants, and eight behavioural determinants) and used. The sample size is 590, but 29 cases were excluded from the inferential analysis. Reasons for exclusion are listed below in the statistical test results and model summaries section, particularly in the case processing summary. Hence, 561 cases are included in the analysis, and then if the 561 is divided by 20, it gives 28.05. This means that the sample size is adequate to use 28 independent variables.

3.6.9 Method of variable selection for analysis

Variable selection means choosing among many variables which ones to include in a particular model, that is, to select appropriate variables from a complete list of variables by removing those that are irrelevant or redundant (Maxwell 2019:2; Chowdhury & Turin 2020:2). Statistical Package for the Social Sciences (SPSS) provides different methods of variable selection for analysis. However, there is no consensus on which method is the best. There are recommendations that all candidate variables should be included in the model, which approach is called the full model/enter method/ approach. A model developed using the full model (enter method) approach has key advantages. The problem of selection bias is absent, and the standard errors and p-values of the variables are correct (Steyerberg & Vergouwe 2014:3; Abdulrahman, Rampal, Othman, Ibrahim, Hayati & Radhakrishnan 2017:6; Warwick, Shackcloth, Mediratta, Page, McShane, Shaw et al. 2013:2). Hence, in this study, the enter method of variable selection was used to predict the outcome variables of data management and information use. It starts with a full model that considers all independent variables that will be included in the model simultaneously. Then, the enter method was used to select 16 independent variables that provided the best fit for the model, allowing accurate predictions of data management and information use to be made (Steyerberg & Vergouwe 2014:3). In general, variable selection serves two purposes. First, it helps determine all of the variables related to the outcome, making the model complete and accurate. Second, it helps select a model with few variables by eliminating irrelevant variables that decrease the precision and increase the complexity of the model (Chowdhury & Turin 2020:2). Initially, 27 independent variables were investigated in this study, and 23 of them were found to be statistically significant in the bivariate logistic regression analysis and eligible for the multivariate logistic regression analysis. Using the enter method of variable selection, however, only 16 indicators were found to be statistically significant predictors of data management and information use.

Additionally, variable selection has a number of benefits, including improving prediction and facilitating data visualization (Chowdhury & Turin 2020:2). The statistical outputs of the SPSS data were appropriately visualized, and the selected variables for data management and information use prediction are listed below:

3.6.9.1 Variable selection to predict the outcomes (data management and information use)

In this method of variable selection,16 statistically significant variables were identified using the enter method, namely the age category, years of experience category, work position, computer skills, average availability of HMIS tools, average knowledge of HMIS tools, average perception of user-friendliness of HMIS tools, availability of data management strategy, availability of information use strategy, the culture of information use, availability separate HMIS plan, motivation to strengthen the HMIS, adequate budget, involvement in data management tasks, knowledge to manage data, and competence in data process to predict the data management and information use.

3.6.10 Statistical test results and model summaries

The case processing summary of this study shows that 95.1% (n=561) of the cases were included in the analysis of data management and information use separately. On the other hand, 4.9% (n=29) of the cases were found under the response of not sure category. And then, when the 4.9% (n=29) cases were included in the multinomial logistic regression analysis to run inferential analysis, the result of the standard errors and value of odds ratio became much inflated. In addition, the result of the statistical model was found unstable, and warring SPSS messages were displayed automatically. In general, these cases have influenced and shifted the exact picture of the study. Hence, as a statistical solution, these cases were excluded from the inferential analysis but included in the descriptive analysis. For that reason, the response of dependent variables becomes Yes=1 and No=0. In this case, the statistical model became stable, and the exaggeration of standard errors and the strength of the odds ratio were corrected and found to be stable in the binary logistic regression analysis. The logistic regression was used to control potential confounders by assessing factors that were significantly associated with data management as well as with the information use in two separate statistical models. The findings from the logistic regression analyses were used to guide strategies for strengthening the data management and information use in public healthcare centres.

Omnibus tests of model coefficients are statistical tests used to determine whether to accept or reject the null hypotheses of the data management and information use separately (George & Mallery 2019:333). The chi-square statistic is used in this test to determine the omnibus tests of model coefficients. This means that this test can determine whether the inclusion of 23 independent variables significantly impacts model fit via the prediction of the dependent variable (data management or information use). Also, a p-value (sig) less than 0.05 in the omnibus tests indicates that the model was statistically significant in predicting the outcome variable (Field 2018:1138). In this case, there are two hypotheses linked to the overall fit of the model:

$H_{0 \text{ (null-hypothesis):}}$ is stated that the model is a good fitting model without the predictors (i.e., the predictors have not a significant effect);

$H_{1 \text{ (alternative hypothesis):}}$ is stated that the model is not a good fitting model without the predictors (i.e., the predictors have a significant effect). As a result, the omnibus tests provided statistical evidence that the overall models were found to be significant when the 23 independent variables were entered to predict the data management and information use as indicated below in table 3.7a (X^2 = 256.427, p< .000 with df = 23); and in table 3.8a (X^2 = 272.093, p< .000 with df = 23), respectively.

Table 3.6: Statistical test results and model summary for data management (n=561)

Block 1: Method = Enter				
Table 3.6a: Omnibus Tests of Model Coefficients				
Step 1		Chi-square	df	Sig.
	Step	256.427	23	0.000
	Block	256.427	23	0.000
	Model	256.427	23	0.000
Table 3.6b: Model Summary				
Step1	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square	
	186.609[a]	0.685	0.866	
a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.				
Table 3.6c: Hosmer and Lemeshow Test				
Step1	Chi-square	Df	Sig.	
	4.620	8	0.797	

Table 3.7: statistical test results and model summary for information use (n=561)

Block 1: Method = Enter				
Table 3.7a: Omnibus Tests of Model Coefficients				
		Chi-square (X^2)	df	Sig.
Step 1	Step	272.093	23	0.000
	Block	272.093	23	0.000
	Model	272.093	23	0.000
Table 3.7: Model Summary				
Step1	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square	
	176.650[a]	0.764	0.887	
a. Estimation terminated at iteration number 20 because maximum iterations have been reached. Final solution cannot be found.				
Table 3.7c: Hosmer and Lemeshow Test				
Step1		Chi-square (X^2)	df	Sig.
		4.556	8	0.804

The model summary was used to determine how well the model fits the data; that is, it is used to assess the goodness of fit using the -2Log likelihood test and the coefficient of "pseudo" R^2 (George & Mallery 2019:333). In this case, the R^2-coefficient provided a rough estimate of variance from the combination of the predictor variables. Henceforth, the result of the model summaries indicated in Table 3.7b and Table 3.8b of Nagelkerke's R^2 showed that approximately 86.6% and 88.7% of the variances can be predicted from the combination of the 23 independent variables whether the data management and information use are well established or not at public healthcare centres, respectively.

The Hosmer and Lemeshow test was used to provide evidence for poor fit if $p<0.05$, and good fit if the value of $P>0.05$ (Boateng & Abaye 2019:8). This means that it is used to determine whether the observed proportions of events are similar to the predicted probabilities of occurrence, and the test statistic follows a χ2 distribution. This means that if the value of χ2 is small with a large P-value (i.e. >0.05), it indicates a good fit to the data. On the other hand, if the value of χ2 is large and has small P-values ($P<0.05$), it indicates a poor fit to the data (Boateng & Abaye 2019:8). Accordingly, the Hosmer-Lemeshow tests in Table 3.7c and Table 3.8c provide statistical evidence of non-significant test results for both the data management and information use when the independent variables entered the model ($X^2=4.620$, $p=0.797$, and $df=8$), and ($X^2=4.556$, $p=0.804$, and $df=8$), respectively. These tests prove that the two models are adequately fitted in predicting the dependent variable of data management processing established and information use established separately using the 23 independent variables.

Interpretation: The level of significance at P-value<0.05, 95% CI for OR (strength of association) and using beta coefficient (b) to determine the direction as positive, negative or zero association in each model separately; and comparison of results was done in relation to the stated objectives of the study. In this study, during the interpretation, the odds ratio was interpreted as the difference in the log odds of the dependent variable for one value of the categorical variable versus the reference group; when the other variables are fixed or controlled.

Reference group or category: When comparing different groups of a predictor variable to one specific group of a predictor variable, dummy coding is used. And then, all odds ratios are compared to the specific group, which is often referred to as the reference group or category (Starkweather 2010:1). Hence, a reference group is a group that can be chosen as the reference or base for comparison, so that all odds ratios are compared to it. This means that when all other independent variables were controlled or fixed, the odds-ratio results were interpreted as each statistically significant independent variable being more or less likely to be statistically associated with data management or information use. However, except for the p-value (significant level), the SPSS software did not generate the odds ratio of Exp (B) and the 95% confidence interval for Exp (B) of each reference category (Berger 2017:24; Wuensch 2021:28; Landau & Everitt 2004:238).

In this study, the statistical findings were interpreted as follows: For example, core process heads of the public health centres were 3.21 times more likely to be statistically associated with the practices of data management processes in comparison with those who are HMIS/HIT officers of the public healthcare centres when the other independent variables are controlled or fixed [OR=3.21, P=0.010, 95%CI: (2.16, 4.88)]. Also, study participants who did not have basic computer skills to manage data were 67% less likely to be statistically associated with the practices of information use than those who had computer skills when the other independent variables are controlled or fixed [OR=0.33, P=0.000, 95%CI: (0.31, 0.49)].

3.7 RIGOUR OF THE STUDY: VALIDITY AND RELIABILITY

3.7.1 Validity and reliability

Internal and external validity, as well as reliability, were assessed. In this study, the following key points have been addressed to ensure internal validity: (1) Content validity is a judgment of how appropriate the items seem to a panel of reviewers who have knowledge of the subject matter (Creswell 2018:274). As a result, the content of the data collection tool is well-reviewed by the supervisor and the researcher. (2) A randomization sampling technique was used to increase the internal validity of the study. (3) Controlling the effects of confounder variables, using appropriate multivariate logistic statistical regression, was used to ensure internal validity. (4) Instrumentation threats were eliminated by designing a relevant survey questionnaire to ensure consistency.

External validity is a property which enables research studies to be generalized to a larger population (Creswell 2018:244). In this study, the following points were addressed to ensure external validity: (1) Selection bias is one of the most significant threats to external validity; and this was managed using a stratified random sampling technique. (2) Clear inclusion and exclusion criteria have been used to ensure external validity. In this study, individual healthcare providers, management members of healthcare centres, health information officers, core process heads, and case team heads were included. On the other hand, healthcare providers with less than one year of experience working in healthcare facilities were ineligible. (3) A representative and adequate sample size (n=590) was used to ensure and support generalization and conclusion.

Reliability (**internal consistency**) refers to the extent to which all of the items in a scale measure the different aspects of the same attribute. Cronbach alpha is often used in assessing the reliability (consistency) of tests. In response to this, a pre-test (n=30) was done to determine the internal consistency of the study items and to calculate the average time required for data collection. Therefore, the value of the Cronbach alpha ranges from r=0 to r=1. Consequently, the result of Cronbach alpha r≥0.7 is considered sufficiently reliable (internally consistent) (Creswell 2018:215). In this study, r≥0.7 was used to test the internal consistency of the study. As a result, the minimum average and maximum average of Cronbach's alpha value were found to be r≥0.823 and 0.940, respectively, which is significantly higher than the pre-defined cut point of Cronbach alpha value r≥0.7.

3.7.2 Reliability analysis of the pilot study

Table 3.8: Reliability analysis of availability, knowledge, and user friendliness of hmis tools (n=590)

SN	Dimensions	Items	Number of items	Intra-class Correlation Coefficient Pilot test (n=30) Cronbach's Alpha	95% CI Lower Bound	Upper Bound	P-value
1	HMIS tools are always available	QTD2.1. Registers	4	0.907	0.837	0.951	0.0001
		QTD2.2. Tally sheets					
		QTD2.3. Report formats					
		QTD2.4. HMIS manuals					
2	Knowledge of HMIS tools	QTD3.1. I have adequate knowledge of how to manage HMIS manuals	5	0.912	0.850	0.953	0.0001
		QTD3.2. I understand the definitions of HMIS indicators					
		QTD3.3. I have adequate knowledge to collect data in HMIS registers					
		QTD3.4. I have adequate knowledge of how to compile data in tallies					
		QTD3.5. I know how to manage data in reporting formats					
3	Perceived user-friendliness of HMIS tools	QTD4.1. It takes a long time to complete data from HMIS registers	5	0.828	0.805	0.849	0.0001
		QTD4.2. HMIS tools are easy to use					
		QTD4.3. Organization of the HMIS tools is practical					
		QTD4.4. I feel comfortable using these HMIS tools					
		QTD4.5. Generally, I am satisfied with HMIS tools					

In this study, r≥0.7 was used to test the internal consistency of the study variables. As a result, Table 3.8 indicates the lists of items of different technical dimensions, including the availability of HMIS tools, knowledge of HMIS tools, and user-friendliness of HMIS tools. Accordingly, the sum of each item was assessed and measured its internal consistency, using the scale reliability test. In view of that, the four items that were summed to create the scale of HMIS tools availability; and then the Cronbach's alpha value of the four items was 0.907, which indicates that the items form a scale that has reasonable and adequate internal consistency. Similarly, the alpha value for the knowledge of HMIS tools and user-friendliness of HMIS tools were found to be 0.912, and 0.828, respectively.

Table 3.9: Reliability analysis for organizational, behavioural, and data management (n=30)

SN	Dimensions	Items	Number of items	Intra-class Correlation Coefficient			
				Pilot test (n=30)			
				Cronbach's Alpha	95% CI		P-value
					Lower Bound	Upper Bound	
1	Organizational determinants of data management processes	QOD1.A written data management strategy is available at the health centre	10	0.836	0.733	0.911	0.0001
		QOD2. A written information use strategy is available at the health centre					
		QOD3.Culture of information use is well promoted at health centre					
		QOD4. Separate HMIS plan is available at the health centre					

		QOD5.Internal supervision is provided monthly at the health centre					
		QOD6. Motivation to strengthen HMIS is always provided					
		QOD7.1. Staff is encouraged to make evidence-based decisions					
		QOD7.2. Onsite training is conducted regularly to strengthen HMIS					
		QOD7.3. Accountability is promoted to strengthen HMIS					
		QOD8.1. An adequate budget is allocated yearly at the health centre					
2	Behavioural determinants of information use	QBD1. I have adequate knowledge to optimize information use	4	0.929	0.877	0.963	0.0001
		QBD2. I am confident in information use					
		QBD3. I am competent in information use					
		QBD4. I am motivated to optimize information use					
3	Behavioural determinants of data management	QBD5. I am involved in data management tasks to optimize information use	4	0.823	0.692	0.908	0.0001
		QBD6. I have adequate knowledge to manage data process activities					
		QBD7. I am confident to manage the data process					
		QBD8. I am competent in data process					
4	Data Management Processes	QDM1.The value of quality data collection is well established	8	0.894	0.661	0.889	0.0001
		QDM2.1.Data compilation processes are often rushed					

		QDM2.2. Do you have adequate knowledge to compile data scientifically?					
		QDM3.1. Do you have the skill to analyze data scientifically?					
		QDM4.There is adequate support for data analysis processes					
		QDM5.1. Do you have the skills to display data using different charts?					
		QDM6.The data presentation is visible at the health centre					
		QDM7.Weekly case presentations are held to manage data problems at health centres					

Table 3.9 indicated the lists of items that were grouped under four dimensions: organizational, behavioural determinants of information use, data management processes, and data management processes. The sum of each item was measured for internal consistency using the scale reliability test. Hence, the ten items that were summed to create a scale of organizational determinants for data management processes and Cronbach's alpha value of the ten items were found to be 0.836, which indicates strong internal consistency. Similarly, the alpha value for the behavioural determinants of information use, behavioural determinants of data management processes, and data management processes were found to be 0.929, 0.823, and 0.894, respectively.

TablE 3.10: Reliability analysis for information use items (n=30)

SN	Dimension	Items	Number of items	Intra-class Correlation Coefficient			
				Pilot test (n=30)			
					95% CI		
				Cronbach's Alpha	Lower Bound	Upper Bound	P-value
1	Information use	QIU1. Information repackaging processes are practised at the health centre	12	0.940	0.903	0.968	0.0001
		QIU2.Information disseminating processes are practised at the health centre					
		QIU3. Are analytical reports of key indicators displayed monthly using graphs					
		QIU4. An evidence-based action plan is prepared at the health centre					
		QIU5. An evidence-based action plan is monitored continuously at the health centre					
		QIU6. Is monthly written feedback given from the board to the health centre?					
		Is the information used at the health centre level to					
		QIU7.1. revise implementation strategies?					
		QIU7.2. implement new strategies?					
		QIU7.3. revise annual plans?					
		QIU7.4. monitor day to day activities?					
		QIU7.5. respond to priority health service needs?					
		QIU7.6. link decisions with evidence?					

Table 3.10 shows the lists of items grouped under the dimension information use. As a result, the sum of each item was analyzed to measure the level of internal consistency using the scale reliability test. The twelve items that were summed to create a scale of information use and Cronbach's alpha value of the 12 items were calculated to be 0.940, which indicates that the items form a scale that has sound internal consistency.

3.7.3 Reliability analysis of the main study

Table 3.11: Reliability analysis of availability, knowledge, and user-friendliness of hmis tools (n=590)

SN	Dimensions	Items	Number of items	Intra-class Correlation Coefficient			
				Main study (n=590)			
				Cronbach's Alpha	95% CI		P-value
					Lower Bound	Upper Bound	
1	HMIS tools are always available	QTD2.1. Registers	4	0.847	0.826	0.866	0.0001
		QTD2.2. Tally sheets					
		QTD2.3. Report formats					
		QTD2.4. HMIS manuals					
2	Knowledge of HMIS tools	QTD3.1. I have adequate knowledge on how to manage HMIS manuals	5	0.911	0.899	0.922	0.0001
		QTD3.2. I understand the definitions of HMIS indicators					
		QTD3.3. I have adequate knowledge to collect data in HMIS registers					
		QTD3.4. I have adequate knowledge on how to compile data in tallies					
		QTD3.5. I know how to manage data in reporting formats					
	Perceived user-friendliness of HMIS tools	QTD4.1. It takes long time to complete data from HMIS registers	5	0.828	0.805	0.849	0.0001
		QTD4.2. HMIS tools are easy to use					
		QTD4.3. Organization of the HMIS tools is practical					
		QTD4.4. I feel comfortable using these HMIS tools					
		QTD4.5. Generally, I am satisfied with HMIS tools					

Table 3.11 indicates that the lists of items have different technical dimensions, including the availability of HMIS tools, knowledge of HMIS tools, and user-friendliness of HMIS tools. Accordingly, the sum of each item was assessed, and its internal consistency was measured using the scale reliability test. Hence, the four items were summed to create the scale of HMIS tools availability, and then the Cronbach's alpha value of the four items was 0.847, which indicates that the items form a scale that has reasonable and adequate internal consistency. Similarly, the alpha value for the knowledge of HMIS tools and user-friendliness of HMIS tools was found to be 0.911 and 0.828, respectively.

Table 3.12: Reliability analysis for organizational, behavioural, and data management items (n=590)

SN	Dimensions	Items	Number of items	Intra-class Correlation Coefficient			
				Main study (n=590)			
				Cronbach's Alpha	95% CI		P-value
					Lower Bound	Upper Bound	
1	Organizational determinants of data management processes	QOD1.A written data management strategy is available at the health centre	10	0.862	0.845	0.878	0.0001
		QOD2. A written information use strategy is available at the health centre					
		QOD3. Culture of information use is well promoted at the health centre					
		QOD4. Separate HMIS plan is available at the health centre					
		QOD5. Internal supervision is provided monthly at the health centre					
		QOD6. Motivation to strengthen HMIS is always provided					
		QOD7.1. Staff is encouraged to make evidence-based decisions					
		QOD7.2. Onsite training is conducted regularly to strengthen HMIS					

		QOD7.3. Accountability is promoted to strengthen HMIS					
		QOD8.1. Adequate budget is allocated yearly at the health centre					
2	Behavioural determinants of information use	QBD1. I have adequate knowledge to optimize information use	4	0.911	0.899	0.922	0.0001
		QBD2. I am confident in information use					
		QBD3. I am competent in information use					
		QBD4. I am motivated to optimize information use					
3	Behavioural determinants of data management	QBD5. I am involved in data management tasks to optimize information use	4	0.922	0.912	0.932	0.0001
		QBD6. I have adequate knowledge to manage data process activities					
		QBD7. I am confident in managing data process					
		QBD8. I am competent in data process					
4	Data Management Processes	QDM1.The value of quality data collection is well established	8	0.803	0.778	0.827	0.0001
		QDM2.1.Data compilation processes are often rushed					
		QDM2.2. Do you have adequate knowledge to compile data scientifically?					
		QDM3.1. Do you have the skill to analyze data scientifically?					
		QDM4.There is adequate support for data analysis processes					
		QDM5.1. Do you have the skills to display data using different charts?					
		QDM6. The data presentation is visible at the health centre					
		QDM7. Weekly case presentations are held to manage data problems at health centres					

Table 3.12 indicates the lists of items that were grouped under four dimensions namely organizational, behavioural determinants of information use, behavioural determinants of data management processes, and data management processes. In view of that, the

sum of each item was measured for internal consistency using the scale reliability test. Hence, the ten items were summed to create a scale of organizational determinants for data management processes, and Cronbach's alpha value of the ten items was found to be 0.862, which indicates strong internal consistency. Similarly, the alpha values for the behavioural determinants of information use, behavioural determinants of data management processes, and data management processes were found to be 0.911, 0.922, and 0.803, respectively. These values indicated strong internal consistency.

Table 3.13: Reliability analysis for information use items (n=590)

SN	Dimension		Items	Number of items	Intra-class Correlation Coefficient			
					Main study (n=590)			
						95% CI		
					Cronbach's Alpha	Lower Bound	Upper Bound	P-value
1	Information use		QIU1. Information repackaging processes are practised at the health centre	12	0.910	0.899	0.920	0.0001
			QIU2.Information disseminating processes are practised at the health centre					
			QIU3. Are analytical reports of key indicators displayed monthly using graphs					
			QIU4. Evidence-based action plan is prepared at the health centre					
			QIU5. Evidence-based action plan is monitored continuously at the health centre					
			QIU6. Is monthly written feedback given from the board to the health centre?					
			Is information used at the health centre level to					
			QIU7.1. revise implementation strategies?					
			QIU7.2. implement new strategies?					
			QIU7.3. revise annual plans?					
			QIU7.4. monitor day-to-day activities?					
			QIU7.5. respond to priority health service needs?					
			QIU7.6. link decisions with evidence?					

Table 3.13 shows the lists of items grouped under the dimension information use. The sum of each item was analyzed to measure the level of internal consistency using the scale reliability test. The twelve items that were summed to create a scale of

information use and the Cronbach's alpha value of the 12 items were calculated to be 0.910, which indicates that the items form a scale that has sound internal consistency.

3.8 ETHICAL CONSIDERATIONS

Ethics is associated with the moral responsibility of the researcher towards the respondent's legal values and professional obligation to be ethical towards the research respondents (Neuman 2014:145). This study also identified human rights that require protection in research, including the right to justice, informed consent, protection from discomfort and risk, the right to anonymity and confidentiality, the right to withdraw and the right to beneficence.

3.8.1 The right to justice

The principle of justice focuses on issues of fairness and equity. The principle of justice also imposes duties to neither neglect nor discriminate against individuals or groups who may benefit from research (Gray, Grove & Sutherland 2017:173). It ensures that people who refuse to participate in the study are treated fairly. This means that to ensure fairness and justice, participants in this study were given an equal opportunity to participate. Participants in this study were not compensated in any way. The researcher, on the other hand, informed participants through the information sheet about how to access the research results. This means that the findings of the research should be made available to participants in an appropriate and meaningful format. In addition, to avoid selection bias and to ensure fairness, the researcher followed the inclusion and exclusion criteria established in this study based on the research problem and study purpose.

3.8.2 The right to informed consent and protection from risk

Informed consent is the prospective subject’s agreement to participate in a study or subject, which is reached after the respondent is informed of essential information and content (National Ethics Advisory Committee (NEAC) 2012:20). In this study, key research information was provided to potential respondents via an information sheet. Hence, after reading and agreeing with the information letter, each study participant signed a consent form indicating his/her willingness to participate in the study (Annexure 8).

The right to protection from risk: The researcher must protect respondents from any kind of harm, including physical, emotional, economic and social aspects (Gray, Grove & Sutherland 2017:174). In this study, the researcher provided training to research assistants. They also signed an agreement form on research ethics to maintain confidentiality and to minimize potential risks. Additionally, the following interventions were implemented to reduce risks. Individual identifiers were not used in the study in order to protect participants from psychological or emotional risks such as fear and distrust. Respondents were also informed about the research's benefits as a result of their active participation in the current study in developing data quality, data management, and information use strategies for policy, healthcare facilities, communities, and healthcare providers.

3.8.3 Anonymity and confidentiality

Confidentiality and anonymity are the basic principles used to protect individual privacy. This means that the individual identities of subjects cannot be linked to the information they provide and would not be publicly disclosed (Gray, Grove & Sutherland 2017:688; Neuman 2014:154). Anonymity is the most secure means of protecting confidentiality and ensuring that information cannot be linked to an individual’s responses (Gray, Grove & Sutherland 2017:172). The researcher gathered data for this study by using anonymous questionnaires. The questionnaire did not require respondents to write their names anywhere. No respondent's identity was linked to any questionnaire or research report. There were no personal identifiers for the respondents, and the study setting (i.e. health centres) was not documented using their facility name but rather a facility code on the questionnaire. This was done to ensure that data are not identifiable with particular individual respondents and study settings. All data collectors returned the completed questionnaire in a sealed envelope addressed directly to the researcher, thereby limiting access by parties not involved in the study. All persons who had a role to play in the data collection and analysis processes were trained in research ethics, emphasising preserving respondents' confidentially and anonymously.

3.8.4 Autonomy

Potential respondents were told that they have the full right to refuse to participate or terminate their participation at any time. They could also choose not to respond to some or all questions. The researcher has made sure that each participant participates voluntarily. Respondents were also told that they had the full right to withdraw from responding to any question any time they wished to, without losing any of their rights as health workers in health institutions.

3.8.5 Dissemination of findings

In order to put research findings into practice, it is necessary to understand how to cater to the communication and dissemination preferences and needs of target audiences, such as past research participants who desire but rarely receive information on research findings while participating in research studies. The vast majority of researchers want to share their findings with others, but they are unsure how to do so in a way that non-experts can understand (Melvin, Harvey, Pittman, Gentilin, Burshell & Kelechi 2020:2). This implies that if the results are not shared, there will be no indication that the research has been done and no one will profit from it. As a result, a written research report containing the study's findings will be provided to UNISA, the Addis Ababa public health research and emergency management directorate, and all of the facilities that took part in it. The publication of articles in a recognized journal and presentations at various conferences will spread the results to a global audience.

3.8.6 Scientific integrity of the study

In the medical field, scientific integrity in scholarly writing is critical. Without high standards of scientific integrity, recommendations may have a negative impact on **Sampling and the use of experts:** the scientific community and the general public. As a result, the scientific integrity of the researcher must be unquestionable, and research data must not be falsified or fabricated (Khadilkar 2018:2). All ethical guidelines and scientific research practices were followed throughout this study by the researcher. The data and conclusions presented in this study were not falsified, the results were presented accurately and without any distortion, and no pertinent data were left out.

3.9 METHODS FOR PHASE III

3.9.1 The Delphi technique

The Delphi technique is defined as a multi-staged survey that seeks to achieve consensus on an important issue. It is based on the premise that expert group opinion is more reliable than individual opinion (Keeney, Hasson & McKenna 2011:3). This method was used to review and validate HIS strategies for improving data quality, data management, and information use. Key findings from the first and second phases were combined and articulated into new meanings.

3.9.2 Sampling and sample size

Delphi does not always use a random sample that is representative of the target population, which is an important point to consider for researchers; instead, it relies on experts. This means that each respondent is an expert in the researcher's field of study (Keeney et al. 2011:7). Experts in health information systems from Addis Ababa University, the Federal Minister of Health, the non-governmental organization known as digital health activity, and the Addis Ababa city administration health bureau were targeted, identified and recruited. These experts were purposefully chosen because they possessed knowledge and practical experience in the field of study to review and validate proposed HIS strategies (Guetterman) (2015:5), which contributed to the field by addressing gaps, shaping and supporting overall HIS policies.

Sample size: Twenty-one experts (n=21) from Addis Ababa University (n=4), the Federal Minister of Health (n=4), the non-governmental organization known as digital health activity (n=6), and the Addis Ababa city administration health bureau (n=7) were included.

3.9.3 Data collection approach

Data collection approach: A structured and closed-ended proposed HMIS strategy with Likert scale three-level options and a column section for comments and modifications were prepared for review and validation in order to achieve consensus.

Preparing a proposed strategy for review:

Round one: The sequences and consistency of the strategies were optimized by categorizing them into data quality, data management, and information us*e.* Based on the combined data sets, the HMIS strategy with specific action plans, responsible bodies, indicator success, and time of implementation was developed. The proposed strategies were sent through email to each expert separately with a consent form which was followed by phone calls and text messages. The expected date of return of the reviewed strategies was agreed to be one week with each expert, and a phone call was made to remind them. The review instructions were clearly stated to each expert to use the Likert scale options to indicate levels of agreement or disagreement with each proposed strategy in the response column, and to write any suggestions or modifications to improve the proposed strategies in the last column under the comment section if the expert strongly disagrees or disagrees with any of the proposed strategies, or if neutral.

Round two: The findings of the first round, including Likert scale values, comments, and strategy modifications, were summarized, incorporated, and refined for expert validation. Five validation criteria, including scope and purpose, clarity and simplicity, feasibility, importance, and quality content, were developed for the final and reviewed strategy; and then two clear validation instructions were prepared and labelled at the top of the page: Instruction-1 advised each expert to read the final reviewed and improved HIS strategies on which the validation was based; and instruction-2 instructed each expert to use a three-point Likert scale, such as (1) if the expert strongly disagreed/disagreed, (2) if the expert was neutral, and (3) if the expert agreed or strongly agreed in the response column.

3.9.4 Data analysis

Descriptive analysis: Many published Delphi studies analyzed data using descriptive statistics such as percentage and mean expert responses (Drennan, Meehan, Kemple, Johnson, Treacy & Butler 2007:3; Madigan & Vanderboom 2005:3). In this study phase, frequency distribution and the central tendency were used as part of the descriptive analysis. This means that the frequency distribution was used to calculate each level of agreement in percentages; for example, the magnitude of each agreement on each proposed strategy was calculated and documented in percentages in Chapter 6; a measure of central tendency was used, for example, to calculate experts' mean consensus on the reviewed strategies in round one; and validated strategies on round two. Moreover, the mean of the experts' consensus on data quality, data management, and information use was calculated. Despite the fact that greater than or equal to 70% of agreement is commonly reported in the literature, there is no accepted set of standards for the target percentage of agreement (Stewart, Gibson-Smith, MacLure, Mair, Alonso, Codina, Cittadini and Fernandez-Llimos 2017:4). In this study, it was assumed that if the level of agreement among experts on the proposed strategies, action plans, responsible body, indicator of success and time of implementation reached greater than or equal to 70% in the first round; and then experts only be asked to put their overall validation agreement based on the five newly designed validation criteria in the second round; and then the validation process would be completed. However, if the level of agreement did not meet the cut point in the first round, the second round was continued for review, and then experts were asked to put their overall validation agreement based on the five newly designed validation criteria in the third round. Figure 3.6 depicts the overall logical flow of findings integration, key gaps identification, and HIS strategy review and validation processes. The details of strategy development, validation, and discussion are presented in Chapter 6.

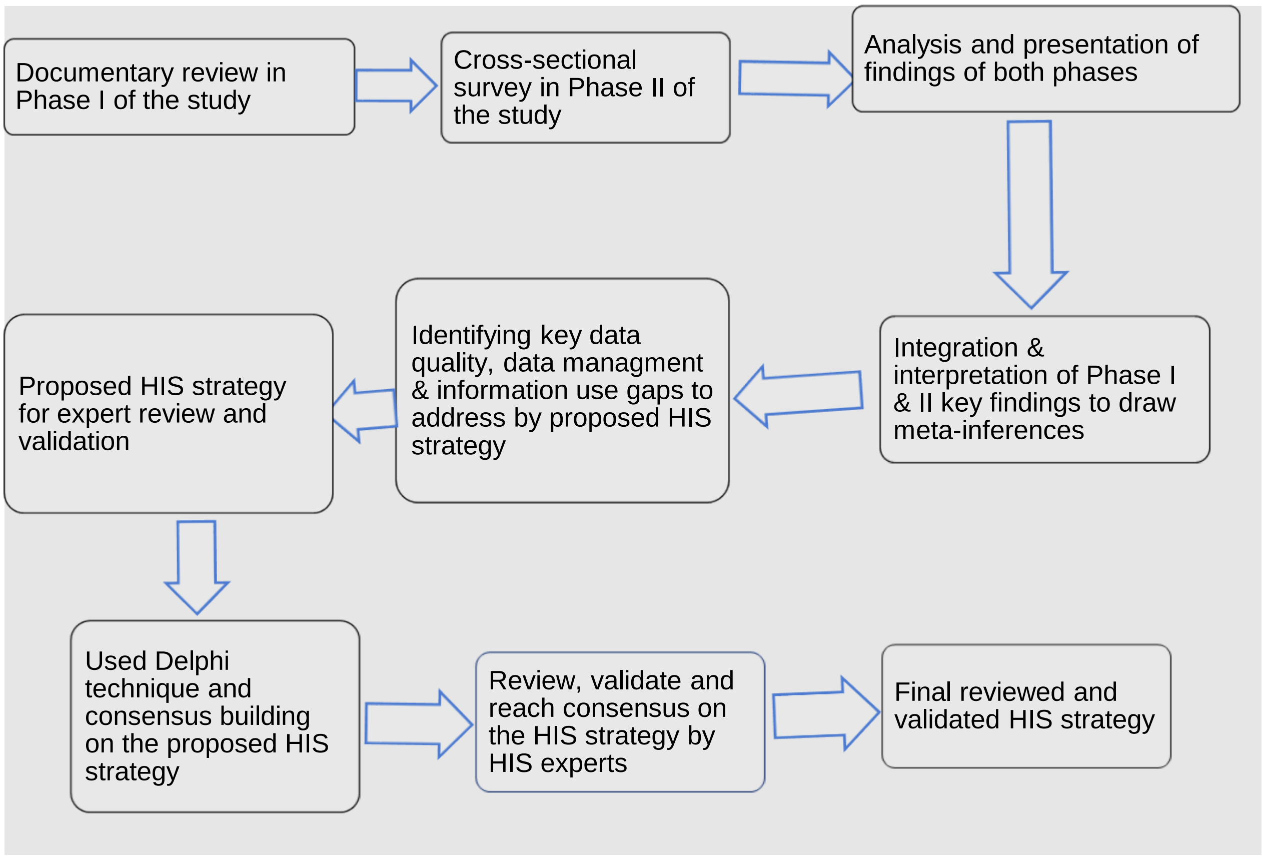

Figure 3.6: The flow of integration, review and validation processes of HIS strategies

3.10 SUMMARY

The research methodology through the three stages of the study was discussed in this chapter. The research pyramid approach and the theoretical framework were presented, which guided the entire study. This means that the research approach, design, and methods through the three phases of the study were discussed. The validity, reliability, and ethical considerations of the study were also discussed and documented. In chapter four, findings from the study of phases one and two are presented and described.

CHAPTER FOUR

ANALYSIS AND PRESENTATION OF FINDINGS

4.1 INTRODUCTION

In this chapter, findings from the study of phases one and two are presented and described. In Phase I, the objective of the quantitative document review was to assess the level of accuracy, completeness, and timeliness of data to assist policymakers in various decision-making processes. As a result, the findings of the document are presented in three sections below. Section one focuses on the level of data accuracy. In addition, the data accuracy of each data element and indicator is compared between different HMIS data sources across the public health centres (n=10) over six months to assess variations and similarities. Section two emphasizes the completeness of the content and different data sources. The level of completeness of each selected data element and indicator is compared based on the evaluation criteria for each data element and indicator.

Finally, section three reports on the timeliness of the reports generated from public health centres from April to September 2019.

4.2 DATA ANALYSIS

The data collected were checked by the researcher and two research assistants for completeness before entering into software for analysis. And then, data were entered into SPSS version 26 primarily to recode, clean, recheck missing data values, and prepare for descriptive analysis, including cross-tabulation. In addition, the data were exported from the SPSS to a spreadsheet for further arrangement and analysis. The results are presented in tables and charts.

4.3 FINDINGS OF QUANTITATIVE DOCUMENT REVIEW

Data quality is defined as data suitable for use that meet specified healthcare system data quality standards. This definition states that data quality depends on the purpose of data use (Measure Evaluation 2018:3). The retrospective quantitative document review was conducted to evaluate the accuracy, completeness, and timeliness of data generated by the ten public health centres from April to September 2019. Sources of data included five registers, tally sheets, reporting forms and DHIS2.

Accuracy refers to measuring data against a referenced source and found to be correct (Gabr et al. 2021:9). In this study, accuracy is defined as all the values of study data elements, and indicators in registers, tally sheets, reporting forms and the database are found uniform and identical for all the six consecutive reporting months from April 2019 to September 2019.

4.3.1 Summary of data elements and indicators used in this review

A data element is the smallest named item within the basic unit used to collect raw facts and generate meaningful information to support various decision-making processes (FMOH 2018:23). In this study, a total of 25 data elements were used to review maternal healthcare data quality that had been preplanned in advance.

An indicator is defined as a variable that helps to measure status or changes over time quantitatively (Measure Evaluation 2015:6). An indicator is a clue or a marker that indicates how close one is to achieve a goal and is used to assess one aspect of a program, project, or health outcome (FMOH 2018:23). In this case, 13 indicators were pre-planned and used to assess the quality of maternal data.

Table 4.1: Data elements, indicators, and hmis tools used to assess data accuracy

SN	Lists of data elements and indicators	Type of data reviewed	Availability of HMIS tools				Register name/type of register reviewed
			Does it have register (Yes=1, No=0)?	Does it have tally (Yes=1, /No=0)?	Does it have reporting forms (Yes=1, /No=0)?	Does it have DHIS2 (Yes/=1, No=9)?	
1	Family planning visit	Indicator	1	1	1	1	Family planning registers
1.1	New contraceptive acceptance rate by age	Data element	1	1	1	1	
1.2	Repeat contraceptive acceptance rate by age	Data element	1	1	1	1	
2	ANC 1st visit	Indicator	1	1	1	1	Antenatal care registers
3	ANC 4th visit	Indicator	1	1	1	1	
4	Syphilis total tested	Indicator	1	1	1	1	
4.1	Syphilis test reactive	Data element	1	1	1	1	
4.2	Syphilis test non-reactive	Data element	1	1	1	1	
5	Hepatitis total tested	Indicator	1	1	1	1	
5.1	Hepatitis test reactive	Data element	1	1	1	1	
5.2	Hepatitis test non-reactive	Data element	1	1	1	1	
6	Abortion care services	Indicator	1	1	1	1	Abortion registers
6.1	safe abortion	Data element	1	1	1	1	
6.2	Post-abortion	Data element	1	1	1	1	
7	Skilled Birth Attendance	Indicator	1	0	1	1	Delivery registers
8	Live birth	Indicator	1	0	1	1	
9	Maternal deaths	Indicator	1	0	1	1	
10	Early postnatal care visit	Indicator	1	0	1	1	PNC registers

Table 4.1 shows that eight data elements and ten indicators were reviewed to check the accuracy of the data in the HMIS tools, including registers (family planning, ANC, delivery, PNC, and abortion); the tally sheets (including family planning, ANC, and abortion); monthly health service reporting forms, and the DHIS2 database. Registers are the sources of the original/primary data and were used as references for comparison with tallies, reporting forms, and DHIS2. The results show that all data elements were represented in the 4 data sources of areas under the review. However, 4 indicators did not have tallies. Therefore, the comparison was made in two different ways. The first comparison included registers, tallies, reporting forms, and DHIS2.3, and the second stage involved those that did not have tally sheets.

4.3.2 Findings of data accuracy

Table 4.2 provides a summary of the first-level analysis. In this case, indicators and data elements containing four data sources were reviewed and cross-checked to measure the extent of variations and similarities in the level of accuracy. Therefore, the detailed findings of the reviews are presented in the tables below.

4.3.2.1 New and repeat contraceptive acceptance rate

Table 4.2: Cross-tabulation of 6 months aggregated data of new and repeat acceptors

Data element/ indicator	Months April 2019 to September 2019	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Form	DHIS2	Register tally	Register form	Register DHIS2.3	
New CAR by age	Apr	671	234	437	685	437 (65%)	234 (35%)	14 (2%)	228 (34%)
	May	835	502	680	803	333 (40%)	155 (19%)	32 (4%)	173 (21%)
	Jun	839	633	804	1024	206 (25%)	35 (4%)	185 (22%)	142 (17%)
	Jul	793	739	839	924	54 (7%)	46 (6%)	131 (17%)	77 (10%)
	Aug	891	699	853	1059	192 (22%)	38 (4%)	168 (19%)	133 (15%)
	Sep	829	918	847	966	89 (11%)	18 (2%)	137 (17%)	81 (10%)
	Total 6	**4858**	**3725**	**4460**	**5461**	**1133 (23%)**	**398 (8%)**	**603 (12%)**	**711 (15%)**
Repeat CAR by age	Apr	1049	753	1040	1380	296 (28%)	9 (1%)	331 (32%)	212 (20%)
	May	1169	990	1494	1504	179 (15%)	325 (28%)	335 (29%)	280 (24%)
	Jun	1208	1147	1491	1491	61 (5%)	283 (23%)	283 (23%)	209 (17%)
	Jul	1202	1214	1535	1535	12 (1%)	333 (28%)	333 (28%)	226 (19%)
	Aug	1260	1283	1546	1556	23 (2%)	286 (23%)	296 (23%)	202 (16%)
	Sep	1609	1743	1857	1885	134 (8%)	248 (15%)	276 (17%)	219 (14%)
	Total 6	**7497**	**7130**	**8963**	**9351**	**367 (5%)**	**1466 (20%)**	**1854 (25%)**	**1229 (16%)**

New contraceptive users refer to the number of modern contraceptive method user clients who receive family planning services from a recognized health facility for the first time. Thus, the findings in Table 4.2 show that 4,858 new users were documented in the family planning registers. However, 23% (n=1133) and 8% (n=398) of these new users were not found in the tally sheets and reporting forms, respectively. Moreover, the new contraceptive users were 12% (n=603) higher in DHIS2.3 compared to the family health register. The highest and lowest difference between registers and reporting forms was 35% (n=234) in April and 2% (n=18) in September, respectively.

Repeat contraceptive users refer to the number of acceptors who previously received family planning services from a recognized family planning facility, irrespective of the method used. The findings in Table 4.2 show that 7497 repeat contraceptive users were identified in the family health registers. Nevertheless, 5% (n=367) of repeat acceptors were not found in the tally sheets. On the other hand, the repeat contraceptive acceptors in reporting forms and DHIS2.3 were found to be 20% (n=1466) and 25% (n=1854) higher when compared to the family health register, respectively.

Average variation of new and repeat contraceptive acceptance rate

The maximum data source variation for new contraceptive users across the HMIS tools was 34% (n=228) in April and 21% (n=173) in May 2019. Moreover, the minimum data source variation across the HMIS tools was 10% (n=77) in July 2019 and 10% (n=81) in September 2019. Over the six months, the overall data variation for new acceptors across the data sources of HMIS tools is 15% (n=711) (Table 4.2). Furthermore, the maximum and minimum data source variations for repeat acceptors across the HMIS tools were 24% (n=280) and 14% (219) in May and September 2019, respectively. Besides, the average data accuracy variation of HMIS tools was found to be 16% (n=1229) in the six months. The average data source variation of repeat acceptors was 1% higher when compared to the new acceptors from April to September 2019 (Table 4.2).

4.3.2.2 Ante-Natal visits

Table 4.3: Cross-tabulation of 6 months aggregated data of the anc first and anc fourth visits

Data element/ Indicator	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Form	DHIS2	Register tally	Register form	Register DHIS2.3	
ANC 1st visit	Apr	1194	447	1089	1210	747 (63%)	105 (9%)	16 (1%)	289 (24%)
	May	1220	743	1223	1223	477 (39%)	3 (0.2%)	3 (0.2%)	161 (13%)
	Jun	1389	867	1405	1405	522 (38%)	16 (1%)	16 (1%)	185 (13%)
	Jul	1256	737	1262	1170	519 (41%)	6 (0.5%)	86 (7%)	204 (16%)
	Aug	1162	679	1199	1210	483 (42%)	37 (3%)	48 (4%)	190 (16%)
	Sep	1435	886	1456	1452	549 (38%)	21 (1%)	17 (1%)	196 (14%)
	Total	**7656**	**4359**	**7634**	**7670**	**3297 (43%)**	**22 (0.3%)**	**14 (0.2%)**	**1111 (15%)**
ANC 4th visit	Apr	699	376	682	1471	323 (46%)	17 (2%)	772 (110%)	371 (53%)
	May	861	638	877	884	223 (26%)	16 (2%)	23 (3%)	262 (10%)
	Jun	840	605	973	899	235 (28%)	133 (16%)	59 (7%)	142 (17%)
	Jul	791	586	915	954	205 (32%)	124 (16%)	163 (21%)	164 (21%)
	Aug	833	615	934	956	218 (26%)	101 (12%)	123 (15%)	147 (18%)
	Sep	893	635	1040	1053	258 (29%)	147 (16%)	160 (18%)	188 (21%)
	Total	**4917**	**3455**	**5421**	**6217**	**1462 (30%)**	**504 (10%)**	**1300 (26%)**	**1089 (22%)**

Antenatal care first visit is defined as the proportion of pregnant women who received antenatal care first visit during the current pregnancy. This indicator has been reviewed using four HMIS data sources. Thus, the findings presented in Table 4.3 show that 7656 the ANC first users were identified in the ANC registers. The difference between registers and reporting forms, as well as registers and DHIS2.3, was found to be only 1%. However, 43% (n=3297) of the ANC first users were not documented in the tally sheets.

Antenatal care fourth visit is defined as the proportion of pregnant women who received antenatal care four or more times during the current pregnancy. The findings in Table 4.3 show that 4,917 ANC fourth users were identified in the ANC registers. In contrast, the numbers of ANC-4 users documented in reporting forms and DHIS2 were 10% (n=504) and 26% (n=1300) higher than in the ANC registers, respectively. In addition, 30% (n=1462) of the ANC fourth users were not documented in the tally sheets compared to registers.

Average variation of ante-natal care visits

Findings presented in Table 4.3 indicate that the maximum and minimum variability in antenatal care first visits across the HMIS tools (registers, tallies, reporting forms and DJIS2.3) was found to be 24% (n=289) and 13% (n=161), respectively in April and May 2019. Moreover, the average data accuracy variation of HMIS tools was found to be 15% (n=1111) from April to September 2019 (Table 4.3). Likewise, the maximum and minimum data source variation of Antenatal care fourth visits across the HMIS tools was 54% (n=371) and 10% (n=262) in April and May 2019, respectively. Henceforth, the mean data accuracy variation of HMIS tools was found to be 22% (n=1089) from April to September 2019 (Table 4.3). Overall, the antenatal care first visit's average data source variance was 7% lower than the antenatal care fourth visits over the six months (Table 4.3).

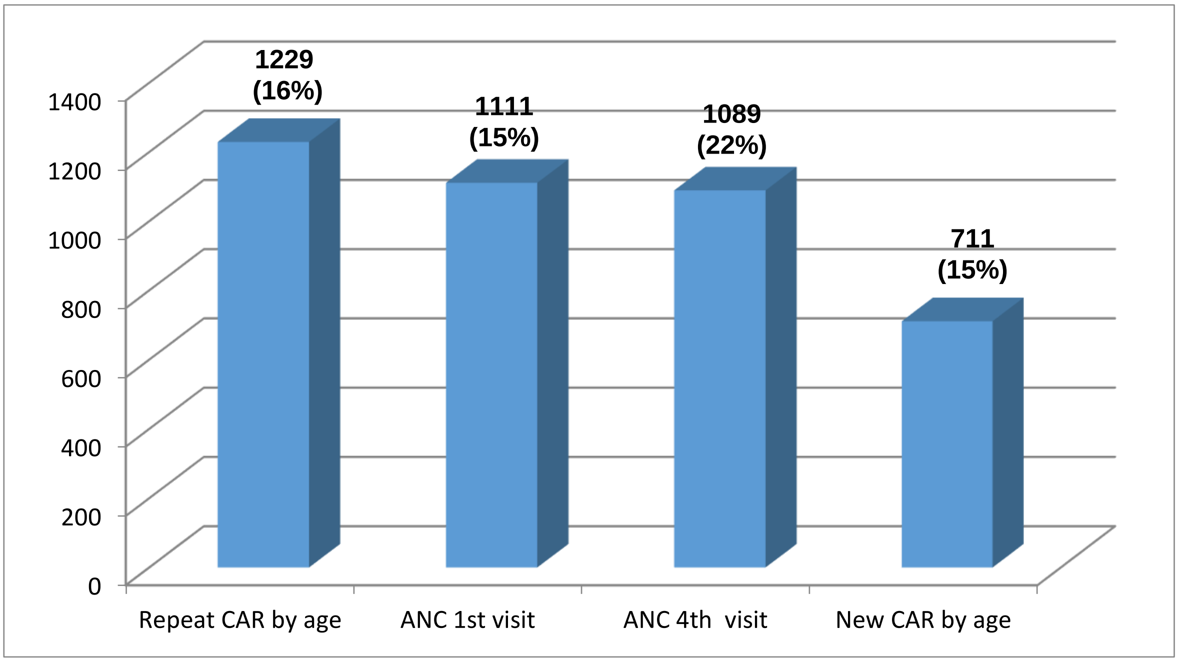

Figure 4.1: Data accuracy variations across data sources

4.3.2.3 Syphilis tests and results

Table 4.4: Cross-tabulation of 6 months of aggregated data of syphilis tests and results

Data element/ indicator	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Form	DHIS2	Register tally	Register form	Register DHIS2.3	
syphilis total tested	Apr	1191	450	1089	1209	741 (62%)	102 (9%)	18 (1.5%)	287 (24%)
	May	1222	534	1215	1223	688 (56%)	7 (1%)	1 (0.1%)	232 (19%)
	Jun	1398	625	1405	1301	773 (55%)	7 (1%)	97 (7%)	292 (21%)
	Jul	1251	540	1262	1270	711 (57%)	119 (1%)	19 (1.5%)	283 (23%)
	Aug	1148	489	1159	1212	659 (57%)	11 (1%)	64 (5.6%)	245 (21%)
	Sep	1433	650	1407	1456	783 (55%)	26 (2%)	23 (1.6%)	277 (19%)
	Total	**7643**	**3288**	**7537**	**7671**	**4355 (57%)**	**106 (1%)**	**28 (0.4%)**	**1496 (20%)**
syphilis test reactive	Apr	8	3	6	77	5 (63%)	2 (25%)	69 (>100%)	25 (>100%)
	May	15	7	10	86	8 (53%)	5 (33%)	71 (>100%)	28 (>100%)
	Jun	8	4	7	114	4 (50%)	1 (13%)	106 (>100%)	37 (>100%)
	Jul	14	3	9	66	11 (79%)	5 (36%)	52 (>100%)	23 (>100%)
	Aug	8	1	3	63	7 (88%)	5 (63%)	55 (>100%)	22 (100%)
	Sep	14	3	9	72	11 (79%)	5 (36%)	58 (>100%)	25 (>100%)
	Total	**67**	**21**	**44**	**478**	**46 (69%)**	**23 (34%)**	**411 (>100%)**	**160 (>100%)**
syphilis test non-reactive	Apr	1183	432	1073	1204	751 (63%)	110 (9%)	21 (2%)	294 (25%)
	May	1207	523	1207	1215	684 (57%)	0 (0%)	8 (1%)	231 (19%)
	Jun	1390	621	1398	1294	769 (55%)	8 (1%)	96 (7%)	291 (21%)
	Jul	1228	537	1253	1262	691 (56%)	25 (2%)	34 (3%)	250 (20%)
	Aug	1139	488	1156	1209	651 (57%)	17 (1%)	70 (6%)	246 (22%)
	Sep	1429	645	1398	1449	774 (55%)	21 (1%)	30 (2%)	275 (19%)
	Total	**7576**	**3246**	**7485**	**7633**	**4320 (57%)**	**81 (1%)**	**67 (1%)**	**1489 (20%)**

Total syphilis tested is defined as the proportion of pregnant women attending antenatal care visits who have been tested for syphilis. Findings provided in Table 4.4 show that a total of 7,643 syphilis-tested mothers have been identified and reviewed from the ANC register. On average, 57% (n=4355) of the total syphilis-tested mothers were not documented in the tally sheets when compared to registers. Moreover, 62%

(n=741) and 2% (n=26) of the mothers were not found in April tally sheets and reporting forms. Likewise, on average, 2% (n=26) of the mothers were not identified in reporting forms compared to registers.

Besides, **syphilis reactive** is defined as the proportion of pregnant women receiving antenatal care who were positive for a syphilis test. Findings presented in Table 4.4 indicate that 67 reactive mothers of syphilis have been documented at the ANC register. However, in DHIS2.3, the number of mothers' test results reactive for syphilis in DHIS2.3 was more than seven times higher than the original data sources. Additionally, those mothers in tallies and reporting forms were found to be 69% (n=46) and 34% (n=23) higher than those in registers, respectively.

In addition, the findings presented in Table 4.4 show that a total of 7,576 mothers were documented as having non-reactive syphilis. However, 57% (n=4320) of these mothers were not properly documented in the tallies. Also, 1% (n=81) of the mothers were not identified in the form. Similarly, 1% (n=67) more mothers were found in DHIS2.3 compared to registers.

Average variation of syphilis tests and results

Table 4.4 shows that the maximum and minimum data source variations of total syphilis tested across the HMIS tools was 24% (n=287) in April and 19% (n=277) in September 2019, respectively. In addition, the average data accuracy variation of total syphilis tested was found to be 20% (n=1496) in the six months. Moreover, Table 4.4 shows that the maximum, minimum and average data source variations of syphilis results reactive were found to be identical and >100% for all scenarios, respectively. Table 4.4 shows that the maximum and minimum data source variations of syphilis non-reactive mothers across the HMIS tools were found to be19% (n=231) in May and 25% (n=294) in April 2019, respectively. Similarly, the average data source variation for syphilis non-reactive mothers across the HMIS tools was found to be 20%. Overall, the average data source variation of syphilis-reactive mothers was >80% higher than syphilis non-reactive mothers in the six months (Table 4.4).

4.3.2.4 Hepatitis tests and results

Table 4.5: Cross-tabulation of 6 months of aggregated data of hepatitis tests and results

Data element/indicator	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Form	DHIS2	Register tally	Register form	Register DHIS2.3	
Hepatitis total tested	Apr	1194	444	1089	1211	750 (63%)	105 (9%)	17 (1%)	291 (24%)
	May	1220	522	1221	1223	698 (57%)	1 (0.1%)	3 (0.2%)	234 (19%)
	Jun	1397	623	1405	1405	774 (55%)	8 (1%)	8 (1%)	263 (19%)
	Jul	1251	538	1261	1270	713 (57%)	10 (1%)	19 (2%)	247 (20%)
	Aug	1145	485	1158	1212	660 (58%)	13 (1%)	67 (6%)	247 (22%)
	Sep	1279	501	1253	1302	778 (61%)	26 (2%)	23 (2%)	276 (22%)
	Total	**7486**	**3113**	**7387**	**7623**	**4373 (58%)**	**99(1%)**	**137 (2%)**	**1536 (21%)**
Hepatitis test reactive	Apr	19	11	19	19	8 (42%)	0 (0%)	0 (0%)	3 (16%)
	May	20	9	19	20	11 (55%)	1 (5%)	0 (0%)	4 (20%)
	Jun	25	7	25	26	18 (72%)	0 (0%)	1 (4%)	6 (24%)
	Jul	12	4	12	12	8 (67%)	0 (0%)	0 (0%)	3 (25%)
	Aug	20	6	14	13	14 (70%)	6 (30%)	7 (35%)	9 (45%)
	Sep	20	9	18	18	11 (55%)	2 (10%)	2 (10%)	5 (25%)
	Total	**116**	**46**	**107**	**108**	**70 (60%)**	**9 (8%)**	**8 (7%)**	**29 (25%)**
Hepatitis test non-reactive	Apr	1175	425	1070	1192	750 (63%)	105 (9%)	17 (1%)	291 (24%)
	May	1200	502	1201	1203	698 (57%)	1(-0.1%)	3 (0.2%)	234 (19%)
	Jun	1372	598	1380	1380	774 (55%)	8(-1%)	8 (1%)	263 (19%)
	Jul	1239	526	1249	1258	713 (57%)	10(-1%)	19 (2%)	247 (20%)
	Aug	1125	465	1138	1192	660 (58%)	13(-1%)	67(6%)	247 (22%)
	Sep	1259	481	1233	1282	778 (61%)	26(2%)	23 (2%)	276 (22%)
	Total	**7370**	**2997**	**7271**	**7507**	**4373 (59%)**	**99 (1%)**	**137 (2%)**	**1536 (21%)**

Total hepatitis tested is defined as the proportion of pregnant women attending antenatal care who have been tested for hepatitis. A total of 7,486 hepatitis-tested mothers were reviewed from the ANC registers, as indicated in Table 4.5. Conversely, 58% (n=4373) and 1% (n=99) of these mothers were not documented in the tally sheets and reporting forms, respectively, compared to registers. On average, 2% (n=137) of the mothers were not registered in the registers compared to DHIS2.3.

Moreover, **hepatitis reactive** is defined as the proportion of pregnant women taking antenatal care who have been positive for hepatitis tests. Findings presented in Table 4.5 show that 116 reactive mothers of hepatitis have been identified over the six months. In particular, the numbers of reactive mothers in reporting forms and registers were the same in April, June and July 2019. In addition, the number of reactive mothers of hepatitis was found to be the same in April, May and July. Yet, 60% (n=70) of them were not found in tally sheets but at registers.

Similarly, **hepatitis non-reactive** is defined as the proportion of pregnant women receiving antenatal care that were negative in hepatitis testing. Likewise, the findings reported in Table 4.5 indicate that a total of 7,370 mothers were non-reactive to hepatitis. But in tallies, on average, 59% (n=4373) of those mothers have not been recorded. In particular, in April and September, 63% (n=63750) and 61% (n=778) of these mothers were not registered in tally sheets, respectively.

Average variation of hepatitis tests and results

The results presented in Table 4.5 show that the maximum and minimum data source variations of total hepatitis tested across the HMIS tools (registers, tallies, reporting forms and DHIS2.3) were 24% (n=291) in April, and 19% (n=234) in May 2019 respectively. In general, the average data accuracy variation of total hepatitis tested was found to be 21% (n=1536) from April to September 2019 (Table 4.5). Besides, the maximum, minimum and average data source variations of hepatitis non-reactive across the HMIS tools were 45% (n=9) in August and 16% (n=3) in April 2019, respectively. In general, the average data sources variation of hepatitis tested reactive was found to be 25% (n=29) (Table 4.5).

And the maximum and minimum variations in data source for hepatitis test non-reactive across the HMIS tools were 24% (n=291) in April and 19% (n=234) in May, respectively. The average variance in data sources for non-reactive hepatitis testing across the HMIS instruments was 21% (n=1536) (Table 4.5). Overall, the average data source variation of hepatitis-reactive mothers was 4% higher than total hepatitis testing and non-reactive mothers with syphilis over the six months (Table 4.5).

4.3.2.5 Safe and post-abortion care

Table 4.6: Cross-tabulation of aggregated data of safe and post-abortion care

Data element	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Form	DHIS2	Register tally	Register form	Register DHIS2.3	
safe abortion care performed	Apr	72	44	39	68	28 (39%)	33 (46%)	4 (6%)	22 (31%)
	May	85	45	56	77	40 (47%)	29 (34%)	8 (9%)	26 (31%)
	Jun	63	37	40	62	26 (41%)	23(37%)	1 (2%)	17 (27%)
	Jul	84	42	69	83	42 (50%)	15 (18%)	1 (1%)	19 (23%)
	Aug	80	44	60	72	36 (45%)	20 (25%)	8 (10%)	21 (26%)
	Sep	56	33	45	53	23 (41%)	11(20%)	3 (5%)	12 (21%)
	Total	**440**	**245**	**309**	**415**	**195 (44%)**	**131 (30%)**	**25 (6%)**	**117 (27%)**
Post-abortion care performed	Apr	32	11	20	28	21 (66%)	12 (38%)	4 (13%)	12 (38%)
	May	22	10	22	25	12 (55%)	0 (0%)	3 (14%)	5 (23%)
	Jun	28	10	26	32	18 (64%)	2 (7%)	4 (14%)	8 (29%)
	Jul	25	14	20	37	11(44%)	5 (20%)	12 (48%)	9 (36%)
	Aug	28	10	22	25	18 (64%)	6 (21%)	3 (11%)	9 (32%)
	Sep	18	8	17	20	10 (56%)	1(6%)	2 (-11%)	4 (22%)
	Total	**153**	**63**	**127**	**167**	**90 (59%)**	**26 (17%)**	**14 (-9%)**	**43 (28%)**

Safe abortion is characterized as the number of women receiving safe abortion care. In this case, Table 4.6 indicates that a total of 440 mothers were identified as safe abortion care users in the abortion registers. In comparison, the tally sheets did not record 44% (n=195) of those safe abortion user mothers. In addition, the number of safe abortion users in the reporting forms was found to be 30% (n=131) lesser compared to the registers.

Post-abortion care performed is defined as the number of women receiving post-abortion care. Hence, this data element was reviewed, and its level of accuracy was determined using the HMIS tools. Findings shown in Table 4.6 indicate that 153 users of post-abortion care were reported from the abortion registers. However, 59% (n=90) of those post-abortion service user mothers were not documented in the tally sheets. In comparison, the number of post-abortion users was found to be 17% (n=26) lower in the reporting forms compared to the registers in 2019 (Table 4.6).

Average variation of safe and post-abortion care

Findings presented in Table 4.6 show that the maximum and minimum differences in data source variations for safe abortion across the HMIS tools were 31% (n=26) in May and 21% (n=12) in September, respectively. And, the average variability in the data sources was found to be 27% (n=117) from April to September 2019. Similarly, the maximum, minimum and average variability in post-abortion data sources across the HMIS tools was 32% (n=12), 22% (n=4), and 28% (n=43), respectively, from April to September. As a whole, the average data source variation of post-abortion performed mothers was 1% higher than safe abortion performed mothers in the six months (Table 4.6).

In summary, in the first level of analysis, all the reviewed four indicators and eight data elements using the four data sources of HMIS tools (registers, tallies, reporting forms, and DHIS2.3) have shown significant variations in each of the reviewed months as well as the sum of the months from April to September 2019 as shown below in Figure 4.2.

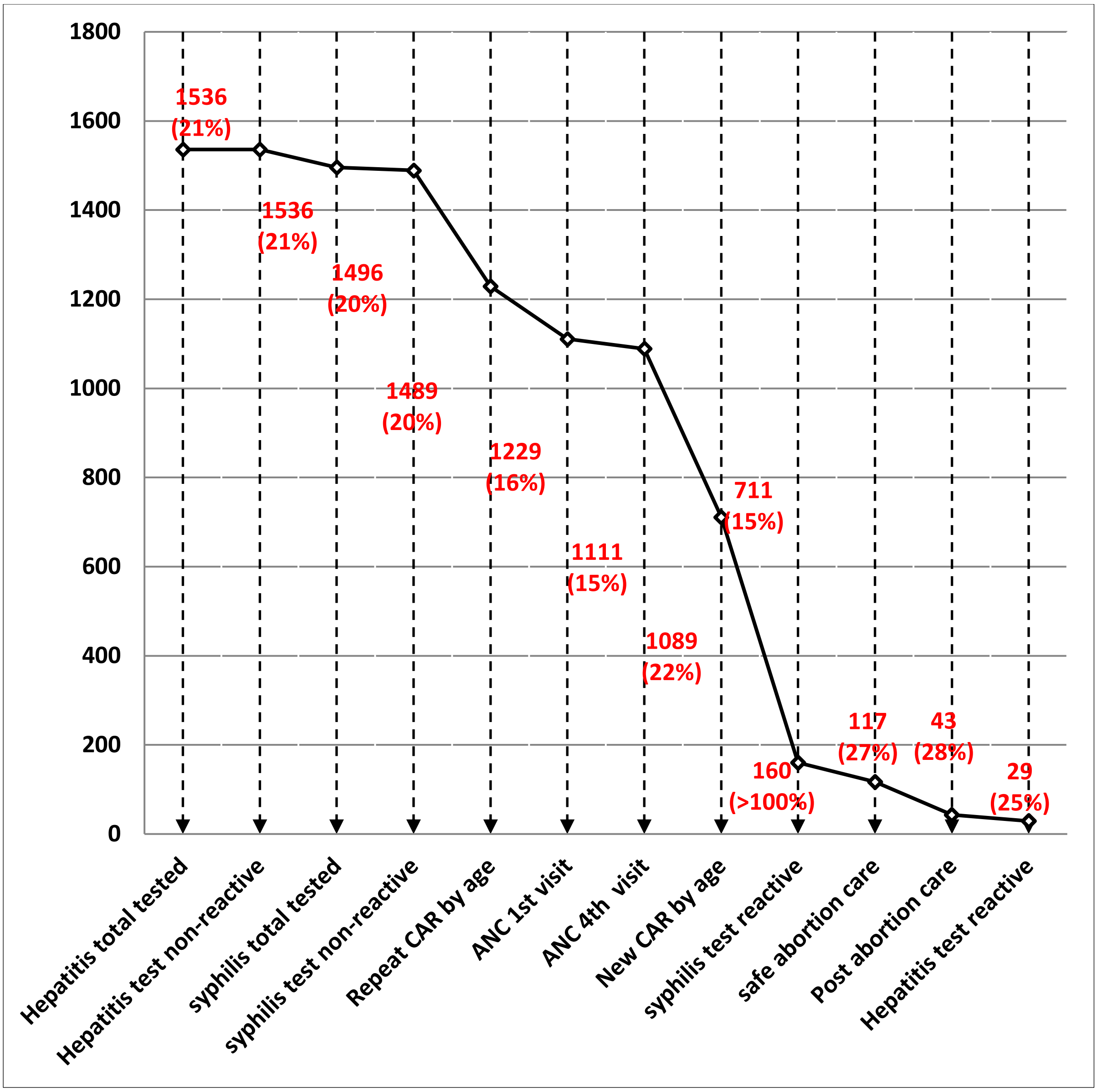

Figure 4.2: Average variation of data elements and indicators across the hmis tools

In the second level of analysis, four indicators, including skilled birth attendance, live births, maternal deaths, and early postnatal care visits, were reviewed across the three data sources of HMIS tools (registers, reporting forms and DHIS2.3) to cross-check the level of data accuracy, and to measure the extent of variation between the tools and across the tools. Thus, the results of reviews are summarized and presented with tables as follows.

4.3.2.6 Skilled birth attendance and live births

Table 4.7: Cross-tabulation of aggregated data of skilled birth attendance and live births

Indicator	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools			Variation between		Average variation of data across sources
		Register	Form	DHIS2	Register form	Register DHIS2.3	
Skilled Birth Attendance	Apr	529	500	529	29 (5%)	0 (0%)	13 (3%)
	May	537	525	540	12 (2%)	3 (1%)	7 (1.4%)
	Jun	578	580	580	2 (0.3%)	2 (0.3%)	2 (0.3%)
	Jul	547	566	566	19 (3%)	19 (3%)	17 (3.5%)
	Aug	562	561	563	1 (0.2%)	1 (0.2%)	1 (0.2%)
	Sep	670	670	665	0 (0%)	5(1%)	2 (0.3%)
	Total	**3423**	**3402**	**3443**	**21 (1%)**	**20(-1%)**	**42 (1.2%)**
Live birth	Apr	529	500	528	29 (5%)	1 (0.2%)	15 (3%)
	May	537	525	538	12 (2%)	1 (0.2%)	6 (1%)
	Jun	578	580	578	2 (0.3%)	0 (0%)	2 (0.2%)
	Jul	564	565	558	1(0.2%)	6 (1%)	3 (1%)
	Aug	561	487	561	74 (13%)	0 (0%)	37 (7%)
	Sep	670	670	670	0 (0%)	0 (0%)	0 (0%)
	Total	**3439**	**3327**	**3433**	**112 (3%)**	**6 (0.2%)**	**62 (2%)**

Skilled birth attendance is characterized as the proportion of births that are attended at a health facility by skilled health personnel. As a consequence, the findings presented in Table 4.7 show that a total of 3,423 skilled birth attendance (SBA) service users have been identified from the delivery registers. In addition, the numbers of SBA users were found to be the same in registers and reporting forms in September. At the same time, SBA users in registers and DHIS2.3 were the same in the month of April. Despite that, 1% (n=21) of SBA users were not documented in the reporting forms compared to the registers. On the other hand, 1% (n=20) of higher SBA users were identified in the DHIS2.3 but not in registers.

Moreover, **live birth** is defined as the proportion of live births obtained from mothers who delivered at a health facility. In this case, as indicated in Table 4.7, a total of 3,439 live births have been reviewed from the delivery registers. In the months of June, August, and September, the numbers of live births were found to be the same in registers and DHIS2.3 On the other hand, compared to the delivery registers, 3% (n=112) of the live births were not identified in the reporting forms.

Average variation of skilled birth attendance and live births

The findings described in Table 4.7 indicate that the maximum, minimum and average variation in the data source of SBA users across the HMIS tools were 2% (n=13), 0.2% (n=1), and 0.4% (n=14), respectively. Besides, the maximum and minimum variance in the data sources for live births was 4% (n=25) in August and 0% (n=0) in September, respectively. Moreover, the live births data has shown a 1% (n=39) average variation across the HMIS data sources in the six months. Altogether, the average data source variation of live births was 0.8% higher than SBA users in the six months (Table 4.7).

4.3.2.7 Maternal death and early postnatal care visit

Table 4.8: Cross-tabulation of aggregated data of maternal death and early postnatal care visit

Indicators	Months from April 2019 to September 2019	Number of cases reviewed from HMIS tools			Variation between		Average variation across data sources of HMIS tools
		Register	Form	DHIS2	Register form	Register DHIS2.3	
Maternal death	Apr	0	0	0	0 (0%)	0 (0%)	0 (0%)
	May	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Jun	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Jul	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Aug	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Sep	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Total	**0**	**0**	**0**	**0 (0%)**	**0 (0%)**	**0 (0%)**
Early Postnatal care visit	Apr	570	342	671	228 (40%)	101 (18%)	165 (29%)
	May	487	385	733	102 (21%)	246 (51%)	174 (36%)
	Jun	507	438	802	69 (14%)	295 (58%)	182 (36%)
	Jul	473	419	821	54 (11%)	348 (74%)	201 (42%)
	Aug	569	481	797	88 (15%)	228 (40%)	158 (28%)
	Sep	621	624	962	3 (0.5%)	341(55%)	172 (28%)
	Total	**3227**	**2689**	**4786**	**538(17%)**	**1559(48%)**	**1052 (33%)**

Maternal death is defined as the proportion of maternal deaths from any cause related to or caused by pregnancy or its management in a health facility. Results presented in

Table 4.8 reveal that all sources of HMIS data have not been recorded for maternal deaths between April and September. Maternal deaths were found to be zero and consistent throughout the HMIS tools, including registers, reporting forms and DHIS2.3 in the public health centres (n=10).

Furthermore, **early postnatal care visit** is defined as the proportion of women who received post-natal care service at least once within seven days after delivery. Findings in Table 4.8 show that a total of 3,227 mothers have been identified as early postnatal care users. Of those mothers, however, 40% (n=228) of the mothers were not registered in the reporting forms in April compared to registers; and also, in the month of June, the number of early post-natal care users in DHIS2.3 was 58% (n=295) higher than registers. In addition, those early postnatal care users in reporting forms and DHIS2.3 were17% (n=538) and 48% (n=1559) higher, respectively when compared to registers (Table 4.8).

Average variation of maternal death and early postnatal visit

Findings presented in Table 4.8 show that the maximum, minimum, and average variations of maternal deaths across HMIS tools were found to be zero. In addition, the average data source variation for early postnatal care visits across the HMIS tools was 33% (n=1052). The maximum variation of early postnatal care was 36% in May and June. Moreover, the minimum variation of early postnatal care was 28% in August and September.

In conclusion, findings from the second level of the analysis show that data values of the indicators, including skilled birth attendance, live births, and early postnatal care visits, were inconsistent from April to September 2019 in all HMIS tools. In contrast, maternal death has been found to be zero and consistent throughout the review of HMIS tools and months.

4.3.3 The level of data accuracy in public health centres

4.3.3.1 New and repeat acceptors

Table 4.9: Cross-tabulation of aggregated new and repeat acceptors data by health centres

Data element	Name of healthcare centre	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Reporting forms	DHIS2	Register tally	Register form	Register DHIS2.3	
New CAR by age	Addis ketema	187	203	217	222	16 (9%)	30 (16%)	35 (19%)	27 (14%)
	Akaki	242	239	239	239	3 (1%)	3 (1%)	3 (1%)	3 (1%)
	Arada	57	6	54	54	51 (89%)	3 (5%)	3 (5%)	19 (33%)
	Amoraw	222	280	237	238	58 (26%)	15 (7%)	16 (7%)	30 (14%)
	Addis Gebeya	309	306	304	1231	3 (1%)	5 (2%)	922 (>100%)	310 (100%)
	Kasanchis	1339	410	1103	1231	929 (69%)	236(18%)	108 (8%)	424 (32%)
	Kolife	755	748	802	742	7 (1%)	47 (6%)	13 (2%)	22 (3%)
	T.haimanot	302	276	286	286	26 (9%)	16 (5%)	16 (5%)	19 (6%)
	Woreda9	65	0	56	56	65 (100%)	9 (14%)	9 (14%)	28 (43%)
	Woreda13	1380	1257	1162	1162	123 (9%)	218(16%)	218 (16%)	186 (13%)
	Total cases	**4858**	**3725**	**4460**	**5461**	**1133 (23%)**	**398 (8%)**	**603 (12%)**	**711 (15%)**
Repeat CAR by age	Addis ketema	526	558	537	565	32 (6%)	11 (2%)	39 (7%)	27 (5%)
	Akaki	638	640	638	638	2 (0.3%)	0 (0%)	0 (0%)	1 (0.1%)
	Arada	427	67	427	437	360 (84%)	0 (0%)	10 (2%)	123 (29%)
	Amoraw	778	891	854	854	113 (15%)	76 (10%)	76 (10%)	83 (11%)
	Addis Gebeya	1249	1267	1249	1249	18 (1%)	0 (0%)	0 (0%)	6 (0.48%)
	Kasanchis	523	281	1375	1649	242 (46%)	852(>10%)	1126 (>100%)	740 (141%)
	Kolife	317	317	876	952	0 (0%)	559(>100%)	635 (>100%)	398 (>100%)
	T.haimanot	1657	1671	1670	1670	14 (1%)	13 (1%)	13 (1%)	13 (0.8%)
	Woreda9	426	223	425	425	203 (48%)	1 (0.2%)	1 (0.2%)	68 (16%)
	Woreda13	956	1215	912	912	259 (27%)	44 (5%)	44 (5%)	116 (12%)
	Total cases	**7497**	**7130**	**8963**	**9351**	**367 (5%)**	**1466 (20%)**	**1854 (25%)**	**1229 (16%)**

The cross-tabulation of reproductive data elements/indicators with each health centre (n=10) was used to evaluate the level of data accuracy by comparing registers with tallies, registers with reporting forms, and registers with the DHIS2.3. Hence, the results presented in Table 4.9 show that performance data recorded for the new and repeat contraceptive users by age were found to be higher by 23% (n=1133) and 5% (n=367) in registers when compared to tallies of all health centres (n=10) respectively.

Similarly, those new and repeat acceptors by age were found to be higher by 8% (n=398) and 20% (n=1466) in registers compared to reporting forms at all health centres (n=10), respectively. In comparison to DHIS2.3, these new and repeat acceptors by age were found to be 12% (n=603) and 25% (n=1854) higher in registers compared to DHIS2.3, respectively, in all public health centres (n=10). In particular, the numbers of new acceptors by age in Woreda 9, Arada, and Kasanchis health centres differed by 100%, 89% and 69%, respectively, between the registers and tally sheets. Furthermore, repeat acceptors in Kasanchis and Kolife health centres were found to be >100% additional mothers in DHIS2 compared to the registers (Table 4.9). This may show that unregistered or unavailable mothers have been incorrectly entered into DHIS2.3.

Average variation of new and repeat acceptors

The findings in Table 4.9 show that the maximum and minimum data source variation for new contraceptive users across the HMIS tools was 100% (n=310) and 1% (n=3) in Addis Gebeya and Akaki public health centres, respectively. In all public health centres (n=10), the overall data variance for new acceptors across the HMIS tools of data sources was 15% (n=711). Furthermore, the maximum and minimum data source variance for repeat users was >100% (n=398) and 0.1% (n=1), respectively, in Kolife and Akaki public health centres. The overall data variability for repeat acceptors across the data sources of HMIS tools was 16% (n=1229) in the ten public health centres. As a whole, the average data source variation of repeat acceptors was 1% higher compared to the new contraceptive users at all public health centres (n=10).

4.3.3.2 Ante-natal care visits

Table 4.10: Cross-tabulation of aggregated anc first and fourth visits data by health centres

Indicator/Data element	Name of healthcare centre	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Reporting forms	DHIS2	Register tally	Register form	Register DHIS2.3	
ANC 1st visit	Addis ketema	779	770	831	844	9 (1%)	52 (7%)	65 (8%)	42 (5%)
	Akaki	1111	1111	1111	1111	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Arada	192	35	154	185	157 (82%)	38 (20%)	7 (4%)	67 (35%)
	Amoraw	753	0	753	761	753 (100%)	0 (0%)	8 (1%)	254 (34%)
	Addis Gebeya	769	747	769	769	22 (3%)	0 (0%)	0 (0%)	7 (1%)
	Kasanchis	407	347	348	432	60 (15%)	59 (14%)	25 (6%)	48 (12%)
	Kolife	1500	0	1509	1409	1500 (100%)	9 (1%)	91 (6%)	533 (36%)
	T.haimanot	304	264	307	307	40 (13%)	3 (1%)	3 (1%)	15 (5%)
	Woreda 9	557	0	572	572	557 (100%)	15 (3%)	15 (3%)	196 (35%)
	Woreda 13	1284	1085	1280	1280	199 (15%)	4 (0.3%)	4 (0.3%)	69 (5%)
	Total cases	**7656**	**4359**	**7634**	**7670**	**3297 (43%)**	**22 (0.3%)**	**14 (0.2%)**	**1111 (15%)**
ANC 4th visit	Addis ketema	594	684	643	650	90 (15%)	49 (8%)	56 (9%)	65 (11%)
	Akaki	829	829	773	1492	0 (0%)	56 (7%)	663 (80%)	240 (29%)
	Arada	127	18	104	134	109 (86%)	23 (18%)	7 (6%)	46 (36%)
	Amoraw	400	0	400	450	400 (100%)	0 (0%)	50 (13%)	150 (38%)
	Addis Gebeya	524	520	524	524	4 (1%)	0 (0%)	0 (0%)	1 (0.3%)
	Kasanchis	61	186	202	236	125 (>100%)	141 (>100%)	175 (>100%)	147 (241%)
	Kolife	1406	0	1406	1406	1406 (100%)	0 (0%)	0 (0%)	469 (33%)
	T.haimanot	50	210	208	212	160 (>100%)	158 (>100%)	162 (>100%)	160 (>100%)
	Woreda 9	195	339	431	383	144 (74%)	236 (>100)	188 (96%)	189 (97%)
	Woreda 13	731	669	730	730	62 (8%)	1 (0.1%)	1 (0.1%)	21 (3%)
	Total cases	**4917**	**3455**	**5421**	**6217**	**1462 (30%)**	**504 (10%)**	**1300 (26%)**	**1089 (22%)**

The findings in Table 4.10 reveal that the data recorded for the ANC first and fourth users in the tallies were lesser by 43% (n=3297) and 30% (n=1462), respectively, compared to registers of all public health centres (n=10). Moreover, the maximum data variations between registers and tallies of the ANC first and fourth users were identified to be >100% in Amoraw and Kolife public health centres. On the other hand, the ANC first users were found to be consistent across all the data sources in Akaki public health centre. Similarly, the ANC first users were found to be accurate across the data sources of Addis Gebeya public health centre except in tally sheets. In the same way, in Kolife public health centre, the ANC fourth visit was found to be accurate across all the data sources except the tally sheets. This means that the ANC first and fourth users were not aggregated from registers to tallies. It also indicates that tally sheets in the mentioned public health centres have not been used properly for the intended purposes. On average, the ANC fourth users in DHIS2.3 were higher by 26% (n=1300) than at registers in all public health centres (n=10).

Average variation of ante-natal care visits

The findings presented in Table 4.10 show that the maximum and minimum data source variation for the ANC first visit across the HMIS tools was 36% (n=533) and 0% (n=0) in Kolife and Akaki public health centres, respectively. The overall data variation for the ANC first visit across the data sources of HMIS tools was found to be 15% (n=1111) in all the public health centres (n=10). Furthermore, the maximum and minimum data source variation for the ANC fourth visit across the HMIS tools was >100% (n=160) in T.haimanot and 0.3% (n=1**)** in Addis Gebeya public health centres, respectively. The overall data variation for the ANC fourth visits across the data sources of HMIS tools was found to be 22% (n=1089) in all public health centres (n=10). As a whole, the average data source variation of the ANC fourth-visit mothers was 7% higher than the ANC first visit user mothers in all public health centres (n=10).

4.3.3.3 Syphilis and hepatitis tests

Table 4.11: Cross-tabulation of aggregated syphilis test results data by health centres

Data Element/s Indictors	Name of healthcare entre	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Reporting forms	DHIS2	Register tally	Register and form	Register DHIS2.3	
syphilis total tested	Addis ketema	765	767	740	844	2 (0.3%)	25 (3%)	79 (10%)	35 (5%)
	Akaki	1111	1111	1111	1111	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Arada	192	35	154	190	157 (82%)	38 (20%)	2 (1%)	66 (34%)
	Amoraw	753	0	753	657	753 (100%)	0 (0%)	96 (13%)	283 (38%)
	Addis Gebeya	769	769	769	769	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	415	325	342	432	90 (22%)	73 (18%)	17 (4%)	60 (14%)
	Kolife	1498	0	1509	1509	1498 (100%)	11 (1%)	11 (1%)	507 (34%)
	T.haimanot	304	281	307	307	23 (8%)	3 (1%)	3 (1%)	10 (3%)
	Woreda 9	556	0	572	572	556 (100%)	16 (-3%)	16 (-3%)	196 (35%)
	Woreda 13	1280	0	1280	1280	1280 (100%)	0 (0%)	0 (0%)	427 (33%)
	Total cases	**7643**	**3288**	**7537**	**7671**	**4355 (57%)**	**106 (1%)**	**28 (0.4%)**	**1496 (20%)**
Syphilis test reactive	Addis ketema	0	0	0	222	0 (0%)	0 (0%)	222 (>100%)	74 (>100%)
	Akaki	12	12	12	239	0 (0%)	0 (0%)	227(>100%)	76 (>100%)
	Arada	1	0	0	0	1 (100%)	1 (100%)	1 (100%)	1 (100%)
	Amoraw	7	0	7	1	7 (100%)	0 (0%)	6 (86%)	4 (57%)
	Addis Gebeya	5	5	5	5	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	7	3	5	5	4 (57%)	2 (29%)	2 (29%)	8 (43%)
	Kolife	25	0	8	2	25 (100%)	17 (68%)	23 (92%)	22 (88%)
	T.haimanot	4	1	1	1	3 (75%)	3 (75%)	3 (75%)	3 (75%)
	Woreda 9	1	0	1	1	1 (100%)	0 (0%)	0 (0%)	0.3 (30%)
	Woreda 13	5	0	5	2	5 (100%)	0 (0%)	3 (60%)	3 (60%)
	Total cases	**67**	**21**	**44**	**478**	**46 (69%)**	**23 (34%)**	**411 (>100%)**	**160 (>100%)**
Syphilis test non-reactive	Addis ketema	765	767	742	844	2 (-0.3%)	23 (3%)	79 (10%)	35 (5%)
	Akaki	1099	1089	1089	1099	10 (1%)	10 (1%)	0 (0%)	7 (1%)
	Arada	191	35	154	190	156 (82%)	37 (19%)	1 (1%)	65 (34%)
	Amoraw	746	0	746	656	746 (100%)	0 (0%)	90 (12%)	279 (37%)
	Addis Gebeya	759	758	764	764	1 (0%)	5 (1%)	5 (-1%)	4 (1%)
	Kasanchis	408	322	337	427	86 (21%)	71 (17%)	19 (5%)	59 (14%)
	Kolife	1468	0	1501	1501	1468 (100%)	33 (2%)	33 (2%)	511 (35%)
	T.haimanot	300	275	306	306	25 (8%)	6 (2%)	6 (2%)	12 (4%)
	Woreda 9	565	0	571	571	555 (100%)	16 (3%)	16 (3%)	196 (35%)
	Woreda 13	1275	0	1275	1275	1275 (100)	0 (0%)	0 (0%)	425 (33%)
	Total cases	**7576**	**3246**	**7485**	**7633**	**4320 (57%)**	**81 (1%)**	**67 (1%)**	**1489 (20%)**

Table 4.12: Cross-tabulation of aggregated hepatitis test results data by health centres

Data Indictors Element/s	Name of healthcare entre	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Reporting forms	DHIS2	Register tally	Register and form	Register DHIS2.3	
Hepatitis total tested	Addis ketema	765	767	740	844	2 (0.3%)	25 (3%)	77 (10%)	35 (5%)
	Akaki	957	957	957	957	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Arada	192	35	154	191	157 (82%)	8 (4%)	1 (1%)	55 (29%)
	Amoraw	753	0	753	761	753 (100%)	0 (0%)	8 (1%)	254 (34%)
	Addis Gebeya	768	764	768	769	4 (0.4%)	0 (0%)	1 (0.1%)	2 (0.2%)
	Kasanchis	415	313	347	432	102 (25%)	38 (9%)	17 (4%)	52 (13%)
	Kolife	1498	0	1509	1509	1494 (98%)	11 (1%)	11 (1%)	505 (34%)
	T.haimanot	304	277	307	307	27 (9%)	3 (1%)	3 (1%)	11 (4%)
	Woreda 9	556	0	572	573	556 (100%)	12 (2%)	17 (3%)	195 (35%)
	Woreda 13	1278	0	1280	1280	1278 (100%)	2 (0.2%)	2 (0.2%)	427 (33%)
	Total cases	**7486**	**3113**	**7387**	**7623**	**4373 (58%)**	**99 (1%)**	**137 (2%)**	**1536 (21%)**
Hepatitis test reactive	Addis ketema	5	5	5	5	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Akaki	26	26	26	26	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Arada	6	1	5	5	5 (83%)	1 (17%)	1 (17%)	2 (33%)
	Amoraw	2	0	2	3	2 (100%)	0 (0%)	1 (50%)	1 (50%)
	Addis Gebeya	5	5	5	5	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	0	3	4	4	3 (100%)	4 (100%)	4 (100%)	4 (>100%)
	Kolife	29	0	20	20	29 (100%)	9 (31%)	9 (31%)	16 (55%)
	T.haimanot	6	6	6	6	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Woreda 9	14	0	11	11	14 (100%)	3 (21%)	3 (21%)	7 (50%)
	Woreda 13	23	0	23	23	23 (100%)	0 (0%)	0 (0%)	8 (35%)
	Total cases	**116**	**46**	**107**	**108**	**70 (60%)**	**9 (8%)**	**8 (7%)**	**29 (25%)**
Hepatitis test non-reactive	Addis ketema	760	762	735	839	2 (0.3%)	25 (3%)	79 (10%)	35 (5%)
	Akaki	931	931	931	931	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Arada	186	34	149	186	152 (82%)	37 (20%)	0 (0%)	63 (34%)
	Amoraw	751	0	751	758	751 (100%)	0 (0%)	7 (1%)	253 (34%)
	Addis Gebeya	763	689	763	764	74 (10%)	0 (0%)	1 (0.1%)	25 (3%)
	Kasanchis	415	310	343	428	105 (25%)	72 (17%)	13 (3%)	63 (15%)
	Kolife	1469	0	1480	1481	1469 (100%)	11 (0.7%)	12 (0.8%)	497 (34%)
	T.haimanot	298	271	301	301	27 (9%)	3 (1%)	3 (1%)	11 (4%)
	Woreda 9	542	0	561	562	542 (100%)	19 (4%)	20 (4%)	194 (36%)
	Woreda 13	1255	0	1257	1257	1255 (100%)	2 (0.2%)	2 (0.2%)	420 (33%)
	Total cases	**7370**	**2997**	**7271**	**7507**	**4373 (59%)**	**99 (1%)**	**137 (2%)**	**1536 (21%)**

The results presented in Table 4.11 show that, in ten of the public health centres, the numbers of total syphilis tested, syphilis reactive and syphilis non-reactive cases were higher in registers compared to tallies by 57% (n=4355), 69% (n=46), and 57% (n=4320), respectively. In addition, the numbers of syphilis tested, syphilis reactive and non-reactive cases documented in tallies were lesser, by >100% in Woreda 9, Woreda 13, Amoraw, and Kolife public health centres, compared to registers. This finding may indicate that tally sheets have not been utilized for data aggregation to achieve the intended purposes of these public health centres (n=4). On the other side, total syphilis tested was accurate across the data sources of HMIS tools in Akaki and Addis Gebeya health centres.

Furthermore, the results presented in Table 4.12 reveal that, on average, the hepatitis total tested was 50% lesser in tallies, 23% lesser in reporting forms, and 23% lesser in DHIS2.3 when compared to registers in all public health centres (n=10). Likewise, total hepatitis tested documented in tallies was >100% lesser than in registers at Woreda 9, Woreda 13, Amoraw, and Kolife, health centres, respectively. Hepatitis test reactive were found to be 60% (n=70) lesser in tallies when compared to registers in all public health centres (n=10). In addition, the numbers of non-reactive hepatitis tests documented in DHIS2.3 were >100% lesser than in registers at Addis ketema, Akaki, Amoraw, Addis Gebeya, Kasanchis, Kolife, and T.haimanot public health centres (n=7).

The average variations across the data sources of HMIS tools for total hepatitis tested, hepatitis reactive and non-reactive were reported at 21% (n=1536), 25% (n=29), and 21% (n=1536), respectively. Hepatitis test reactive were accurate across the data sources of HMIS tools in Akaki, Addis ketema, Addis Gebeya, and T.haimanot healthcare centres.

In conclusion, all the values of the four data elements and two indicators reviewed above, Table 4.11 and Table 4.12, have not been found consistent in registers, tallies, reporting forms, and DHIS2.3 in all of the public health centres (n=10).

Average variation of syphilis and hepatitis tests

The findings presented in Table 4.11 and Table 4.12 show that the maximum data source variations were 38% (n=283) for total syphilis tested and 37% (n=297) for syphilis non-reactive mothers in the Amoraw public health centre. Moreover, the maximum data source variation of syphilis reactive was >100% in Addis ketema, Akaki and Arada public health centres. At the same time, the minimum data source variations have been identified as zero Addis Gebeya for both total syphilis tested and syphilis non-reactive mothers. The average data sources variations across HMIS tools have been reported 20% (n=1489), >100% (n=160) and 20% (n=1489) for total syphilis tested, syphilis reactive and non-reactive, respectively. As a whole, the average data source variation of syphilis reactive was 40% higher compared to both total syphilis tested and syphilis non-reactive mothers in the ten public health centres. Furthermore, the maximum data source variations across HMIS tools have been reported as 35% (n=195), >100% (n=4), and 36% (n=194) for total hepatitis tested, hepatitis reactive, and hepatitis non-reactive mothers at Woreda 9, Kasanchis and Woreda 9 public health centre, respectively. The average data sources variations across HMIS tools have been documented as 21% (n=1536), 25% (n=29), and 21% (n=1536) for total hepatitis tested, hepatitis reactive, and hepatitis non-reactive, respectively. In a similar way, the average data source variation of hepatitis reactive was 4% higher compared to both total hepatitis tested and hepatitis non-reactive mothers in the ten public health centres.

4.3.3.4 Safe and post-abortion care services

Table 4.13: Cross-tabulation of aggregated safe and post-abortion care services data by health centres

Data Element	Name of healthcare entre	Number of cases reviewed from HMIS tools				Variation between			Average variation across data sources of HMIS tools
		Register	Tally	Reporting forms	DHIS2	Register tally	Register and form	Register DHIS2.3	
safe abortion	Addis ketema	14	0	14	2	14 (100%)	0 (0%)	12 (86%)	9 (62%)
	Akaki	62	0	51	51	62 (100%)	11 (18%)	11 (18%)	28 (45%)
	Arada	9	8	9	9	1 (11%)	0 (0%)	0 (0%)	1 (4%)
	Amoraw	56	56	56	56	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Addis Gebeya	14	14	14	14	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	68	55	59	72	13 (19%)	9 (3%)	4 (6%)	9 (13%)
	Kolife	112	112	0	105	0 (0%)	112 (100%)	7 (6%)	38 (34%)
	T.haimanot	36	0	36	36	36 (100%)	0 (0%)	0 (0%)	12 (33%)
	Woreda 9	38	0	39	39	38 (100%)	1 (3%)	1 (3%)	13 (35%)
	Woreda 13	31	0	31	31	31 (100%)	0 (0%)	0 (0%)	10 (33%)
	Total cases	**440**	**245**	**309**	**415**	**195 (44%**	**131 (30%)**	**25 (6%)**	**117 (27%)**
Post-abortion	Addis ketema	16	0	16	8	16 (100%)	0 (0%)	8 (5%)	7 (44%)
	Akaki	14	0	18	18	0 (0%)	18 (>100%)	18 (>100%)	10 (71%)
	Arada	8	0	0	0	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Amoraw	16	16	16	16	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Addis Gebeya	5	5	5	5	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	16	7	8	12	9 (56%)	8 (50%)	4 (25%)	6 (38%)
	Kolife	35	35	0	44	0 (0%)	0 (0%)	9 (26%)	3 (9%)
	T.haimanot	11	0	11	11	11 (100%)	0 (0%)	0 (0%)	4 (36%)
	Woreda 9	18	0	17	17	18 (100%)	1 (6%)	1 (6%)	5 (28%)
	Woreda 13	36	0	36	36	36 (100%)	0 (0%)	0 (0%)	8 (22%)
	Total cases	**153**	**63**	**127**	**167**	**90 (59%)**	**26 (17%)**	**14 (9%)**	**43 (28%)**

The findings presented in Table 4.13 show that 44% of safe and 59% of post-abortion users were not documented in the tally sheets but documented at registers in all public health centres (n=10). In addition, 30% and 6% of safe abortion users were not documented in the reporting forms and DHIS2.3, respectively, compared to the respective registers of all public health centres (n=10).

In particular, safe abortion in registers and reporting forms was found identical in six public health centres except for Akaki, Kasanchis, Kolife and Woreda 9 public health centres. In the same fashion, safe abortion in registers, reporting forms and DHIS2.3 was found to be consistent in 50% (n=5) of the public health centres. Furthermore, safe abortion was found to be consistent across the data sources in Amoraw and Addis Gebeya health centres. However, safe abortion data was not documented on the tally sheets in 50% of the public health centres. In addition, safe abortion data were not documented in the reporting forms at Kolife health centre.

Similarly, post-abortion was found to be accurate across the data sources in Arada, Amoraw, and Addis Gebeya. Moreover, post-abortion data was consistent in registers and reporting forms in 70% of the public health centres. However, post-abortion was not documented in the tally sheets and reporting forms in 60% (n=6) and 20% (n=2) of the public health centres, respectively. In addition, 17% of post-abortion users were not documented in the reporting forms when compared to the registers in all public health centres (n=10). Also, 9% of post-abortion user mothers were not documented in registers, but this has been documented fully in DHIS2.3 in all the public health centres (n=10).

Average variation of safe and post-abortions care services

The findings presented in Table 4.13 show that the maximum data source variation for both safe and post-abortion data was 45% (28) and 71% (10), respectively, in Akaki public health centre. Besides, the average data variations across the data sources of HMIS tools for safe and post-abortion were reviewed to be 27% (n=117) and 28% (n=43), respectively. The minimum data source variation for safe abortion was documented in Amoraw and Addis Gebeya public health centres. Simultaneously, the minimum data source variation for post-abortion was reported from three health centres, as indicated in Table 4.13.

4.3.3.5 Skilled birth attendance and live birth

Table 4.14: Cross-tabulation of aggregated skilled birth attendance and live birth data by health centres

Indictor	Name of healthcare entre	Number of cases reviewed from HMIS tools			Variation between		Average variation across data sources of HMIS tools
		Register	Reporting forms	DHIS2	Register and form	Register DHIS2.3	
Skilled birth Attendance	Addis ketema	398	398	397	0 (0%)	1 (0.3%)	1 (0.3%)
	Akaki	491	509	510	18 (4%)	19 (4%)	19 (4%)
	Arada	53	36	52	17 (32%)	1 (2%)	9 (17%)
	Amoraw	259	259	259	0 (0%)	0 (0%)	0 (0%)
	Addis Gebeya	239	239	239	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	133	112	134	21 (16%)	1 (1%)	11 (8%)
	Kolife	962	962	964	0 (0%)	2 (0.2%)	1 (0.1%)
	T.haimanot	89	89	90	0 (0%)	1 (1%))	1 (0.6%))
	Woreda 9	223	222	222	1 (0.4%)	1 (0.4%)	1 (0.4%)
	Woreda 13	576	576	576	0 (0%)	0 (0)	0 (0%)
	Total cases	**3423**	**3402**	**3443**	**21 (1%)**	**20 (0.6%)**	**42 (1.2%)**
Live birth	Addis ketema	396	324	397	72 (18%)	1 (0.3%)	37 (9%)
	Akaki	509	509	509	0 (0%)	0 (0%)	0 (0%)
	Arada	52	35	51	17 (33%)	1 (2%)	9 (17%)
	Amoraw	259	259	259	0 (0%)	0 (0%)	0 (0%)
	Addis Gebeya	239	239	239	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	133	112	134	21 (16%)	1 (1%)	11 (8%)
	Kolife	963	962	964	1 (0.1%)	1 (0,1%)	1 (0.1%)
	T.haimanot	89	89	89	0 (0%)	0 (0%)	0 (0%)
	Woreda 9	223	222	222	1 (0.4%)	1 (0.4%)	1 (0.4%)
	Woreda 13	576	576	569	0 (0%)	7 (1%)	4 (1%)
	Total cases	**3439**	**3327**	**3433**	**112 (3%)**	**6 (0.2%)**	**62 (2%)**

The findings recorded in Table 4.14 show that the numbers of skilled birth attendance users in registers, reporting forms and DHIS2 were found to be the same in Amoraw, Addis Gebeya, and Woreda 13 public health centres (n=3). In particular, skilled birth attendance in registers and reporting forms was found to be identical in six public health centres except for Akaki, Kasanchis, Kolife and Woreda 9 public health centres. In the same way, skilled birth attendance was found to be consistent across the data sources in 30% (n=3) of the health centres.

Moreover, the findings in Table 4.14 show that the numbers of live births in registers, reporting forms and DHIS2 were identified as accurate in Akaki, Amoraw, Addis Gebeya, and T.haimanot public health centres (n=4). In the same fashion, live births in registers and reporting forms were found to be consistent in 50% (n=5) of the public health centres. However, live births in registers and DHIS2.3 were not found consistent in 60% of the public health centres.

Average variation of skilled birth attendance and live birth

The maximum data source variation for both skilled birth attendance and live births data was 17% (n=9) in Arada public health centre. Simultaneously, the minimum data source variations for skilled birth attendance and live births have been documented at Amoraw and Addis Gebeya public health centres, as indicated in Table 4.14. In particular, the average variations between registers and reporting forms for live birth were identified as 3% (n=112) in all the public health centres (n=10). As a whole, the average data variations across the data sources of HMIS tools for skilled birth attendance and live births were reviewed at 1.2% (n=42) and 2% (n=62), respectively.

4.3.3.6 Maternal deaths and early postnatal care visit

Table 4.15: Cross-tabulation of aggregated maternal deaths and early postnatal care visit data by health centres

Indictors	Name of healthcare entre	Number of cases reviewed from HMIS tools			Variation between		Average variation across data sources of HMIS tools
		Register	Reporting forms	DHIS2	Register and form	Register DHIS2.3	
Maternal deaths	Addis ketema	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Akaki	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Arada	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Amoraw	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Addis Gebeya	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Kasanchis	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Kolife	0	0	0	0 (0%)	0 (0%)	0 (0%)
	T.haimanot	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Woreda 9	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Woreda 13	0	0	0	0 (0%)	0 (0%)	0 (0%)
	Total cases	**0**	**0**	**0**	**0 (0%)**	**0 (0%)**	**0 (0%)**
Early Postnatal care visit	Addis ketema	473	480	480	7 (1%)	7 (1%)	7 (1%)
	Akaki	448	448	517	0 (%)	69 (15%)	35 (8%)
	Arada	47	45	69	2 (4%)	22 (47%)	12 (26%)
	Amoraw	112	112	491	0 (0%)	379 (>100%)	190 (>100%)
	Addis Gebeya	272	274	274	2 (4%)	2 (4%)	2 (1%)
	Kasanchis	216	136	197	80 (37%)	19 (9%)	50 (23%
	Kolife	619	110	1650	509 (82%)	1031 (>100%)	692 (112%)
	T.haimanot	92	91	91	1 (1%)	1 (1%)	1 (1%)
	Woreda 9	225	278	278	53 (24%	53 (24%	53 (24%)
	Woreda 13	723	715	739	8 (1%)	16 (2%)	12 (2%)
	Total cases	**3227**	**2689**	**4786**	**538 (17%)**	**1559 (48%)**	**33% (1052)**

The findings described in Table 4.15 show that the maternal death indicator is found to be consistent throughout the HMIS tools, including registers, reporting forms and DHIS2.3 in all the public health centres (n=10).

Besides, findings presented in Table 4.15 show that early postnatal care users were found to be 17% (n=538) lesser in reporting forms and 48% (n=1559) higher in DHIS2 when compared to registers in all public health centres (n=10). Early postnatal care visits were found to be consistent in registers and reporting forms at Akaki and Amoraw public health centres. However, early postnatal care in DHIS2.3 was higher by >100%

(n=379) and >100% (n=1031) when compared to registers in Amoraw and Kolife, respectively.

In summary, the accuracy of data sources of HMIS tools that have been used in reviewing safe abortion, post-abortion, skilled birth attendance, live birth and early postnatal care visits were not shown to be accurate/consistent in all the public health centres (n=10) (Table 4.13, Table 4.14, and Table 4.15)

Average variation of maternal deaths and early postnatal care visit

The maximum data source variation for early postnatal care across HMIS tools was found to be >100% (n=190) in Amoraw health centre. Likewise, on average, 33% (n=1052) of the data sources of HMIS tools have shown variations for early postnatal care users in all the public health centres (n=10). Similarly, the minimum, maximum, and average data source variation of maternal deaths was found to be 0% (n=0) and consistent in all public health centres.

Table 4.16: Cross tabulation of data accuracy summary at the level of addis ababa

SN	Data elements and indicators		Numbers of cases reviewed in each HMIS tool				Variation between			Average variation across data sources of HMIS tools
			Registers	Tally sheets	Reporting forms	DHIS2.3	Register tally	Register form	Register DHIS2.3	
1	CAR	New	4858	3725	4460	5461	1133 (23%)	398 (8%)	603 (-12%)	711 (15%)
		Repeat	7497	7130	8963	9351	367 (5%)	1466 (-20%)	1854 (25%)	1229 (16%)
2	ANC	First	7656	4359	7634	7670	3297(43%)	22 (0.3%)	14 (0.2%)	1111 (15%)
		Fourth	4917	3455	5421	6217	1462 (30%)	504 (10%)	1300 (26%)	1089 (22%)
3	syphilis	Total tested	7643	3288	7537	7671	4355 (57%)	106 (1%)	28 (0.4%)	1496 (20%)
		Reactive	67	21	44	478	46 (69%)	23 (34%)	411 (>100%)	160 (>100%)
		Non- reactive	7576	3246	7485	7633	4320 (57%)	81 (1%)	67 (1%)	1489 (20%)
4	Hepatitis	Total tested	7486	3113	7387	7623	4373 (58%)	99 (1%)	137 (2%)	1536 (21%)
		Reactive	116	46	107	108	70 (60%)	9 (8%)	8 (7%)	29 (25%)
		Non- reactive	7370	2997	7271	7507	4373 (59%)	99 (1%)	137 (2%)	1536 (21%)
5	Abortion	Safe	440	245	309	415	195 (44%)	131 (30%)	25 (6%)	117 (27%)
		Post	153	63	127	167	90 (59%)	26 (17%)	14 (9%)	43 (28%)
Average level of data accuracy based on the four data sources of HMIS tools			**4648**	**2641**	**4729**	**5025**	**2007 (43%)**	**249 (5%)**	**383 (8%)**	**879 (19%)**
1	Skilled Birth Attendance (SBA)		3423		3402	3443		21 (1%)	20 (1%)	42 (1.2%)
2	Live birth		3439		3327	3433		112 (3%)	6 (0.2%)	62 (2%)
3	Maternal deaths		0		0	0		0	0	0
	EPNC visit		3227		2689	4786		538 (17%)	1559 (48%)	1052 (33%)
Average accuracy based on the three HMIS tools			**3363**		**3139**	**3887**		**224 (7%)**	**528 (16%)**	**385 (11%)**

4.3.4 Summary of data elements used to review content completeness

Completeness: This refers to the extent to which data on registers/reporting forms/cards are complete, including all necessary data elements, and it reflects the ability to determine what data are missing and whether omissions are acceptable (Gabr et al. 2021:11; Ramasamy & Chowdhury 2020:3; FMOH 2018:20). In this study, content completeness is defined as the presence of all the values of data elements and indicators in registers (family planning, antenatal care, skilled birth attendance, and postnatal care). Therefore, the results presented in Table 4.17 below indicate that 17 data elements were used as evaluation criteria for reviewing the completeness of four indicators. Henceforth, registers are the original/primary data sources and were used as references to review data completeness of 4 indicators over the six months in 10 public healthcare centres.

Table 4.17: Lists of 17 data elements used as criteria to assess content completeness

SN	Indicators	Lists of data elements expected to be filled in completely for each client in the six months (April-September 2019)	Total data elements
1	**Family planning Visits:** Are the **two** data elements completely filled in under counselling and testing?	HIV Test performed	2
		Target population code filled	
2	**ANC 1st visit:** Are the **six** data elements completely filled in under personal information?	Serial number	6
		Name of the client	
		Medical record number	
		Age	
		Last Menstruation Period (DD/MM/YY)	
		Expected data of delivery (DD/MM/YY)	
3	**ANC 1st visit:** Are the **two** data elements completely filled in under HIV Assessment?	HIV Test accepted	2
		Target population code filled	
4	**ANC 1st visit:** Are the **four** data elements completely filled in in under counselling?	Infant feeding	4
		Identified and counselled on danger signs	
		Family planning methods	
		Maternal Nutrition	
5	**Skilled Birth Attendance (SBA):** Are the **two** data elements completely filled in under immediate postpartum family planning (IPPFP)	Type of contraceptive acceptance filled (New or repeat)	1
6	**Early postnatal Care visit:** Are the **two** data elements completely filled in under HIV Assessment?	HIV test performed	2
		Target population code filled	
Total data elements used as criteria to review document			**17**

4.3.5 Findings of data completeness

Table 4.17 shows the specific number of data elements used to determine the data completeness of certain indicators. Therefore, the detailed findings of the data completeness are presented in the tables below.

4.3.5.1 Content completeness of family planning (FP) and ANC first Visits

Table 4.18: Six months aggregated data of fp and anc first visits

Indicators	Expected data elements to be filled in completely	# of cases and level of content completeness	Six months						
			Apr	May	Jun	Jul	Aug	Sep	**Total cases**
Family panning visits	1) HIV Test performed; 2) Target population code filled in	Total cases documented in FP-registers	1720	2004	2047	1995	2151	2438	**12355**
		Total cases completely filled in	498 (29%)	718 (36%)	686 (34%)	562 (28%)	809 (38%)	798 (33%)	**4071 (33%)**
		Total cases not completely filled in at least with one data element	1222 (71%)	1286 (64%)	1361 (66%)	1433 (72%)	1342 (62%)	1640 (67%)	**8284 (67%)**
ANC 1st visit: personal information	1) Serial number; 2) Client name; 3) Medical record number; 4) Age; 5) Last Menstruation Period; 6) Expected data of delivery	Total cases documented in ANC registers	1194	1220	1389	1256	1162	1423	**7656**
		Total cases completely filled in	1109 (93%)	1160 (95%)	1316 (95%)	1185 (94%)	1101 (95%)	1326 (93%)	**7372 (96%)**
		Total cases not completely filled in, at least with one data element	85 (7%)	60 (5%)	73 (5%)	71 (6%)	61 (5%)	97 (7%)	**284 (4%)**
ANC 1st visit: HIV Assessment	1) HIV Test accepted; 2) Target population code filled in	Total cases documented in ANC registers	1194	1220	1389	1256	1162	1423	**7656**
		Total cases completely filled in	899 (75%)	863 (71%)	996 (72%)	947 (75%)	888 (76%)	1056 (74%)	**5649 (74%)**
		Total cases not completely filled in, at least with one data element	295 (25%)	357 (29%)	393 (28%)	309 (25%)	274 (24%)	367 (26%)	**2007 (26%)**
ANC 1st visit: Counselling	Infant feeding; Identified and counselled on danger signs; Family planning Maternal Nutrition	Total cases documented in ANC register	1194	1220	1389	1256	1162	1423	**7656**
		Total case completely filled in	987 (83%)	966 (79%)	1056 (76%)	982 (78%)	960 (83%)	1104 (78%)	**6055 (79%)**
		Total cases not completely filled in in at least with one data element	207 (17%)	254 (21%)	333 (24%)	274 (22%)	202 (17%)	319 (22%)	**1601 (21%)**

Table 4.18 shows the results of content completeness of family planning and ante-natal care visits that were reviewed in the six months. Hence, a total of 12,355 new and repeat family planning users were documented in the family planning registers from April to September 2019. Nevertheless, 67% (n=8,284) of the cases were found incomplete with at least one data element: either the HIV test performed or the target population code from April to September 2019. In addition, the maximum and minimum data values that were incomplete were 72% (n=1,433) in July 2019 and 62% (n=1,342) in August 2019, respectively.

Results provided in Table 4.18 indicate that a total of 7,656 ANC first users were documented in the ante-natal care registers over the six months. As a result, the antenatal care first visit was evaluated in three levels of analysis. In the first level of analysis, six data elements which were located under personal information, including serial number, client name; medical record number, age, last menstruation period, and expected data of delivery, were used to check the content completeness of the ANC first visits of the ten public health centres. Thus, the six evaluation criteria of the data elements were complete in 96% (n=7,372) of recorded mothers (Table 4.18). The maximum data values of completeness in the ANC first registers under personal information were reported at 95% in May, June, and August, respectively. Also, the minimum data value of completeness in the ANC first registers under personal information was identified and reviewed to be 93% in April and September 2019, respectively.

In the second level of analysis, two data elements placed under counselling and testing, including the HIV test accepted and target population code filled, were used to assess the content completeness of the ANC first visits. Hence, 26% (n=2007) of the data value of antenatal care first user mothers under counselling and testing were found incomplete (Table 4.18). Moreover, the maximum and minimum data values of completeness in the ANC first register under the counselling and testing were reported to be 29% (n=357) and 24% (n=274) in May and August, respectively.

In the third level of analysis, four data elements located under the counselling column, including counselling of infant feeding; identified and counselled on danger signs;

family planning; and maternal nutrition, were reviewed to measure the content completeness of the ANC first visits in the six months. Henceforth, 21% (n=1601) of the data value of antenatal care first user mothers was found incomplete (Table 4.18). The minimum data value of incompleteness in the ANC first registers under counselling was reported to be 17% in April and August 2019.

4.3.5.2 Content completeness of skilled Birth Attendance and early postnatal visit

Table 4.19: Six months aggregated data of skilled birth attendance and early postnatal care visit

Indicators	Expected data elements to be filled completely	Number of cases and level of content completeness	Six months						
			Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	**Total cases**
Skilled Birth Attendance (SBA	1) Type of contraceptive acceptance (New or repeat)	Total cases documented in delivery register	529	537	578	547	562	670	**3423**
		Total cases completely filled in	33 (6%)	28 (5%)	29 (5%)	34 (6%)	21 (4%)	24 (4%)	**169 (5%)**
		Total cases not completely filled in at least with one data element	496 (94%)	509 (95%)	549 (95%)	513 (94%)	541 (96%)	646 (96%)	**3254 (95%)**
Early postnatal Care visit (EPNC)	1) HIV test performed; 2) Target population code filled	Total cases documented in postnatal care register	570	487	507	473	569	621	**3227**
		Total cases completely filled in	116 (20%)	93 (19%)	94 (19%)	77 (16%)	98 (17%)	115 (19%)	**593 (18%)**
		Total cases not completely filled in at least with one data element	454 (80%)	394 (81%)	413 (81%)	396 (84%)	471 (83%)	506 (81%)	**2634 (82%)**

Table 4.19 shows the content completeness of skilled birth attendance and early postnatal care visit. In general, a total of 3423 skilled birth attendance users were documented in the delivery registers from April to September 2019. Furthermore, the content completeness of skilled birth attendance was reviewed based on the family planning visit type data element. Nevertheless, 95% (n=3254) of the data value for the

skilled birth attendance user mothers who were found under the immediate postpartum family planning were incomplete in the six months (Table 4.19). Moreover, the maximum content incompleteness of skilled birth attendance users was seen in August 2019 at 96% (n=541) and in September 2019 at 96% (n=646), respectively. In addition, the minimum data incompleteness of skilled birth attendance users was found to be 94% (n=496) in April 2019.

In the same way, the content completeness of early postnatal care visit (EPNC) was assessed using two data elements, including the HIV test performed and the target population code filled. Hence, the finding of the review provided in Table 4.19 shows that a total of 3,227 mothers were identified from early postnatal health service users. However, the data value of the postnatal care visit indicator was found incomplete for the majority, 82% (n=2634) of the mothers from April to September 2019. Moreover, the maximum and minimum data value incompleteness of early postnatal care visit users were seen in July 2019, 84% (n=396) and in April 2019, 80% (n=454), respectively.

4.3.6 The level of data value completeness in public health centres

4.3.6.1 Family planning visit completeness in public health centres

Table 4.20: Family planning visit completeness by health centres

Indicator	Name of health centres	# of expected data elements to be complete	# of clients documented in registers	# of clients completely filled in in registers		# of clients not completely filled in with at least one data element	
				#	%	#	%
Family planning visit	Addis ketema	2	713	10	1%	703	99%
	Akaki	2	880	814	92.5%	66	7.5%
	Arada	2	484	60	12%	424	88%
	Amoraw	2	1000	4	0.4%	996	99.6%
	Addis Gebeya	2	1558	567	36%	991	64%
	Kasanchis	2	1862	104	6%	1758	94%
	Kolife	2	1072	19	2%	1053	98%
	T.haimanot	2	1959	43	2%	1916	98%
	Woreda 9	2	491	114	23%	377	77%
	Woreda 13	2	2336	2336	100%	0	0%
	Total		**12355**	**4071**	**33%**	**8284**	**67%**

Family planning visit: Findings indicated in Table 4.20 show that, in the six months, 12,355 mothers were registered in and reviewed from the family health registers. As a result, two data elements were used to evaluate the data completeness of the registers. Nevertheless, the data value of family planning visits was found incomplete in 90% of the public health centres. For example, the highest value of data incompleteness were recognized and documented to be 99.6% (n=996) in Amoraw, 99% (n=703) in Addis ketema, 98% (n=1053) in Kolife, 98% (n=1916) in T.haimanot, 94% (n=1758) in Kasanchis , and 88% (n=424) in Arada, respectively. Whereas family planning visits in Woreda 13 and Akaki public health centres were found complete by 100% (n=2336) and 92.5% (n=814), respectively. On average, 67% (n=8284) of the data value of family planning visits was not completed in all of the public health centres (n=10).

4.3.6.2 ANC first visit completeness in public health centres

Table 4.21: ANC first visits personal information, hiv assessment and counselling

Indictor	Name of health centres	# of expected data elements to be complete	# of clients documented in registers	# of clients completely filled in in registers		# of clients not completely filled in with at least one data element	
				#	%	#	%
ANC 1st visit: personal information	Addis ketema	6	779	654	84%	125	16%
	Akaki	6	1111	1111	100%	0	0%
	Arada	6	192	153	80%	39	20%
	Amoraw	6	753	753	100%	0	0%
	Addis Gebeya	6	769	769	100%	0	0%
	Kasanchis	6	407	300	74%	107	26%
	Kolife	6	1500	1500	100%	0	0%
	T.haimanot	6	304	303	100%	1	0%
	Woreda 9	6	557	557	100%	0	0%
	Woreda 13	6	1284	1272	99%	12	1%
	Total		**7656**	**7372**	**96%**	**284**	**4%**
ANC 1st visit: HIV Assessment	Addis ketema	2	779	756	97%	23	3%
	Akaki	2	1111	448	40%	663	60%
	Arada	2	192	189	98%	3	2%
	Amoraw	2	753	744	99%	9	1%
	Addis Gebeya	2	769	769	100%	0	0%
	Kasanchis	2	407	360	88%	47	12%
	Kolife	2	1500	1494	100%	6	0%
	T.haimanot	2	304	296	97%	8	3%
	Woreda 9	2	557	557	100%	0	0%
	Woreda 13	2	1284	36	3%	1248	97%
	Total		**7656**	**5649**	**74%**	**2007**	**26%**
ANC 1st visit: counselling	Addis ketema	4	779	659	85%	120	15%
	Akaki	4	1111	877	79%	234	21%
	Arada	4	192	192	100%	0	0%
	Amoraw	4	753	753	100%	0	0%
	Addis Gebeya	4	769	769	100%	0	0%
	Kasanchis	4	407	360	88%	47	12%
	Kolife	4	1500	1494	100%	6	0%
	T.haimanot	4	304	304	100%	0	0%
	Woreda 9	4	557	557	100%	0	0%
	Woreda 13	4	1284	90	7%	1194	93%
	Total		**7656**	**6055**	**79%**	**1601**	**21%**

Findings provided in Table 4.21 indicate that a total of 7,656 ante-natal care first users were documented. The six evaluation criteria of the data elements were completed for 96% (n=7372) of mothers in the ten public health centres. Furthermore, 60% (n=6) of the public health centres had 100% completed data of ante-natal care registers under the data elements of personal information. Also, the minimum data value of completeness in the ANC first registers was documented to be 74% in Kasanchis health centre.

In the second stage of analysis, two data elements which are located under counselling and testing, including the HIV test accepted and target population code filled in, were reviewed to assess the data value completeness of the ANC first visits. As a result, 70% (n=7) of the reviewed public health centres had >97% of the completed data value of ante-natal care first-visit registers. On the other hand, 26% (n=2007) of the data value for the indicator of antenatal care first-visit mothers were incomplete in all of the health centres (n=10). Furthermore, the minimum data value incompleteness of ante-natal care first visit registers was reported to be 0% (n=0) in Addis Gebeya and Woreda 9, respectively. Also, the maximum data value incompleteness was documented to be 97% (n=1284) in Woreda 13 health centre.

In the third stage of analysis, four data elements, counselling on infant feeding, identifying and counselling on danger signs, counselling on family planning, and counselling on maternal nutrition, were studied to measure the data value completeness of the ANC first visits in ten of the public health centres. It was found that 60% (n=6) of the public health centres had 100% completed ante-natal care registers under the data elements of counselling. On the other side, on average, 21% (n=1601) of the data value of antenatal care first visit mothers were found incomplete in all of the public health centres. In addition, the maximum data incompleteness of the ANC first registers under the column of counselling was reported to be 93% (n=1194) in Woreda 13.

4.3.6.3 Skilled Birth Attendance (SBA) and early postnatal visit completeness

Table 4.22: Skilled birth attendance and early postnatal care visit

Indicator	Name of health centres	# of expected data elements to be complete	# of clients documented in registers	# of clients completely filled in		# of clients not completely filled in with at least one data element	
				#	%	#	%
Skilled Birth Attendance	Addis ketema	1	398	73	18%	325	82%
	Akaki	1	491	0	0%	491	100%
	Arada	1	53	0	0%	53	100%
	Amoraw	1	259	35	14%	224	86%
	Addis Gebeya	1	239	49	21%	190	79%
	Kasanchis	1	133	1	1%	132	99%
	Kolife	1	962	0	0%	962	100%
	T.haimanot	1	89	0	0%	89	100%
	Woreda 9	1	223	0	0%	223	100%
	Woreda 13	1	576	11	2%	565	98%
	Total		**3423**	**169**	**5%**	**3254**	**95%**
Early postnatal Care visit (EPNC)	Addis ketema	2	473	0	0%	473	100%
	Akaki	2	448	0	0%	448	100%
	Arada	2	47	0	0%	47	100%
	Amoraw	2	112	0	0%	112	100%
	Addis Gebeya	2	272	270	99%	2	1%
	Kasanchis	2	216	192	89%	24	11%
	Kolife	2	619	10	2%	609	98%
	T.haimanot	2	92	92	100%	0	0%
	Woreda 9	2	225	0	0%	225	100%
	Woreda 13	2	723	29	4%	694	96%
	Total		**3227**	**593**	**18%**	**2634**	**82%**

Findings provided in Table 4.22 indicate that a total of 3,423 skilled birth attendance users were documented in and reviewed from the delivery registers of ten public health centres**.** Henceforth, the data completeness of skilled birth attendance was reviewed using the family planning visit type as evaluation criteria. Subsequently, 3,423 mothers were identified and reviewed from the registers. Nevertheless, 95% (n=3254) of the data value for the skilled birth attendance user mothers that were found under the immediate postpartum family planning were found incomplete in ten of the public health centres. Moreover, the maximum data value incompleteness of skilled birth attendance users was found to be 100% in 50% (n=5) of the public health centres, including Akaki, Arada, Kolife, T.haimanot, and Woreda 9, respectively. In the same way, the minimum data value incompleteness of skilled birth attendance users was found to be 82% (n=325) in Addis ketema.

Similarly, the data value of completeness of early postnatal care visits (EPNC) were assessed using two data elements, including the HIV test performed and target population code filled in. Hereafter, the findings of the review provided in Table 4.22 show that a total of 3,227 early postnatal care service user mothers were identified in the registers. However, on average, the data value of the postnatal care visit indicator was found incomplete by 82% (n=2634) in all of the public health centres (n=10). Moreover, the maximum data value incompleteness of early postnatal-care visits was found to be 100% in 50% (n=5) of the public health centres, including Addis ketema, Akaki, Arada, Amoraw, and Woreda 9, respectively. Also, the minimum data value incompleteness of early postnatal care visit users was seen as 0% (n=0) in T.haimanot, and 1% (n=2) in Addis Gebeya, respectively.

4.3.6.4 Summary of data completeness in public health centres

Table 4.23: Summary of data completeness in (n=10) of the health centres

Indicators	Status of the reviewed registers	(#)	Decision on completeness
Family planning visits: Are the **two** data elements completely filled in in Counselling & testing?	**FP users documented in FP-registers**	**12355**	
	FP users completely filled in	3617 (29%)	Complete
	FP users not completely filled in	8738 (71%)	Incomplete
ANC 1st visit: Are the **six** data elements completely filled in under personal information?	**ANC-1 users documented in ANC-registers**	**7656**	
	ANC-1 users completely filled in	7072 (92%)	Complete
	ANC-1 users not completely filled in based on personal information	584 (8%)	Incomplete
ANC 1st visit: Are the **two** data elements completely filled in under HIV Assessment?	**ANC-1 users documented in ANC-registers**	**7656**	
	ANC-1 users completely filled in	5651 (74%)	Complete
	ANC-1 users not completely filled in based on HIV assessment	2005 (26%)	Incomplete
ANC 1st visit: Are the **four** data elements completely filled in in under Counselling?	**ANC-1 users documented in ANC-registers**	**7656**	
	ANC-1 users completely filled in under counselling	6057 (79%)	Complete
	ANC-1 users not completely filled in	1599 (21%)	Incomplete

Skilled Birth Attendance: Are the **one** data elements completely filled in in immediate postpartum family planning	**SBA users documented in ANC-registers**	**3423**	
	SBA users completely filled in based on immediate postpartum family planning	169 (5%)	Complete
	SBA users not completely filled in based on immediate postpartum family planning	3254 (95%)	Incomplete
Early postnatal Care visit (EPNC): Are the **two** data elements completely filled in in HIV Assessment?	**EPNC users documented in ANC-registers**	**3227**	
	EPNC users completely filled in based on HIV assessment	593 (18%)	Complete
	EPNC users not completely filled in based on HIV assessment	2634 (82%)	Incomplete
Average/index of completeness of the **17** data elements	**Total users documented in all registers**	**41973**	
	Total users/cases completely filled in	23159 (55%)	Complete
	Total users/cases not completely filled in	18814 (45%)	Incomplete

Overall, Table 4.23 shows that a total of 41,973 cases were reviewed from the family planning, ANC, delivery and postnatal care registers from April to September 2019. Hereafter, the findings of the review indicate that the content completeness of the reproductive health records of the ten public health centres was not filled in completely with at least one data element for about 45% (n=18, 814) of the recorded mothers. Also, the results of the review indicate that the ANC indicator was found to be relatively better complete than the other indicators. In contrast, the skilled birth attendance indicator was identified as having the lowest data value completeness compared to the other reproductive health indicators.

4.3.7 Documentation of data elements in the data quality monitoring logbook

The data quality monitoring logbook is defined as a register that is prepared to monitor the monthly data quality status of each case team as well as the public health centre. This logbook is used to document the data quality-related evidence, including complete documentation of expected and reported data elements; complete documentation of intra-data elements with inconsistency; possible causes of inconsistencies, and action taken by the performance review team to improve data consistency.

4.3.7.1 Documentation of expected and reported data elements

Table 4.24: Documentation of expected and reported data elements from case teams

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, N2o=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Number of expected reportable data elements from the case team documented in the data quality monitoring logbook	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	1	1	0	2(33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**3**	**3**	**4**	**3**	**2**	**18 (30%)**	**42 (70%)**
Number of reportable data elements reported from each case team and documented in the data quality monitoring logbook	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	1	0	1	2 (33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**3**	**3**	**4**	**2**	**3**	**18 (30%)**	**42 (70%)**

Findings presented in Table 4.24 indicate that the expected reportable data elements from case teams were not 100% documented in the data quality monitoring logbook over six months by 60% of the public health centres, including Addis ketema, Arada, Amoraw, Kasanchis, Woreda 9 and Woreda 13, respectively. On the other hand, the expected reportable data elements were reported from all case teams and 100% documented in the data quality logbook of Addis Gebeya and T.haimanot public health centres. The maximum and minimum complete documentation of reportable data elements from case teams were recognized in July and September 2019, respectively.

Similarly, documentation of reported data elements from case teams was reviewed in the six months, as indicated in Table 4.24 . It was found that the reported data elements of each case team were not documented 100%, in the data quality monitoring logbook, by 60% (n=6) of the public health centres, including Addis ketema, Arada, Amoraw, Kasanchis, Woreda 9 and Woreda 13, respectively. The maximum and minimum documentation of reportable data elements from case teams were recognized in July and September 2019, respectively. The maximum and minimum documentation of the actual reports of data elements from case teams were recognized in July and August 2019, respectively.

In summary, 60% (n=6) of health facilities did not document the expected and actually reported data elements over the six months.

4.3.7.2 Monitoring of data element inconsistencies

Table 4.25: Documentation of data elements with inconsistency, possible causes and actions taken

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Data elements with inconsistency documented in the intra-data element inconsistency check sheet	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	1	1	0	2(33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**1**	**1**	**1**	**2**	**2**	**1**	**8 (13%)**	**52 (87%)**
Possible causes of intra-data element inconsistency documented in the performance monitoring logbook	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	1	1	0	2 (33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**1**	**1**	**2**	**4**	**2**	**1**	**8 (13%)**	**52 (87%)**
Actions taken for intra-data element inconsistency documented in the performance monitoring logbook	Addis ketema	0	0	0	0	0	0	0(0%)	6(100%)
	Akaki	0	0	0	0	0	0	0(0%)	6(100%)
	Arada	0	0	0	0	0	0	0(0%)	6(100%)
	Amoraw	0	0	0	0	0	0	0(0%)	6(100%)
	Addis Gebeya	0	0	0	0	0	0	0(0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0(0%)	6(100%)
	Kolife	0	0	0	0	0	0	0(0%)	6(100%)
	T.haimanot	0	0	0	1	1	1	3 (50%)	3 (50%)
	Woreda 9	0	0	0	0	0	0	0(0%)	6(100%)
	Woreda 13	0	0	0	0	0	0	0(0%)	6(100%)
	Total	**0**	**0**	**0**	**1**	**1**	**1**	**3 (5%)**	**57 (95%)**

Data element inconsistencies refer to differences identified in the value of data elements across the HMIs tools, including registers, tally sheets, reporting forms and DHIS2.3 during monthly LQAS assessments of service and outpatient and inpatient reports. In this case, findings provided in Table 4.25 indicate that from April to September 2019, 80% (n=8) of the public health centres did not record all inconsistent data elements that were expected to be documented in the data quality monitoring logbook after performing monthly LQAS assessments of service and outpatient and inpatient reports. On the other side, throughout the six months, only one health centre documented inconsistent data elements in the data quality monitoring logbook. Akaki health centre recorded inconsistent data elements only in July and August 2019.

Similarly, documentation of possible causes of data element inconsistencies was not identified and documented 100% on a monthly basis in the data quality monitoring logbooks by 80% (n=8) of the public health centres for over six months. In particular, 90% of the public health centres did not identify and document the possible causes of data element inconsistency in the months of April, May and September 2019. The maximum documentation of possible causes of data element inconsistency was reviewed in 40% (n=4) of the public health centres in the month of July 2019.

The results provided in Table 4.25 show that documentation of actions taken for inconsistencies of data elements was not performed 100% in 90% (n=9) of the public health centres in the last six months, except for T.haimanot.

4.3.8 Implementation status of different data quality improvement activities

Data quality improvement activities are defined as measurable actions that are expected to be implemented monthly and documented in the data quality monitoring logbook by the performance review team. These include the implementation of a monthly Lot Quality Assurance Sampling technique; discussion of how to improve data quality; monthly problem prioritization; monthly action plan preparation and implementation; monthly Routine Data Quality Assessment (RDQA) to monitor data quality at the health centre, core processes and case team levels; and monthly provision of written feedback to improve data quality.

4.3.8.1 Implementation status of lot quality assurance sampling (LQAS)

Table 4.26: Implementation of lot quality assurance sampling (LQAS) by facilities

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total (Yes =1)	 (No =0)
Lot Quality Assurance Sampling (LQAS) performed for service report	Addis ketema	1	1	1	1	1	1	6 (100%)	0 (0%)
	Akaki	1	1	1	1	1	1	6 (100%)	0 (0%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kasanchis	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 13	1	1	1	1	1	1	6 (100%)	0 (0%)
	Total	**8**	**8**	**8**	**8**	**7**	**7**	**46 (76%)**	**14 (24%)**
LQAS performed for outpatient department (OPD) report	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	1	1	1	1	1	1	6(100%)	0 (0%)
	Arada	0	0	0	0	0	1	1 (17%)	5 (83%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	0	0	0	0	0	1 (17%)	5 (83%)
	Kasanchis	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	0	1	1	1	1	1	5 (83%)	1 (17%)
	Woreda 9	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 13	1	1	1	1	1	1	6 (100%)	0 (0%)
	Total	**6**	**6**	**6**	**6**	**5**	**6**	**35 (58%)**	**25 (42%)**
Lot Quality Assurance Sampling (LQAS) performed for inpatient department (IPD) report	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	0	0	0	0(0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kasanchis	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 9	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**3**	**3**	**3**	**3**	**3**	**18 (30%)**	**42 (70%)**

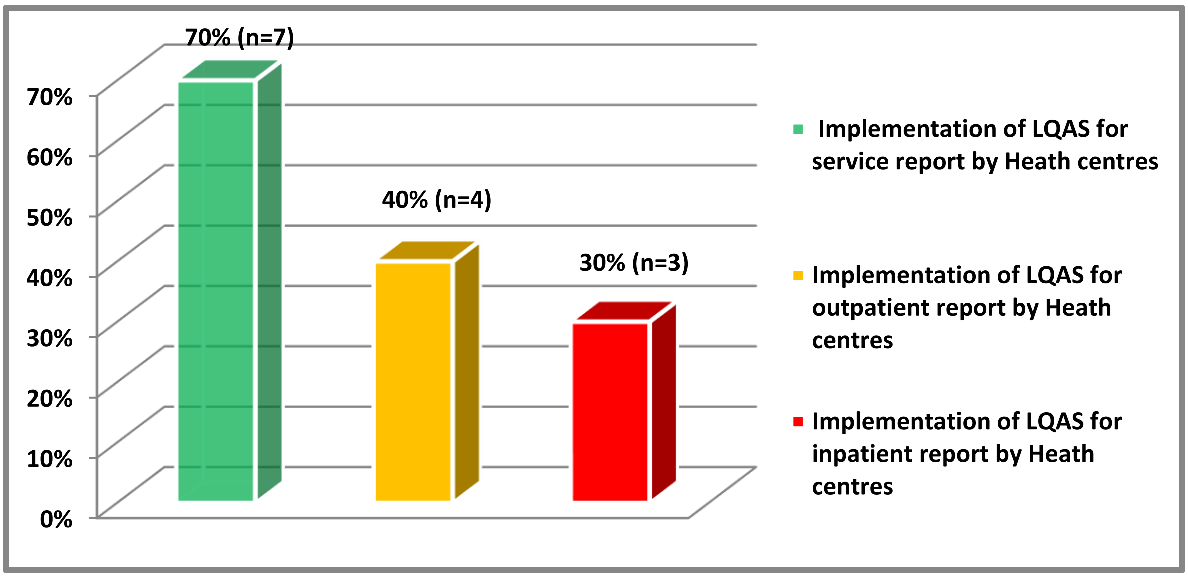

Figure 4.3: 100% LQAS performed in public health centres over six months

A Lot Quality Assurance Sampling (LQAS) technique is done monthly by the performance review team of each health centre to assess the quality of service, and outpatient and inpatient reports, respectively. Consequently, the data quality monitoring logbook was studied, at three levels of analysis, to review documentation of the monthly LQAS implementation.

In the first level of analysis, the data quality monitoring logbook was reviewed over the six months to measure the monthly implementation of LQAS in relation to service reports. The data quality monitoring logbook shows that LQAS assessments for service reports were achieved by 70% (n=7) of the health centres from April to September 2019. Also, the maximum LQAS assessments for service reports were implemented from April to July 2019 by 80% (n=8) of the facilities except for Arada and Amoraw.

In the second level of review, the data quality monitoring logbook was checked to identify the quality of outpatient reports through the implementation of LQAS over the past six months. It was found that 40% (n=4) of the public health centres achieved LQAS assessments from April to September 2019 to improve the data quality of the outpatient reports. Correspondingly, the maximum number of LQAS assessments of outpatient reports were carried out in 60% of the public health centres except in August 2019.

In the third level of review, the level of LQAS implementation was reviewed, from the data quality monitoring logbook, to determine the data quality of inpatient reports over the six months. In 70% (n=7) of the public health centres, LQAS for inpatient reports was accomplished at 0% (n=7) from April to September 2019.

4.3.8.2 Evidence of discussion on data quality

Table 4.27: Data quality discussions made by public health centres

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Discussion on data quality	Addis ketema	1	1	0	0	0	1	3 (50%)	3 (50%)
	Akaki	0	0	0	0	0	0	0(0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	0	0	0	1	3 (50%)	3(50%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	0	0	1	1	1	1	4 (67%)	2 (33%)
	Woreda 9	1	1	1	0	0	0	4 (67%)	2 (33%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**3**	**2**	**1**	**1**	**3**	**13 (21%)**	**47 (79%)**

Findings provided in Table 4.27 indicate that the data quality monitoring logbook did not show any evidence of discussion on data accuracy, completeness and timeliness in 60% (n=6) of the public health centres. Furthermore, in July and August 2019, nine of the ten public health centres did not hold a discussion on how to improve data quality at the health centre and levels below. The maximum number of discussions on data quality was conducted for four months in the T.haimanot health centre. The minimum number of discussions on data quality was made only once in August and September 2019.

4.3.8.3 Implementation status of problem prioritization

Table 4.28: Problem prioritization by health centres

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Health problems prioritized by the performance monitoring team (PMT) based on Magnitude of the problem	Addis ketema	1	0	0	0	0	0	1 (17%)	5 (83%)
	Akaki	0	0	0	0	0	0	0(0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	1	1	1	1	1	0	5 (83%)	1 (17%)
	Woreda 9	1	1	1	0	1	0	4 (67%)	2 (33%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**4**	**3**	**3**	**2**	**2**	**0**	**14 (23%)**	**46 (77%)**
Health problems prioritized by the performance monitoring team (PMT) based on community concern of the problem	Addis ketema	0	0	0	0	0	0	0 (0%)	6(100%)
	Akaki	0	0	0	1	1	0	2(33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	1	1	1	0	1	0	4 (67%)	2 (33%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**2**	**2**	**2**	**2**	**3**	**1**	**12 (20%)**	**48 (80%)**
Health problems prioritized by the performance monitoring team (PMT) based on seriousness of the problem	Addis ketema	0	0	0	0	0	0	0 (0%)	6(100%)
	Akaki	1	0	0	1	0	0	2(33%)	4 (67%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	0	0	0	1	1	1	3 (50%)	3 (50%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**1**	**0**	**0**	**2**	**1**	**1**	**5 (8%)**	**55 (92%)**
Health problems prioritized by the performance monitoring team (PMT) based on feasibility of interventions?	Addis ketema	0	0	0	0	0	0	0 (0%)	6(100%)
	Akaki	1	0	0	0	0	0	1 (17%)	5 (83%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	0	0	0	1	1	1	3 (50%)	3 (50%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**1**	**0**	**0**	**1**	**1**	**1**	**4 (7%)**	**56 (93%)**

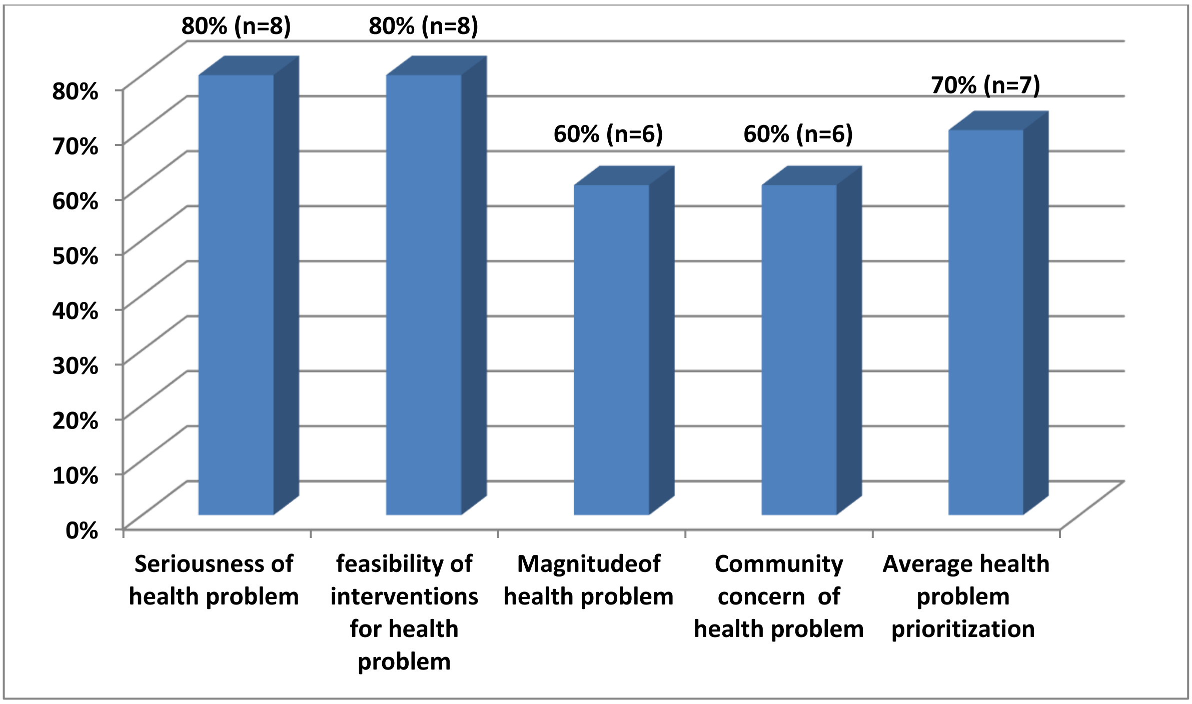

Figure 4.4: Percentage of health centres that have not prioritized health problems

Implementation of problem prioritization was evaluated using four measurement dimensions, including the magnitude of the problem, community concern, seriousness of the problem, and feasibility of interventions. These problem prioritization criteria are expected to be used monthly by the performance review team of each health centre. The findings in Table 4.28 and Figure 4.4 indicate that, on average, the criteria of health problem prioritization were not implemented by 70% (n=7) of the public health centres over the six months.

The magnitude of a health problem is defined as the number or percentage of people affected by a health condition in a particular area. However, on average, the magnitude of health problems was not prioritized by 60% (n=6) of the public health centres over the six months. Moreover, not one of the public health centres (n=10) prioritized health problems by 100% in September 2019. The month with the maximum prioritization of health problems was in April.

The second dimension of health problem prioritization is a **community concern**. Hence, the findings provided in Table 4.28 show that the performance monitoring team did not prioritize health problems in 70% (n=7) of the public health centres during the six months based on community concerns. Specifically, from April to July 2019, only two public health centres used the dimension of community concern to prioritize health problems. **The seriousness of the health problem** is defined as the potential of a health problem to result in severe disability or death in a particular area. In practice, the seriousness of the health problems was not used as one of the dimensions to prioritize health problems by the performance review team in 80% (n=8) of the public health centres over the six months. Moreover, all the public health centres (n=10) did not give priority to health problems based on the seriousness in May and June 2019, respectively. Also, 90% (n=9) of the public health centres did not review the health problems based on their seriousness in April, August and September 2019, respectively.

Furthermore, 80% (n=8) of the public health centres did not prioritise the feasibility of interventions from April to September 2019. The dimension of the feasibility of interventions was also not applied to prioritize health problems in all public health centres during May and June 2019. Similarly, 90% (n=9) of the public health centres did not prioritize health problems based on feasible interventions in April, July, August, and September 2019.

Generally, in 100% of all public health centres over the six months, the prioritization of health problems based on their magnitude, community concern, seriousness, and feasibility of interventions did not occur.

4.3.8.4 Implementation of action points and routine data quality assessments

Table 4.29: Documentation of action points and rdqa implementations

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Action plan implementation to solve prioritized problems	Addis ketema	0	0	0	0	0	0	0 (0%)	6(100%)
	Akaki	0	0	0	0	0	0	0 (0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	0	1	1	1	1	0	4 (67%)	2 (33%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**0**	**1**	**1**	**1**	**1**	**0**	**4 (7%)**	**56 (93%)**
Routine Data Quality Assessment (RDQA) implemented by the health centre to monitor data quality	Addis ketema	0	0	0	0	0	0	0 (0%)	6(100%)
	Akaki	0	0	0	0	0	0	0 (0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	0	0	0	0 (0%)	6(100%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**1**	**1**	**1**	**1**	**1**	**1**	**6 (10%)**	**54 (90%)**

Implementation and documentation of action plans are critical for addressing priority health problems. However, the review provided in Table 4.29 shows that, in 90% (n=9) of the public healthcare centres, action points were not only not prepared by the performance review team but also not documented in the data quality monitoring logbook during the six months. In addition, in April and September 2019, none of the public health centres' performance review teams prepared action points or documented it in the data quality monitoring logbook. Only one public health centre prepared and documented action points from May to August 2019.

Implementation of Routine Data Quality Assessment (RDQA) is vital for public health centres to monitor and improve the health data quality verification at the levels of health centres, core processes and case teams. As indicated in Table 4.29 , only one public health centre (T.haimanot) implemented RDQA from April to September 2019. In contrast, the other nine public health centres did not conduct RDQA during the six months.

4.3.8.5 Documentation summary of data elements

Table 4.30: Documentation summary of data elements at health centres in Addis Ababa

SN	Documentation of data elements in the data quality monitoring logbook	Response category	Total response in numbers (Yes/No)	Expected numbers of responses in the six months in 10 health centres (Yes/No), i.e. (6*10=60)
1	Are the number of expected reportable data elements from the case team documented in the data quality monitoring logbook?	Yes (=1)	18 (30%)	60
		No (=0)	42 (70%)	
2	Are the number of completed reportable data elements from the case team documented in the monitoring logbook?	Yes (=1)	18 (30%)	60
		No (=0)	42 (70%)	
3	Are data elements with inconsistency documented in the quality monitoring logbook?	Yes (=1)	8 (13%)	60
		No (=0)	52 (87%)	
4	Are possible causes of intra-data element inconsistency documented in the	Yes (=1)	8 (13%)	60
		No (=0)	52 (87%)	

	performance monitoring logbook?			
5	Are actions taken for intra-data element inconsistency documented in the performance monitoring logbook?	Yes (=1)	3 (5%)	60
		No (=0)	57 (95%)	
	Average data element documentation in the data quality monitoring logbook	Yes (=1)	55 (18%)	300
		No (=0)	245 (82%)	

4.3.8.6 Implementation summary of different data quality improvement activities

Table 4.31: Implementation summary of different data quality activities in Addis Ababa

SN	Implementation summary of different data quality-improving activities	Response category	Total response in numbers (Yes/No)	Expected numbers of responses in the six months in 10 health centres (Yes/No), i.e. (6*10=60)
1	Is Lot Quality Assurance Sampling (LQAS) performed for the service report?	Yes (=1)	46 (76%)	60
		No (=0)	14 (24%)	
2	Is Lot Quality Assurance Sampling (LQAS) performed for outpatient department report?	Yes (=1)	35 (58%)	60
		No (=0)	25 (42%)	
3	Is Lot Quality Assurance Sampling (LQAS) performed for Inpatient Department (IPD) report?	Yes (=1)	18 (30%)	60
		No (=0)	42 (70%)	
4	Is the discussion on the data quality documented in the data quality monitoring logbook?	Yes (=1)	13 (21%)	60
		No (=0)	47 (79%)	
5	Is a health problem prioritized based on the magnitude of the problem?	Yes (=1)	14 (23%)	60
		No (=0)	46 (77%)	
6	Is a health problem prioritized based on community concern for the problem?	Yes (=1)	12 (20%)	60
		No (=0)	48 (80%)	
7	Is a health problem prioritized based on the seriousness of the problem?	Yes (=1)	5 (8%)	60
		No (=0)	55 (92%)	
8	Is a health problem prioritized based on the feasibility of interventions?	Yes (=1)	4 (7%)	60
		No (=0)	56 (93%)	
	Average health problems prioritization	Yes (=1)	35 (15%)	240
		No (=0)	205 (85%)	
9	Is the action plan documented to solve prioritized problems?	Yes (=1)	4 (7%)	60
		No (=0)	56 (93%)	
10	Was Routine Data Quality Assessment (RDQA) implemented by the health centre?	Yes (=1)	6 (10%)	60
		No (=0)	54 (90%)	
	Average implementation of different data quality-improving activities	Yes (=1)	157 (26%)	600
		No (=0)	443 (76%)	

In conclusion, the documentation of data elements at public health centres has shown different levels of documentation. For example, all lists of expected reportable data elements and reported data elements from all case teams within each health centre were not documented in the data quality monitoring logbooks by 60% (n=6) of public health centres over six months. In addition, from April to September 2019, 80% (n=8) of the public health centres did not document all inconsistent data elements that are expected to be documented in the data quality monitoring logbook after performing monthly LQAS assessments of service, outpatient and inpatient reports. Similarly, documentation of possible causes of data element inconsistencies was not identified and documented 100% every month in the data quality monitoring logbooks by 80% of the public health centres for over six months. As well, documentation of actions taken for inconsistencies of data elements was not performed 100% in 90% (n=9) of the public health centres in the six months, except for T.haimanot.

The implementation statuses of data quality activities have different levels of achievement over the six months. For example, the LQAS assessments for service, outpatient, and inpatient reports were not performed by 30% (n=3), 60% (n=6), and 70% (n=7) of the public health centres, respectively, over the six months investigated. At the same time, in 60% (n=6) of the public health centres, the monthly data quality review was not undertaken by the performance review team and minutes were not recorded in the data quality monitoring logbook over the six months. On average, in 70% (n=7) of the public health centres, health problems related to magnitude, community concern, seriousness, and feasibility of intervention were not prioritized by the performance review team from April to September 2019. Furthermore, there was no evidence of action point planning and implementation by the performance review team in the data quality monitoring logbook in 90% (n=9) of the public healthcare centres during the six months. Moreover, 90% (n=9) of the public health centres did not perform RDQA over the six months.

4.3.9 Findings of timeliness

Timeliness is the degree to which data represent reality from the desired purpose in time (Gabr et al. 2021:16; Ramasamy & Chowdhury 2020:3). In this study, timeliness is defined as all the expected report types from case teams and public health centres being checked and reported to their following levels on stipulated times from April to September 2019.

Table 4.32: Report received date, feedback, and service reports timeliness by facilities

Different data sources expected to be complete	Name of health centres	Six months							
		Apr (Yes=1, No=0)	May (Yes=1, No=0)	Jun (Yes=1, No=0)	Jul (Yes=1, No=0)	Aug (Yes=1, No=0)	Sep (Yes=1, No=0)	Total	
								(Yes =1)	(No =0)
Report received date from case teams documented in the data quality monitoring logbook	Addis ketema	1	1	0	1	0	0	3 (50%)	3 (50%)
	Akaki	0	0	0	0	0	0	0 (0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	0	0	0	1	1	0	2 (33%)	4 (67%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	1	1	1	1	0	0	4 (67%)	2 (33%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	0	1	1	1	0	0	3 (50%)	3 (50%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**4**	**3**	**5**	**2**	**1**	**18 (30%)**	**40 (70%)**
Written feedback about the report timeliness provided from the HMIS unit for case teams	Addis ketema	0	0	0	0	0	0	0 (0%)	6 (100%)
	Akaki	0	0	0	0	0	0	0 (0%)	6 (100%)
	Arada	0	0	0	0	0	0	0 (0%)	6 (100%)
	Amoraw	0	0	0	0	0	0	0 (0%)	6 (100%)
	Addis Gebeya	1	1	0	1	1	0	4 (67%)	2 (33%)
	Kasanchis	0	0	0	0	0	0	0 (0%)	6 (100%)
	Kolife	0	0	0	0	0	0	0 (0%)	6 (100%)
	T.haimanot	1	1	1	1	1	1	6 (100%)	0 (0%)
	Woreda 9	1	0	0	1	0	0	2 (33%)	4 (67%)
	Woreda 13	0	0	0	0	0	0	0 (0%)	6 (100%)
	Total	**3**	**2**	**1**	**3**	**2**	**1**	**12 (20%)**	**48 (80%)**
Health centre been reporting its service reports to the next level on a timely basis using DHIS2	Addis ketema	1	1	1	1	1	1	6 (100%)	0 (0%)
	Akaki	0	1	0	0	0	0	1 (17%)	5 (83%)
	Arada	0	1	0	1	0	0	2 (33%)	4 (67%)
	Amoraw	1	1	1	1	1	1	6 (100%)	0 (0%)
	Addis Gebeya	1	1	1	1	1	1	6 (100%)	0 (0%)
	Kasanchis	1	0	0	1	0	1	3 (50%)	3 (50%)
	Kolife	1	1	1	1	1	1	6 (100%)	0 (0%)
	T.haimanot	1	1	0	1	1	0	4 (67%)	2 (33%)
	Woreda 9	0	0	0	0	0	0	0 (0%)	6 (100%)
	Woreda 13	1	1	0	0	0	0	2 (33%)	4 (67%)
	Total	**7**	**8**	**4**	**7**	**5**	**5**	**36 (60%)**	**24 (40%)**

4.3.9.1 Documentation of report received date on the data quality logbook

The findings presented in Table 4.31 indicate that the receipt of report date from case teams was not documented 100% in 50% (n=5) of public health centres, among which Akaki, Arada, Amoraw, Kasanchis and Woreda 13. In addition, only five public health centres documented the maximum number of dates on which the report was received in the data quality monitoring logbook in July. Only two public health centres documented the actual date of receipt of the report from each case team in August and September. In particular, the report received from each case team during the six months was 100% correctly recorded in the T.haimanot Health Centre data quality monitoring logbook. Notably, in September 2019, except for T.haimanot, 90% (n=9) of the public health centres did not document the report received date of each case team in the data quality monitoring logbook (n=9). On average, 70% of the reports sent from case teams did not document their received date in the data quality monitoring logbook at all public health centres.

4.3.9.2 Provision of written feedback on reporting timeliness for case teams

Written feedback is valuable information used to make important decisions to improve performance and is a tool for continuous and effective learning. However, the results presented in Table 4.31 indicate that, on average, 70% (n=7) of HMIS units in public health centres did not provide written feedback to their respective case teams on the timeliness of the report every month at least once over six months. Specifically, the minimum number of written feedback provided to HMIS case teams from HMIS units of public health centres was provided by only one out of ten health centres in June and September. In general, the HMIS units of T.haimanot, Addis Gebeya and Woreda 9 public health centres provided written feedback on the timeliness of the reports to their specific case teams.

4.3.9.3 Timeliness of service report submitted to DHIS 2.3 database

The findings presented in Table 4.31 show that, on average, 60% of the healthcare centres did not submit service reports to the next level on a timely basis through the

DHIS2.3 database over the six months. In addition, in August and September, 50% of the public health centres did not send service reports to the next level on time. In particular, Woreda 9 and Akaki health centres did not send service reports on time for the last six and five months, respectively. In addition, Arada and Woreda 13 public health centres did not submit service reports on time for the months indicated. Likewise, the maximum and minimum numbers of service reports submitted on time were in May and June.

In conclusion, 70% (n=7) of the reports sent from case teams did not document their received date in the data quality monitoring logbook at all public health centres. Similarly, on average, 70% (n=7) of HMIS units in public health centres did not provide written feedback to their respective case teams on the timeliness of the report every month at least once in the six months. Simultaneously, 60% (n=6) of the healthcare centres did not submit service reports to the next level on a timely basis through the DHIS2 database in the six months.

4.4 ANALYSIS AND PRESENTATION OF FINDINGS FOR PHASE II

Phase II of Chapter 4 focuses on descriptive and inferential findings, which are presented and described in two main sections. Furthermore, sections one and two have been divided into six and two sub-sections, respectively. In view of that, section one focuses on the descriptive findings of the cross-sectional survey. The sub-sections are as follows:

Socio-demographic characteristics include age, sex, years of experience in the present position, work position, and level of education of the study participants.

Technical determinants: the effect of technical determinants on data management and information use in public healthcare centres has been identified in this sub-section. Key findings and the level of significance of the technical determinants focus on computer literacy, availability of HMIS tools, knowledge of HMIS tools, and the perception of the user-friendliness of HMIS tools.

Organizational determinants: Sub-section three presents the effect of organizational determinants on data management and information use in the public health centres. The main results and the level of significance of the organizational determinants were concentrated on the availability of strategies for data management and information use; the culture of information use; the availability of a separate HMIS plan; the provision of internal supervision; the motivation to strengthen HMIS; staff empowerment; onsite training; accountability, and budget allocation.

Behavioural determinants: Sub-section four presents the effect of behavioural determinants on data management and information use in the public health centres. Core findings and the level of significance of the behavioural determinants were evaluated based on the knowledge to optimize information use and to manage data process activities; confidence in information use and in managing data processes; competence in information use and in managing data processes; motivation to optimize information use; and the level of involvement in data management tasks to optimize information use.

Practices of data management processes: Sub-section five describes the practices of data management processes in public healthcare centres. In this study, eight study variables, including the value of data collection; data compilation processes; knowledge to compile data; skills to analyze data; the adequacy of support for data analysis processes; the skills to display data using different charts; data presentation visibility, and weekly case presentations have been used to define the processes of data management practices. This sub-section presents the value of data quality; data documentation; routine data quality assurance (RDQA) practice, and implementation of lot quality assurance sampling (LQAS) at the level of public healthcare centres, core processes, and case teams.

Practices of information use: Sub-section six addresses the extent of information use in public health centres. Vital findings of the information use practices were measured based on the level of information re-packaging and dissemination; analytical report production; action plan preparation and monitoring; the culture of feedback provision, and information use dimensions.

Finally, section two of Phase II emphasises the inferential findings of the cross-sectional survey, and it has two main sub-sections under the bivariate and multivariate logistic regression analysis.

4.4.1 Data management and analysis

The data collected were checked for completeness before entering into SPSS software for analysis. And then, data were entered into IBM SPSS Version 26 primarily to identify its type of measurement, recheck for missing data, recode, compute indexes/averages, and conduct a descriptive and inferential analysis. Besides, the following key techniques of data management processes were applied before statistical analysis was conducted and processed.

Recoding is a technique that allows combining or re-grouping numbers of responses into a new small number of responses to simplify the analysis process, improve the accuracy of estimations, and summarize or visualize the findings for readers in a simple manner *(*Dey 2003:209). For that reason, in this study, the numbers of responses listed in the Likert scales and continuous variables were regrouped/ recoded meaningfully. The details of the recoding or re-grouping are briefly discussed in the methodology chapter, Section 3.6.7

4.4.2 Findings of the cross-sectional survey

4.4.2.1 Socio-demographic Characteristics of the Sample

Socio-demographic characteristics of the respondents are necessary for quantitative research as it enables the readers to understand the sources of the data and assist in the interpretation of the findings.

Table 4.33: Socio-demographic characteristics of the study respondents (n=590)

Socio-demographic Determinants (SD)	Level of category	Frequency	Per cent	Valid per cent
Age Groups	20-33	442	74.9	74.9
	34-47	113	19.2	19.2
	48-61	35	5.9	5.9
Sex	M	195	33.1	33.1
	F	395	66.9	66.9
Years of experience in the present position	1-5 years	276	46.8	46.8
	6-10 years	233	39.5	39.5
	>=11 years	81	13.7	13.7
Work position	Healthcare provider	446	75.6	75.6
	Case team head	71	12.0	12.0
	Core process head	34	5.8	5.8
	Medical director	10	1.7	1.7
	HMIS/HIT officer	29	4.9	4.9
Level of Education	Diploma	203	34.4	34.4
	Baccalaureus degree	365	61.9	61.9
	Master's degree and above	22	3.7	3.7

The socio-demographic characteristics of the study respondents are presented in detail in Table 4.33 . The response rate of the studied participants was 100% (n=590). Complete data from all participants were obtained. The mean age and years of experience in the present position of the respondents were 31.1 years (SD=7.5) and 7.5 years (SD=6.8), respectively. 66.9% (n=395) of the respondents were female. The majority (75.6%, n=446) of the participants were healthcare providers in their current work position. Moreover, 61.9% (n=365) of the participants had a Baccalaureus degree.

4.4.2.2 Factors Influence the Practice of Data Management and Information Use

4.4.2.2.1 Technical Determinants

Technical Determinants are defined as the specialized know-how and technology required to develop, manage, and improve routine health information system processes and performance (Measure Evaluation 2015:88). In this study, technical determinants are defined concerning computer literacy, the availability of HMIS tools (registers, tally sheets, report formats, and HMIS manuals), knowledge of HMIS tools, and the perception about the user-friendliness of HMIS tools to manage data and use information in public healthcare centres.

Table 4.34: Technical determinants (n=590)

Code	Technical Determinants (TD)	Level of responses					
		Strongly Disagree or disagree		Neither agree nor disagree		Strongly agree or agree	
		#	%	#	%	#	%
QTD1	Computer literacy						
QTD11	I have basic computer skills in managing data	498	84.4	0.0	0.0	92	15.6
QTD2	Availability of HMIS tools						
QTD21	Registers are always available	156	26.4	62	10.5	372	63.1
QTD22	Tally sheets are always available	142	24.1	59	10.0	389	65.9
QTD23	Report formats are always available	148	25.1	64	10.8	378	64.1
QTD24	HMIS manuals are always available	148	25.1	66	11.2	376	63.7
QTD3	Knowledge of HMIS tools						
QTD31	I have adequate knowledge of how to manage HMIS manuals	472	80.0	59	10.0	59	10.0
QTD32	I understand the definitions of HMIS indicators	392	66.4	80	13.6	118	20.0
QTD33	I have adequate knowledge of how to collect data in HMIS registers	295	50.0	59	10.0	236	40.0
QTD34	I have adequate knowledge of how to compile data in tallies	384	65.1	58	9.8	148	25.1
QTD35	I know how to manage data in reporting formats	413	70.0	59	10.0	118	20.0
QTD4	Perceived user-friendliness of HMIS tools						
QTD41	It takes a long time to complete data from HMIS registers	442	74.9	59	10.0	89	15.1
QTD42	HMIS tools are easy to use	437	74.0	59	10.0	94	16.0
QTD43	Organization of the HMIS tools is practical	413	70.0	57	9.7	120	20.3
QTD44	I feel comfortable using these HMIS tools	470	79.7	49	8.3	71	12.0
QTD45	Generally, I am satisfied with HMIS tools	439	74.4	62	10.5	89	15.1

Computer literacy: In this study, computer literacy is defined as the knowledge and skills to use a computer for data management processes and practices of information use in public healthcare centres, core processes and case teams. The findings in Table 4.34 show that 84.4% (n=498) of the participants did not report having basic computer skills to manage data.

The availability of HMIS tools is crucial for data collection, data compilation, and report summarization, as well as to guide the processes of data management and information use activities at the level of healthcare centres, core processes and case teams. In this case, findings reported in Table 4.34 show that, on average, 25.1% (n=148) of the participants strongly disagree or disagree with the availability of HMIS tools, including registers, tally sheets, report formats, and HMIS manuals at public healthcare centres.

Knowledge of HMIS tools is essential for data collection, compilation, report summarization, and proper HMIS manual utilization. In this study, however, 80% (n=472) of the participants did not have adequate knowledge of how to manage HMIS manuals. 66.4% (n=392) of the participants reported not understanding the definitions of HMIS indicators. Also, 50.0% (n=295) of the participants said they did not know how to collect data in HMIS registers adequately, and 65.1% (n=384) did not know how to compile data in tallies. On average, 66.4% (n=392) of the participants did not have adequate knowledge of the HMIS tools, including definitions of HMIS indicators, how to collect data in HMIS registers, how to compile data in tallies, and how to manage data in reporting formats.

Perception of the user-friendliness of HMIS tools: In this study, 74.9% (n=442) of the study participants strongly agreed or agreed that it takes a long time to complete HMIS registers daily. In addition, 74.1% (n=437) strongly disagreed or disagreed about HMIS tools being easy to utilise. 70.0% (n=413) of the participants strongly disagreed or disagreed about the practical organization of HMIS tools. 79.7% (n=470) of them strongly disagreed or disagreed about feeling comfortable using these HMIS tools at the level of public health centres. 74.4% (n=439) of the study participants were unsatisfied with HMIS tools.

On average, 75.1% (n=443) of the participants strongly disagreed or disagreed with the user-friendliness of HMIS tools, including the long time taken to complete data from HMIS registers, the easiness of HMIS tools to use, the practical organization of the HMIS tools, feeling comfortable on using HMIS tools, and the level of satisfaction with these HMIS tools at the level of public health centres.

4.4.2.2.2 Organizational Determinants

Organizational Determinants are defined concerning the organisation's structure, resources, procedures, support services and promotion of an information culture. Organizational factors include management, planning, availability of resources, training and capacity building, supervision, distribution of information and information use culture (Measure Evaluation 2015:88). In this study, organizational determinants are defined concerning the availability of written data management and information use strategies, the culture of information use, the availability of a separate HMIS plan, provision of internal supervision, motivation to strengthen HMIS, staff empowerment, onsite training, accountability, and budget allocation to strengthen the HMIS in the health centres.

Table 4.35: Organizational determinants (n=590)

Code	Organizational Determinants (OD)	Level of responses					
		Strongly Disagree or disagree		Neither agree nor disagree		Strongly agree or agree	
		#	%	#	%	#	%
QOD1	A written data management strategy is available at the						
QOD11	health centre level	480	81.4	29	4.9	81	13.7
QOD12	core process level	496	84.1	40	6.8	54	9.2
QOD13	case team level	513	86.9	28	4.7	49	8.3
QOD2	A written information use strategy is available at the						
QOD21	health centre level	484	82.0	29	4.9	77	13.1
QOD22	core process level	496	84.1	27	4.6	67	11.4
QOD23	case team level	507	85.9	30	5.1	53	9.0

QOD3	Culture of information use is well-promoted at						
QOD31	health centre level	437	74.1	57	9.7	96	16.3
QOD32	core process level	472	80.0	42	7.1	76	12.9
QOD33	case team level	485	82.2	42	7.1	63	10.7
QOD4	A separate HMIS plan is available at the						
QOD41	health centre level	471	79.8	89	15.1	30	5.1
QOD42	core process level	491	83.2	36	6.1	63	10.7
QOD43	case team level	484	82.0	47	8.0	59	10.0
QOD5	Internal supervision is provided monthly to strengthen HMIS at						
QOD51	health centre level	469	76.1	30	5.1	91	15.4
QOD52	core process level	489	82.9	29	4.9	72	12.2
QOD53	case team level	501	83.9	24	4.1	65	11.0
QOD6	Motivation to strengthen HMIS is always encouraged at						
QOD61	health centre level	443	75.1	59	10.0	88	14.9
QOD62	core process level	472	80.0	48	8.1	70	11.9
QOD63	case team level	490	83.1	45	7.6	55	9.3
QOD64	individual level	502	85.1	30	5.1	58	9.8
QOD7	Staff empowerment, onsite training, and accountability						
QOD71	Staff is encouraged to make evidence based decisions	427	72.4	71	12.0	92	15.6
QOD72	Onsite training is conducted regularly to strengthen HMIS	456	77.3	51	8.6	83	14.1
QOD73	Accountability is promoted to strengthen HMIS	437	74.1	59	10.0	94	15.9
QOD8	Budget						
QOD81	An adequate budget is allocated yearly to strengthen HMIS	501	84.9	30	5.1	59	10.0

The availability of data management and information use strategies enables a common set of goals and objectives across the healthcare system to ensure how healthcare service data are managed and used effectively at the level of public health centres, core processes and case teams. The findings in Table 4.35 show that 81.4% (n=480) and 82.0% (n=484) of the participants strongly disagree or simply disagree about the availability of written data management and information use strategies, respectively. 84.3% (n=497) and 84.0% (n=496) of the participants strongly disagree or disagree about the availability of written data management and information use strategies, respectively, at the three levels of the public healthcare facilities, namely healthcare centres, core processes and case teams. On the other hand, 5.4% (n=32) and 5.0% (n=29) of the participants neither agree nor disagree about the availability of written data management and information use strategies, respectively, at the level of public health centres.

A culture of information use is crucial in promoting evidence-based decision-making processes at the public health centres, core processes and case teams. However, results in Table 4.35 show that 74.0% (n=437), 80.0% (n=472), and 82.2% (n=485) of the participants strongly disagree or disagree about the level of promotion in ensuring a culture of information use at the three levels of the public health facilities (healthcare centres, core processes and case teams) respectively. On average, 78.0% (n=460) of the participants strongly disagree or disagree.

The availability of a separate HMIS plan is essential to monitor, guide and strengthen the HMIS as well as to improve the practice of data management processes and information use at the level of public health facilities. Findings in Table 4.35 show that 79.8% (n=471), 83.2% (n=491), and 82.0% (n=484) of the participants strongly disagree or disagree about the availability of a separate HMIS plan at the three levels of the public health facilities respectively. On average, 82.0% (n=482) of the participants strongly disagree or disagree about the availability of a separate HMIS plan at the three levels of health facilities.

Internal supervision is used to support, motivate and enable the development of good data management and information use practices by healthcare providers at public health centres, in core processes, and by case teams. However, the findings presented in Table 4.35 show that 76.1% (n=449) of the participants strongly disagree or disagree about the presence of internal supervision to strengthen HMIS at the level of public health centres. In addition, 80.0% (n=472) and 83.9% (n=495) of the participants strongly disagree or disagree about the internal supervision at the level of core processes and case teams every month. On average, 80.0% (n=472) of the participants strongly disagree or disagree about the monthly internal supervision.

Motivation to strengthen HMIS is closely associated with job satisfaction which keeps and inspires healthcare providers to strengthen the practices of data management processes and information use at the different levels of public health facilities. In this study, 75.1% (n=443), 80.0% (n=472), and 83.1% (n=490) of the participants strongly disagreed or disagreed about the level of motivation to strengthen HMIS at the level of public health centres, core processes, and case teams, respectively. Moreover, on average, 81.0% (n=477) of the participants chose “strongly disagree” or “disagree” about the level of encouragement to ensure motivation on strengthening HMIS.

Staff empowerment, onsite training, and accountability: In this study, 72.4% (n=427) of the participants indicated they strongly disagree or disagree about staff encouragement to make evidence-based decisions at the level of public health centres. 77.3% (n=456) of those participants strongly disagreed or disagreed about the provision of onsite training to strengthen HMIS at the level of public health centres. 74.1% (n=437) of participants chose “strongly disagree” or “disagree” about the promotion of accountability to strengthen the HMIS. Besides, 84.9% of the participants strongly disagreed or disagreed about the adequate budget allocation to strengthen the HMIS yearly.

4.4.2.2.3 Behavioural Determinants

Behavioural Determinants: These include data demand from RHIS users, skills in data quality checking, competence and problem-solving skills for RHIS tasks, levels of confidence in their ability to perform RHIS tasks, and motivation for peak performance. Technical and organizational determinants influence these behavioural determinants (Measure Evaluation 2015:88).

Table 4.36: Behavioural determinants (n=590)

Code	Behavioural Determinants (BD)	Level of responses					
		Strongly Disagree or disagree		Neither agree nor disagree		Strongly agree or agree	
		#	%	#	%	#	%
QBD1	I have adequate **knowledge** to optimize information use	472	80.0	48	8.1	70	11.9
QBD2	I am **confident** in information use	466	79.0	65	11.0	59	10.0
QBD3	I am **competent** in information use	460	78.0	71	12.0	59	10.0
QBD4	I am **motivated** to optimize information use	454	76.9	65	11.0	71	12.0
QBD5	I am **involved** in data management tasks to optimize information use	485	82.2	46	7.8	59	10.0
QBD6	I have adequate **knowledge** to manage data process activities	434	73.6	59	10.0	97	16.4
QBD7	I am **confident** in managing the data process	413	70.0	77	13.1	100	16.9
QBD8	I am **competent** in data process	425	72.0	70	11.9	95	16.1

In this study, a behavioural determinant is defined as the knowledge to optimize information use and to manage data process activities, confidence in information use and in managing data processes, competence in information use and in managing data processes, motivation to optimize information use, and the level of involvement in data management tasks to optimize information use in public health centres.

Behavioural determinants of information use: In this study, the combination of four study variables, including adequate knowledge to optimize information use, confidence in information use, competence in information use, and motivation to optimize information, was used to calculate the single mean score of the behavioural determinant of information use. Findings presented in Table 4.36 show that 80.0% (n=472) of the participants did not have adequate knowledge to optimize information use at the level of public health centres. Similarly, 79.0% (n=466) and 78.0% (n=460) of the participants did not have confidence and competency in information use, respectively. In addition, 76.9% (n=454) of the participants did not have a motivation to optimize information use. On average, 78.3% (n=463) of the participants did not have adequate knowledge, confidence, competency, and motivation to strengthen the use of information at the level of public health centres.

Behavioural determinants of data management processes: In this study, the combination of four study variables, including involvement in data management tasks to optimize information use, adequate knowledge to manage data process activities, confidence to manage data process, and competence in data processing was used to calculate the single mean score of the behavioural determinant of data management processes. The key findings presented in Table 4.36 show that 82.2% (n=485) of the participants were not involved in data management tasks to optimize information use. At the same time, 73.6% (n=434) of the participants did not have adequate knowledge to manage data processes or activities. Likewise, 70.0% (n=413), and 72.0% (n=425) of the participants did not have confidence and competency to manage data processes, respectively. On average, 74.0% (n=439) of the participants did not have adequate knowledge, confidence, competency, and involvement to strengthen the data management processes at the level of public health centres. On the other hand, on average, 10.5% (n=62), and 11.0% (n=63) of the participants neither agree nor disagree about the behavioural determinants of information use and data management processes respectively.

4.4.2.3 Data Management Processes and Information Use

4.4.2.3.1 Data Management Processes

Data management is the development, application and monitoring of plans, policies and practices for controlling, protecting, providing and improving the value of data and information assets (Stedman 2019:2; National Data Management Office (NDMO) 2021:4). In this study, the combination eight study variables including the value of data collection, data compilation processes, knowledge to compile data, skills to analyze data, adequacy of support for data analysis processes, skills to display data using different charts, data presentation visibility, and weekly case presentation have been used to define the processes of data management practices.

Table 4.37: Data management processes (n=590)

Code	Data Management (DM)	Level of responses					
		Yes		No		Not sure	
		#	%	#	%	#	%
Data collection							
QDM1	The value of quality data collection is well-established at						
QDM11	health centre level	59	10.0	501	84.9	30	5.1
QDM12	core process level	50	8.5	510	86.4	30	5.1
QDM13	case team level	45	7.6	520	88.1	25	4.2
QDM2	Data collation/compilation						
QDM21	Data compilation processes are often rushed at the health centre	489	82.9	71	12.0	30	5.1
QDM22	Do you have adequate knowledge to compile data scientifically?	60	10.2	530	89.8	0	0.0
Data analysis							
QDM3	Do you have the skill to analyze data scientifically?	41	6.9	549	93.1	0	0.0
QDM4	There is adequate support for data analysis processes at						
QDM41	health centre level	118	20.0	442	74.9	30	5.1
QDM42	core process level	89	15.1	472	80.0	29	4.9
QDM43	case team level	58	9.8	502	85.1	30	5.1
Data presentation							
QDM5	Do you have the skills to display data using different charts?	45	7.6	545	92.4	0	0.0
QDM6	The data presentation is visible at						
QDM61	health centre level	88	14.9	472	80.0	30	5.1
QDM62	core process level	69	11.7	493	83.6	28	4.7
QDM63	case team level	56	9.5	507	85.9	27	4.6
QDM7	Weekly case presentations are held to manage data problems at						
QDM71	health centre level	118	20.0	442	74.9	30	5.1
QDM72	core process level	88	14.9	472	80.0	30	5.1
QDM73	case team level	60	10.2	502	85.1	28	4.7
QDM1-7	On average, the value of data management is established at						
QDM1-71	health centre level	81	13.7	480	81.4	29	4.9
QDM1-72	core process level	58	9.8	502	85.1	30	5.1
QDM1-73	case team level	31	5.3	531	90.0	28	4.7

Code	Data Quality, Data documentation, RDQA and LQAS	Level of responses					
		Yes		No		Not sure	
		#	%	#	%	#	%
QDM8	**Data accuracy:** The value of data accuracy is not adequately established at						
QDM81	health centre level	472	80.0	89	15.1	29	4.9
QDM82	core process level	496	84.1	64	10.8	30	5.1
QDM83	case team level	508	86.1	52	8.8	30	5.1
QDM9	**Data completeness:** The value of data completeness is not adequately established at						
QDM91	health centre level	461	78.1	101	17.1	28	4.7
QDM92	core process level	487	82.5	74	12.5	29	4.9
QDM93	case team level	502	85.1	59	10.0	29	4.9
QDM10	**Report timeliness:** The value of report timeliness is not adequately established at						
QDM101	health centre level	481	81.5	80	13.6	29	4.9
QDM102	core process level	499	84.6	61	10.3	30	5.1
QDM103	case team level	513	86.9	50	8.5	27	4.6
QDM11	**Data documentation:** The value of data documentation is not adequately established at						
QDM111	health centre level	500	84.7	60	10.2	30	5.1
QDM112	core process level	512	86.8	50	8.5	28	4.7
QDM113	case team level	520	88.1	42	7.1	28	4.7
QDM12	Routine data quality assurance (**RDQA)** is an important data management practice at						
QDM121	health centre level	530	89.8	42	7.1	18	3.1
QDM122	core process level	532	90.2	33	5.6	25	4.2
QDM123	case team level	531	90.0	35	5.9	24	4.1
QDM13	Lot quality assurance sampling (LQAS) implementation is done to improve data quality at						
QDM131	health centre level	295	50.0	265	44.9	30	5.1
QDM132	core process level	0	0.0	560	94.9	30	5.1
QDM133	case team level	0	0.0	562	95.3	28	4.7

Value of quality data collection: Data collection is the first and most important step in data management processes that involves identifying data to be collected, selecting data collection methods, and collecting data. Findings presented in Table 4.37 show that 84.9% (n=501), 86.4% (n=510), and 88.1% (n=520), of the participants reported that the value of quality data collection is not well established to optimize the data management processes at the level of public health centres, core processes and case teams, respectively. On average, 86.4% (n=510) of the participants indicated that the value of quality data collection is not established well enough to optimize the data management processes. On the other hand, on average, 5.0% (n=28) of the participants are unsure about the value of quality data collection.

Data collation/compilation: Data collation is the second critical step of the data management process. This stage involves aggregating data elements and indicators from the healthcare register into summary sheets and reporting formats. Key findings presented in Table 4.37 show that 82.9% (n=489) of the participants indicated that the data compilation processes are often rushed at the level of public health centres. On the other hand, 5.1% (n=30) of the participants are not sure about the status of data compilation processes at the level of public health centres. In addition, 89.8 % (n=530) of the participants did not have adequate knowledge to compile data scientifically.

Data analysis skills and adequate support: Data analysis is the third key step in data management processes. Data from different sources are collected, collated and analysed to form some conclusion and justification. The findings in Table 4.37 show that 93.1% (n=549) of the participants did not have adequate skills to analyse data scientifically.

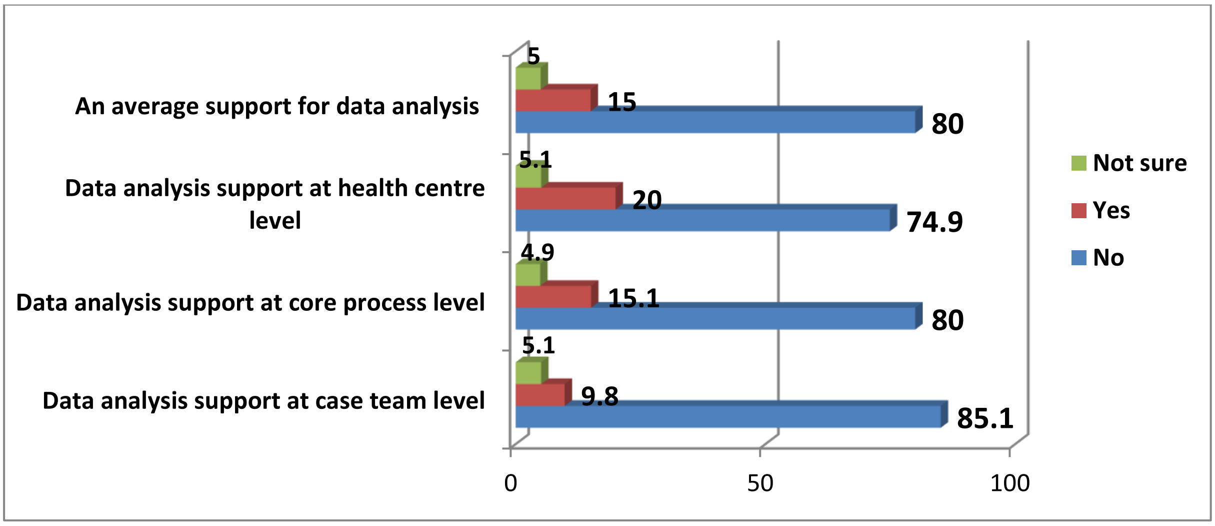

Figure 4.5: The proportion of data analysis support at different healthcare levels

Figure 4.5 displays the proportion of data analysis support provided at different healthcare levels. The level of support for data analysis drops significantly from the top to the bottom levels, such as from public healthcare centres to core processes and then to case teams. At the same time, case teams did not receive adequate support compared to core processes. Data analysis support generally decreased from the higher level of the healthcare centre to the following consecutive levels.

Data presentation is the fourth essential phase in the process of data management. Thus, the analysed data should be well presented in an effective format regardless of the amount of data and information; otherwise, it would be a significant loss for both users and readers. In this study, 92.4% (n=545) of the participants did not have the skills to display data using different charts at different healthcare system levels. Moreover, 80.0% (n=472), 83.6% (n=493), and 85.9% (n=507), of the participants reported that data presentation is not visible to optimize the data management processes at the level of public health centres, core processes and case teams, respectively. On average, 83.40 (n=491) of the participants indicated that data presentation is not visible at the three levels of the health facilities. On the other side, on average, 5.0% (n=28) of the participants were unsure about the visibility of data presentation at the level of health centres, core processes and case teams. Furthermore, 74.9% (n=442), 80.0% (n=472), and 85.1% (n=502), of the participants indicated that weekly case presentations were not held to manage data problems at the level of public health centres, core processes and case teams, respectively. On average, 80.0 (n=472) of the participants indicated that weekly case presentations were not held to manage data problems at the health facilities' three levels, namely the public health centres, core processes and case teams.

The practices of the data management process: The concept of the data management process is essential in producing standard quality data at all healthcare system levels. In this study, eight indicators/items (including the value of data collection, data compilation processes, knowledge to compile data, skills to analyze data scientifically, adequacy of support for data analysis processes, skills to display data using different charts, data presentation visibility, and weekly case presentations) have been used to calculate a single mean score of data management processes. It was found that, on average, 81.4% (n=480), 85.1% (n=502), and 90.0% (n=531) of the participants indicated that the value of the data management processing is not established at healthcare centres, core processes, and case teams, respectively. On average, only 5.0% (n=29) of the participants are sure about the practice of data management at the three levels of the health facilities. On average, 85.0% (n=504) of the study participants reported that the value of data management processes is not established at healthcare centres, core processes and case team levels. In general, the value and practices of data management processes have been shown to follow a decreasing trend from the level of the public health centre to the levels of core processes and case teams.

Data accuracy is essential for reviewing and comparing data between registers of health facilities and monthly reporting forms, as well as data accuracy between monthly reporting forms and the DHIS2 software of health centres, respectively. Key findings presented in Table 4.37 show that 80.0% (n=472), 84.1% (n=496), and 86.1% (n=508) of the participants reported that the value of data accuracy is not well established to optimize the data quality processes at the levels of public health centres, core processes and case teams, respectively. On average, 83.0 (n=492) of the participants indicated that the value of data accuracy is not well established at public health centres, core processes and case teams.

Data completeness is achieved when all data elements and indicators are recorded on data collection registers, summary sheets, report formats and DHIS2 software. This data quality dimension is used to compare the proportion of recorded data elements and indicators against the required standards. The main findings recorded in Table 4.37 show that 78.1% (n=461), 82.5% (n=487) and 85.1% (n=502) of the participants stated that the value of data completeness is not sufficiently established to enhance the data quality processes at the levels of public health centres, core processes and case teams, respectively. On average, 82.0 (n=483) of the participants indicated that the value of data completeness is not well established at public health centres, core processes and case teams.

Timeliness refers to the extent to which the age of data represents the time the information was required. It is a fundamental aspect of data quality to ensure various decision-making processes. In this study, the main findings recorded in Table 4.37

show that 81.5% (n=481), 84.6% (n=499) and 86.9% (n=513) of the participants felt that the value of report timeliness was not established well enough to improve the data quality processes at the level of public health centres, core processes and case teams, respectively. On average, 84.2% (n=497) of the participants indicated that the value of report timeliness is not well established at public health centres, core processes and case teams. In general, on average, 5.0% (n=29) of the participants were not sure about the good practice of data accuracy, data completeness, and report timeliness at public health centres, core processes and case teams.

Data documentation is an important part of data management that supports decision-making processes at different healthcare system levels. In this study, critical findings recorded in Table 4.37 show that 84.7% (n=500), 86.8% (n=512) and 88.1% (n=520) of the participants replied that the value of data documentation is not adequately established to improve the data management processes at the level of public health centres, core processes and case teams, respectively. In addition to that, on average, 87.0% (n=511) of the participants specified that the value of data documentation was not established well enough to improve data management processes.

Routine Data Quality Assessment (RDQA) is important for public health centres to monitor and improve the quality of health data at the levels of health centres themselves, core processes and case teams. In this study, important findings documented in Table 4.37 reveal that 89.8% (n=530), 90.2% (n=532) and 90.0% (n=531) of the participants responded that the routine data quality assurance (RDQA) as an important data management process, is not practised routinely at the level of public health centres, core processes and case teams, respectively.

Besides, on average, 90.0% (n=3) of the participants indicated that routine data quality assurance (RDQA) is not well implemented and recognized to improve data management processes. Only 3.1% (n=18), 4.2% (n=25) and 4.1% (n=24) of the participants were not sure about the level of routine data quality assessments at the levels of healthcare centres, core processes and case teams, respectively.

The Lot Quality assurance sampling (LQAS) technique is vital for performance reviewing and assessing the quality of the health service, outpatient, and inpatient reports on a monthly basis at health centres, core processes, and case teams. In this study, significant findings documented in Table 4.37 indicate that 44.9% (n=265), 94.9% (n=560) and 95.3% (n=562) of the participants responded that lot quality assurance sampling (LQAS) is not implemented consistently to improve data quality at the level of health centres, core processes and case teams, respectively. Moreover, on average, 90.0% (n=3) of the study participants indicated that routine data quality assurance (RDQA) is not well implemented.

4.4.2.3.2 Information Use Practice

Information use: The use of processed and interpreted data in decision-making at various levels, such as community, facility, and administrative, is referred to as information use (FHOM 2015:157). In this study, information use is defined as the level of information re-packaging and dissemination, analytical report production, action plan preparation and monitoring, culture of written feedback provision, and information use dimensions to strengthen HMIS in public health centres and lower levels.

Table 4.38: The level of information use (n=590)

		Level of responses					
		Yes		No		Not sure	
Code	Information Use	#	%	#	%	#	%
QIU1	Information repackaging processes are practised at						
QIU11	health centre level	58	9.8	502	85.1	30	5.1
QIU12	core process level	40	6.8	520	88.1	30	5.1
QIU13	case team level	30	5.1	531	90.0	29	4.9
QIU2	Information disseminating processes are practised at						
QIU21	health centre level	90	15.3	472	80.0	28	4.7
QIU22	core process level	59	10.0	501	84.9	30	5.1
QIU23	case team level	29	4.9	531	90.0	30	5.1
QIU3	Are analytical reports of key indicators displayed monthly using graphs at						
QIU31	health centre level?	89	15.1	472	80.0	29	4.9
QIU32	core process level?	55	9.3	505	85.6	30	5.1
QIU33	case team level?	32	5.4	531	90.0	27	4.6

QIU4	Evidence-based action plan is prepared at						
QIU41	health centre level	57	9.7	502	85.1	31	5.3
QIU42	core process level	40	6.8	520	88.1	30	5.1
QIU43	case team level	30	5.1	531	90.0	29	4.9
QIU44	individual level	24	4.1	536	90.8	30	5.1
QIU5	Evidence based action plan is monitored continuously at						
QIU51	health centre level	58	9.8	502	85.1	30	5.1
QIU52	core process level	40	6.8	520	88.1	30	5.1
QIU53	case team level	30	5.1	531	90.0	29	4.9
QIU54	individual level	24	4.1	534	90.5	32	5.4
Feedback, information use and new knowledge development							
QIU6	Is monthly written feedback given from						
QIU61	board to health centre?	59	10.0	501	84.9	30	5.1
QIU62	health centre to core processes?	54	9.2	508	86.1	28	4.7
QIU63	core process to case teams?	42	7.1	520	88.1	28	4.7
QIU64	case team to individuals?	33	6.0	531	90.0	26	4.0
QIU7	Is the information used at health centre level to						
QIU71	revise implementation strategies?	47	8.0	531	90.0	12	2.0
QIU72	implement new strategies?	36	6.1	542	91.9	12	2.0
QIU73	revise annual plans?	59	10.0	503	85.3	28	4.7
QIU74	monitor day-to-day activities?	117	19.8	443	75.1	30	5.1
QIU75	. respond to priority health service needs	89	15.1	472	80.0	29	4.9
QIU76	link decisions with evidence	60	10.2	500	84.7	30	5.1
	Average information use for various decisions	**68**	**12.0**	**499**	**84.0**	**24**	**4.0**
QIU1-7	On average, the value of information use is practised at						
QIU1-71	health centre level	77	13.1	484	82.0	29	4.9
QIU1-72	core process level	61	10.3	502	85.1	27	4.6
QIU1-73	case team level	45	7.6	520	88.1	25	4.2

Information repackaging is a way to organize analysed data or information in a form that is more appropriate and functional for users. This is important to interpret and convert information into a form that can be easily understood by the different target users to improve the sustainability of service utilization. In this study, key findings documented in Table 4.38 show that 85.1% (n=502), 88.1% (n=520) and 90.0% (n=531) of the participants indicated that the information repackaging process is not well practised in improving information use at the level of public health centres, core processes and case teams, respectively. In addition, on average, 88.0% (n=518) of the participants indicated that the information repackaging process is not well established at the levels. In contrast, only 5% (n=30) of the participants, on average, said they were unsure of the success of the process.

Information dissemination is the process of sharing information products with users at the level of public health centres, core processes, and case teams. The repackaged information should be disseminated to users. Thus, information produced in public health centres, where staff and the communities can access it, should be disseminated adequately and regularly. Key findings recorded in Table 4.38 show that 80.0% (n=472), 84.0% (n=501), and 90.0% (n=531) of those who participated in this study indicated that the information disseminating process was not well established at the different levels. Approximately 85.0% (n=501) of those who were surveyed indicated that the information dissemination process was not well recognized. By contrast, on average, 5.0% (n=29) of the participants were not sure about the success of information dissemination.

Displaying analytical reports using graphs is one of the important approaches to information use at the different levels of the healthcare system. The main findings recorded in Table 4.38 show that 80.0% (n=472), 85.6% (n=505), and 90.0% (n=531) of those who participated in this study pointed out that analytical reports of key indicators were not displayed monthly using different graphs at the different levels. In addition, almost 85.2% (n=503) reported that analytical reports of key indicators were not displayed or utilized monthly using different graphs at different levels. In contrast, on average, only 5.0% (n=29) of the participants were unsure whether the reports were displayed or not.

Evidence-based action plans are critical for addressing data problems at the different levels of healthcare centres, core processes, case teams, and individuals. Key findings recorded in Table 4.38 indicate that 85.1% (n=502), 88.1% (n=520), 90.0% (n=531), and 91.3% (n=531) of participants indicated that evidence-based action plans were not prepared consistently at the different levels. On average, 67.0% (n=397) reported that evidence-based action plans were not prepared regularly at the levels. On the other hand, on average, 4.0% (n=22) of the participants were not sure about this.

Evidence-based action plan monitoring is one of the critical methods of information use to follow the progress of implementation at the different healthcare system levels.

In this study, key findings recorded in Table 4.38 indicate that 85.1% (n=502), 88.1% (n=520), 90.0% (n=531), and 90.5% (n=534) of participants indicated that evidence-based action plans were not monitored continuously at all levels. In addition, on average, 67.0% (n=396) of those who participated indicated that evidence-based action plans were not monitored continuously.

Written feedback is conceptually an essential component of the cycle of the use of health information, facilitating open communication and encouraging discussion and problem-solving. Significant findings recorded in Table 4.38 indicate that 84.9% (n=501), 86.1% (n=508), 88.1% (n=520), and 84.4% (n=498) of participants mentioned that monthly written feedback was not given by the board to health centres, by health centres to core processes, by core processes to case teams, and by case teams to individuals, respectively. Moreover, on average, 84.9% (n=501) of participants indicated that monthly written feedback was not given at all levels. On the other hand, on average, 5.1% (n=30) of participants were unsure about monthly written feedback provision across the various levels.

Health information for evidence-based decision-making: Evidence-based decision-making is one of the essential management tasks. One of the many benefits of developing a culture of evidence-based decision-making is that different users can benefit according to their own needs and requirements from the health management information system. Key findings in Table 4.38 indicate, however, that, on average, 84.0% (n=499) of the participants clearly reported that information was not used for various decision-making practices, including for revision of implementation strategies, implementing new strategies, revising annual plans, monitoring day-to-day activities, responding to priority health service needs, and linking decisions with core evidence. In particular, 80.0% (n=472) and 84.7% (n=500) of participants reported that health information was not utilized to respond to priority health service needs and to link decisions with core evidence, respectively, at the levels. On the other hand, only 4.0% (n=24) of participants were not sure about this.

The practices of information use: The use of data and information is of critical importance across a range of healthcare system activities to promote and maintain the quality of primary, secondary and tertiary healthcare systems. Health information's significant value and power are determined by the overall utilization of data at all levels of the public healthcare system. In this study, as indicated in Table 4.38 , twelve study variables have been used to calculate a single mean score of information use. These variables are information repackaging processes, information disseminating processes, displaying of analytical reports of key indicators using graphs, evidence-based action plan preparation, evidence-based action plan monitoring, the provision of written feedback, information use to revise implementation strategies, information use to implement new strategies, information use to revise annual plans, information use to monitor day-to-day activities, information use to respond to priority health service needs, and information use to link decisions with evidence. It was found that, on average, 82.0% (n=484), 85.1% (n=502), and 88.1% (n=520) of the participants indicated that the value of the information use process was not well established at all levels. Overall, on average, 85.0% (n=504) of the participants stated that the value of information use processes was not well established at levels. On the other hand, on average, 5.0% (n=27) of the participants were not sure of this. In general, the value and practice of information-use processes have shown a decreasing trend from the level of the public health centres to core processes and from core processes to case teams.

4.4.3 Determinants of data management and information use

4.4.3.1 Logistic regression

Logistic regression is the appropriate regression analysis when the dependent variable is dichotomous (binary). Like all regression analyses, logistic regression is a predictive analysis (Garson 2014:12). In this study, logistic regression (bivariate and multivariate logistic regression analyses) was used to determine the effects of independent variables (listed under the section of socio-demographic determinants, technical determinants, organizational determinants, and behavioural determinants) on the practices of data management processes, and practices of information use.

4.4.3.2 Bivariate and multivariate logistic regression analysis

In this study, logistic regression was used to address the following key points: (1) to estimate the average effect of independent variables on the practices of the data management process and practices of information use; (2) to determine the effect size of each independent variable on the dependent variables; (3) to rank the relative importance or effects of the independent variables on the dependent variables; (4) and to show the real effect of independent variables by controlling the effect of cofounder variables. Hence, the effect of predictor/independent variables is usually explained in terms of odds ratios, which is the key effect size measured in logistic regression analysis (Garson 2014:12). For that reason, firstly, bivariate logistic regression analysis was used to determine the effect of each independent variable on the practices of data management processes, and practices of information use separately. Bivariate analysis is one of the simplest forms of statistical analysis. It is used to find out whether there is an effect or association between two variables or not (i.e. between the dependent and independent variables) without considering the contributions or effects of the other independent variables (Garson 2014:13).

Furthermore, multivariate logistic regression analysis was applied (1) to measure the direction of the effect (either positively or negatively) based on the value of the beta coefficient derived from the logistic regression during the analysis; (2) to calculate the strength of the effect using the value of odds ratio; (3) to determine the true population of the study using the level of confidence interval; (4) and to measure the level of statistical significance of each independent variable using the P-value. Simultaneously, the multivariate logistic regression analysis was used to control potential confounders, assess factors that have a statistically significant effect on the practices of data management processes and practices of information in separate statistical models, and develop statistical estimation on the practices of data management processes, and practices of information use.

4.4.3.2.1 Determinants of data management (bivariate analysis)

Table 4.39: Variables not in the equation used to estimate the data management (n=561)

SN	Variables not in the Equation	Response level/category	Bivariate logistic regression		
			Score	df	Sig.
1	Age Groups	20-33	0.08	2	0.961
		34-47	0.08	1	0.779
		48-61	0.06	1	0.808
2	Sex	M	0.21	1	0.647
		F	0.30	1	0.674
3	Years of experience	1-5 years	7.84	2	0.020
		6-10 years	2.75	1	0.097
		>=11 years	7.45	1	0.006
4	Work position	Healthcare provider	0.75	4	0.945
		Case team head	0.52	1	0.469
		Core process head	0.34	1	0.558
		Medical director	0.03	1	0.856
		HMIS/HIT officer	0.30	1	0.587
5	Level of Education	Diploma	2.06	2	0.356
		Degree	1.99	1	0.158
		Master & above	1.48	1	0.224
6	Computer skill to manage data	SD or disagree	49.75	1	0.000
		SA or agree	9.25	1	0.070
7	Average availability of HMIS tools	SD or disagree	62.92	2	0.000
		Neutral	61.11	1	0.000
		SA or agree	0.02	1	0.893
8	Average knowledge on HMIS tools	SD or disagree	25.64	2	0.000
		Neutral	24.60	1	0.000
		SA or agree	2.48	1	0.115
9	Average User-friendliness of HMIS tools	SD or disagree	6.66	2	0.036
		Neutral	5.08	1	0.024
		SA or agree	0.05	1	0.817
10	Availability of data management strategy	SD or disagree	11.26	2	0.004
		Neutral	6.53	1	0.011
		SA or agree	3.02	1	0.082
11	Availability of information use strategy	SD or disagree	8.39	2	0.015
		Neutral	7.63	1	0.006
		SA or agree	0.00	1	0.968
12	Culture of information use	SD or disagree	11.53	2	0.003
		Neutral	5.65	1	0.017
		SA or agree	6.06	1	0.014
13	Separate HMIS plan	SD or disagree	46.50	2	0.000
		Neutral	8.04	1	0.005
		SA or agree	0.21	1	0.644

SN	Variables not in the Equation	Response level/category	Bivariate logistic regression		
			Score	df	Sig.
14	Monthly internal supervision	SD or disagree	11.53	2	0.003
		Neutral	10.57	2	0.005
		SA or agree	0.21	1	0.644
15	Motivation to strengthen HMIS	SD or disagree	30.83	2	0.000
		Neutral	25.91	1	0.000
		SA or agree	22.92	1	0.000
16	Staff makes decisions	SD or disagree	0.68	2	0.712
		Neutral	0.61	1	0.434
		SA or agree	0.45	1	0.503
17	Accountability to strengthen HMIS	SD or disagree	0.47	2	0.789
		Neutral	0.01	1	0.905
		SA or agree	0.25	1	0.618
18	Adequate budget	SD or disagree	11.90	2	0.003
		Neutral	6.64	1	0.010
		SA or agree	0.26	1	0.611
19	Involvement in data management tasks	SD or disagree	30.17	2	0.000
		Neutral	20.61	1	0.000
		SA or agree	0.19	1	0.666
20	Knowledge to manage data	SD or disagree	26.41	2	0.000
		Neutral	26.40	1	0.000
		SA or agree	8.36	1	0.004
21	Confidence to manage data	SD or disagree	3.93	2	0.140
		Neutral	3.36	1	0.067
		SA or agree	2.92	1	0.088
22	Competence in data process	SD or disagree	16.73	2	0.000
		Neutral	16.26	1	0.000
		SA or agree	7.85	1	0.005
23	Behavioural determinants of data management	SD or disagree	6.30	2	0.043
		Neutral	6.24	1	0.013
		SA or agree	3.02	1	0.082
Overall Statistics			218.24	23	0.000

Key findings of the bivariate logistic regression analysis are listed in Table 4.39 . In this analysis, 16 of the 23 variables, namely years of work experience, computer skills, availability of HMIS tools (scale), knowledge of HMIS tools (scale), perceived user-friendliness of HMIS tools (scale), behavioural determinant of data management processes (scale), availability of written strategy on data management, availability of written strategy on information use, the culture of information use, HMIS plan, internal supervision, motivation to strengthen the HMIS, budget, involvement in data management tasks, knowledge to manage data processes, and competency in data process were identified as individually statistical significant variables associated with the practice of data management processes at the level of public health centres. On the other hand, seven independent variables, namely age, sex, work position, level of education, staff encouragement, promotion of accountability, and confidence to manage data processes, were not found as significant individual predictors for the practice of data management processes at the level of public health centres. The overall statistics of the bivariate logistic regression model or the equation was found to be statistically significant at (X^2 = 218.24, df= 23, n=561, p< .000).

4.4.3.2.2 Determinants of information use (bivariate analysis)

Table 4.40: Variables not in the equation used to estimate the information use (n=561)

SN	Variables not in the Equation	Response level/category	Bivariate logistic regression		
			Score	df	Sig.
1	Age Groups	20-33	0.04	2	0.980
		34-47	0.02	1	0.890
		48-61	0.03	1	0.960
2	Sex	M	0.09	1	0.770
		F	0.30	1	0.674
3	Years of experience	1-5 years	6.57	2	0.040
		6-10 years	3.64	1	0.060
		>=11 years	6.57	1	0.010
4	Work position	Healthcare provider	1.13	4	0.890
		Case team head	0.39	1	0.530
		Core process head	0.47	1	0.500
		Medical director	0.06	1	0.810
		HMIS/HIT officer	0.34	1	0.560
5	Level of Education	Diploma	2.62	2	0.270
		Degree	2.58	1	0.110
		Master & above	2.02	1	0.160
6	Computer skills to manage data	SD or disagree	47.64	1	0.000
		SA or agree	9.25	1	0.070
7	The average availability of HMIS tools	SD or disagree	24.43	2	0.000
		Neutral	23.37	1	0.000
		SA or agree	0.03	1	0.950
8	Average knowledge of HMIS tools	SD or disagree	4.04	2	0.130
		Neutral	9.29	1	0.007
		SA or agree	2.26	1	0.130

9	Average User-friendliness of HMIS tools	SD or disagree	11.54	2	0.000
		Neutral	10.33	1	0.001
		SA or agree	0.09	1	0.760
10	Availability of data management strategy	SD or disagree	7.55	2	0.020
		Neutral	7.12	1	0.010
		SA or agree	7.17	1	0.010
11	Availability of information use strategy	SD or disagree	7.79	2	0.020
		Neutral	9.19	1	0.014
		SA or agree	4.98	1	0.030
12	Culture of information use	SD or disagree	47.64	2	0.000
		Neutral	9.35	1	0.002
		SA or agree	1.47	1	0.230

SN	Variables not in the Equation	Response level/category	Bivariate logistic regression		
			Score	df	Sig.
13	Availability of separate HMIS plan	SD or disagree	9.28	2	0.010
		Neutral	0.34	1	0.050
		SA or agree	7.61	1	0.010
14	Monthly internal supervision	SD or disagree	24.72	2	0.000
		Neutral	22.07	1	0.000
		SA or agree	4.16	1	0.040
15	Motivation is encouraged	SD or disagree	9.28	2	0.010
		Neutral	0.34	1	0.050
		SA or agree	16.64	1	0.000
16	Staff makes decisions	SD or disagree	1.46	2	0.480
		Neutral	1.44	1	0.230
		SA or agree	0.35	1	0.560
17	Accountability to strengthen HMIS	SD or disagree	0.19	2	0.910
		Neutral	0.09	1	0.760
		SA or agree	0.18	1	0.670
18	Adequate budget	SD or disagree	18.67	2	0.000
		Neutral	0.07	1	0.790
		SA or agree	14.09	1	0.000
19	knowledge to optimize information use	SD or disagree	66.73	2	0.000
		Neutral	55.05	1	0.000
		SA or agree	53.71	1	0.000
20	Confident in information use	SD or disagree	23.17	2	0.000
		Neutral	21.61	1	0.000
		SA or agree	5.92	1	0.020
21	Competent in information use	SD or disagree	19.33	2	0.000
		Neutral	18.63	1	0.000
		SA or agree	12.93	1	0.000
22	Motivation to optimize information use	SD or disagree	11.84	2	0.000
		Neutral	9.33	1	0.000
		SA or agree	0.54	1	0.460
23	Behavioural determinants of information use	SD or disagree	5.57	2	0.060
		Neutral	5.57	1	0.020
		SA or agree	2.03	1	0.150
	Overall Statistics		227.8	23	0.000

Key findings of the binary logistic regression are recorded in Table 4.40 . In this analysis, 17 of the 23 independent variables, namely years of work experience, computer skills, the availability of HMIS tools (scale), knowledge of HMIS tools (scale), perceived user-friendliness on HMIS tools (scale), the behavioural determinant of data management processes (scale), the availability of a written strategy on data management, the availability of a written strategy on information use, the culture of information use, an HMIS plan, internal supervision, motivation to strengthen the HMIS, the budget, knowledge to optimize information use, confidence in information use, competency in information use, and motivation to optimize information use were identified as individually statistical significant independent variables for the practices of information use at the level of public health centres. On the other hand, six independent variables, namely age, sex, work position, level of education, staff encouragement, and promotion of accountability, were not found as individually significant predictors for the practice of information use in public health centres. The overall statistics of the binary logistic regression model or the equation was found statistically significant at (X^2 = 227.8, df= 23, n=561, p< .000).

4.4.3.3 Data management and information use (multivariate logistic regression)

Table 4.41: Statistical test results and model summary for data management (n=561)

<table>
<tr><td colspan="5">Block 1: Method = Enter</td></tr>
<tr><td colspan="5">Table 4.41a: Omnibus Tests of Model Coefficients</td></tr>
<tr><td rowspan="4">Step 1</td><td></td><td>Chi-square</td><td>df</td><td>Sig.</td></tr>
<tr><td>Step</td><td>256.427</td><td>23</td><td>0.000</td></tr>
<tr><td>Block</td><td>256.427</td><td>23</td><td>0.000</td></tr>
<tr><td>Model</td><td>256.427</td><td>23</td><td>0.000</td></tr>
<tr><td colspan="5">Table 4.41b: Model Summary</td></tr>
<tr><td rowspan="2">Step1</td><td>-2 Log likelihood</td><td>Cox & Snell R Square</td><td>Nagelkerke R Square</td><td></td></tr>
<tr><td>186.609[a]</td><td>0.685</td><td>0.866</td><td></td></tr>
<tr><td colspan="5">a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.</td></tr>
<tr><td colspan="5">Table 4.41C: Hosmer and Lemeshow Test</td></tr>
<tr><td rowspan="2">Step1</td><td>Chi-square</td><td>df</td><td>Sig.</td><td></td></tr>
<tr><td>4.620</td><td>8</td><td>0.797</td><td></td></tr>
</table>

Table 4.42: Statistical test results and model summary for information use (n=561)

Block 1: Method = Enter				
Table 4.42a: Omnibus Tests of Model Coefficients				
		Chi-square (X^2)	df	Sig.
Step 1	Step	272.093	23	0.000
	Block	272.093	23	0.000
	Model	272.093	23	0.000
Table 4.42b: Model Summary				
Step1	-2 Log likelihood	Cox & Snell R Square		Nagelkerke R Square
	176.650[a]	0.764		0.887
a. Estimation terminated at iteration number 20 because maximum iterations have been reached. Final solution cannot be found.				
Table 4.42c: Hosmer and Lemeshow Test				
Step1		Chi-square (X^2)	df	Sig.
		4.556	8	0.804

The most important multivariate statistical analysis of the omnibus tests, model summaries, and Hosmer and Lemeshow tests are presented in Table 4.41 and Table 4.42. The omnibus tests provided statistical evidence that the overall models were statistically significant when the 23 independent variables were analyzed to measure the practices of data management processes and practices of information use as it is indicated in Table 4.41a (X^2 =256.427, p<.000 with df=23); and Table 4.42a (X^2=272.093, p<.000 with df=23), respectively.

The model summary tables report the strength of the relationship between the model and the dependent variables using R-squared values. It shows a linear correlation between the observed data and the model-predicted values of the dependent variables. In this case, if the R-squared value is > 0.7, this value is generally considered evidence to have a strong effect size on the dependent variables due to the independent variables analyzed in the models. Given that, the results of the model summaries reported in Table 4.41b and Table 4.42b provide evidence of a strong relationship between the practices of data management processes, and practices of information use and the 23 independent variables applied in the two models separately. For example, the Nagelkerke's-R^2 showed (Table 4.41b and Table 4.42b) approximately 86.6% and 88.7% of the practices of data management processes and practices of information use found to be strongly associated with the 23 independent variables that were analyzed in the multivariate logistic regression models, separately, and respectively. Similarly, the Hosmer and Lemeshow test is a statistical test used to measure and evaluate the goodness of fit for logistic regression models. In this test, small p-values or statistically significant values show that the model is a poor fit or there is a problem with the model. The goodness of fit tells us how well the collected data fit the models to predict the dependent variables (practices of data management processes and practices of information use) (Yu, Xu & Zhu 2017:2). As a result, the Hosmer and Lemeshow tests reported in Table 4.41c and Table 4.42c provide statistical evidence of non-significant test results (i.e. the p-value is >0.05) and small chi-square values which indicate a good fit of the data to predict the practices of data management processes, and practices of information use using the independent variables in the two models separately (X^2=4.620, p=0.797, and df= 8), and (X^2= 4.556, p=0.804, and df= 8), respectively.

4.4.3.4 Determinants of data management (multivariate logistic regression)

In the bivariate logistic regression analysis, 16 of the 23 independent variables were identified as individually statistically significant (Table 4.39). In the next step, a multivariate logistic regression analysis was conducted using the entering variable selection method. This method is more inclusive and provides an equal chance for all the potential independent variables. Moreover, it keeps all the variables in the final model according to their level of statistical significance. In particular, the omnibus test of the model coefficient was applied to test the following research hypotheses (the practices of data management processes and practices of information use).

Null hypothesis (Ho) for practices of data management processes: The predictor variables listed under the socio-demographic, technical, organizational and behavioural determinants do not have any effect on practices of data management processes (scale).

Alternative hypothesis (HA) for practices of data management processes: The predictor variables listed under the socio-demographic, technical, organizational and behavioural determinants have an effect, at least by one of the predictor variables, on practices of data management processes (scale).

Null hypothesis (Ho) for practices of information use: The predictor variables listed under the socio-demographic, technical, organizational and behavioural determinants do not have any effect on practices of information use (scale).

Alternative hypothesis (HA) for practices of information use: The predictor variables listed under the socio-demographic, technical, organizational and behavioural determinants have an effect, at least by one of the predictor variables, on practices of information use (scale). As a result, the omnibus tests of model coefficients showed (in Table 4.41a and Table 4.42a) the overall statistical significance of the models when the independent variables were analyzed in each of the models separately, and these tests did not provide any evidence to accept the null hypotheses stated for practices of data management processes, and practices of information use, separately and, respectively. Overall, 91.1% and 92.9% of the practices of data management processes and information use practices were classified correctly by the classification tables generated in the multivariate logistic regression models, separately and respectively.

Table 4.43: Determinants of data management in multivariate logistic regression (n=561)

SN	Variables in the Equation	Response level/category	Multivariate logistic regression			
			Sig.	Adjusted Odds Ratio (AOR) of Exp (B)	95% C.I. for EXP(B)	
					Lower	Upper
1	Age Groups	20-33	0.030	3.10	1.29	7.94
		34-47	0.130	13.46	0.64	3.20
		48-61	0.080	Reference		
2	Sex	M	0.300	1.66	0.24	1.55
		F	0.280	Reference		
3	Years of experience	1-5 years	0.350	0.49	0.13	0.23
		6-10 years	0.020	3.04	1.34	2.40
		>=11 years	0.080	Reference		
4	Work position	Healthcare provider	0.370	7.43	0.30	4.71
		Case team head	0.300	7.64	0.30	8.53
		Core process head	0.010	3.21	2.16	4.88
		Medical director	0.100	13.22	0.48	1.06
		HMIS/HIT officer	0.200	Reference		
5	Level of Education	Diploma	0.790	2.04	0.09	6.02

		Degree	0.990	2.69	0.13	7.53
		Master & above	0.830	Reference		
6	Computer skills to manage data	SD or disagree	0,000	0.33	0.30	0.38
		SA or agree	0,070	Reference		
7	Average availability of HMIS tools	SD or disagree	0.000	0.49	0.62	0.65
		Neutral	0.070	3.16	0.96	5.24
		SA or agree	0,080	Reference		
8	Average knowledge of HMIS tools	SD or disagree	0.000	0.44	0.59	0.67
		Neutral	0.750	4.52	0.07	7.85
		SA or agree	0.110	Reference		
9	Average User-friendliness of HMIS tools	SD or disagree	0.020	0.57	0.63	0.74
		Neutral	0.080	0.52	0.03	1.20
		SA or agree	0.060	Reference		
10	Availability of data management strategy	SD or disagree	0.001	0.25	0.79	0.84
		Neutral	0.070	5.25	0.08	3.56
		SA or agree	0.090	Reference		
11	Availability of information use strategy	SD or disagree	0.000	0.33	0.64	0.75
		Neutral	0.070	5.25	0.08	3.56
		SA or agree	0.130	Reference		
12	Culture of information use	SD or disagree	0,000	0.35	0.50	0.53
		Neutral	0.060	3.05	0.16	1.24
		SA or agree	0.210	Reference		
13	Availability of separate HMIS plan	SD or disagree	0.000	0.41	0.32	0.37
		Neutral	0.070	0.22	0.23	1.27
		SA or agree	0.340	Reference		

SN	Variables in the Equation	Response level/category	Multivariate logistic regression			
			Sig.	Adjusted Odds Ratio (AOR) of Exp (B)	95% C.I. for EXP(B)	
					Lower	Upper
14	Monthly internal supervision	SD or disagree	0.720	3.35	0.39	3.85
		Neutral	0.630	5.11	0.15	23.50
		SA or agree	0.880	Reference		
15	Motivation is encouraged	SD or disagree	0.000	0.34	0.44	0.50
		Neutral	0.080	0.49	0.03	1.26
		SA or agree	0.450	Reference		
16	Staff makes decisions	SD or disagree	0.180	7.32	0.63	11.52
		Neutral	0.100	16.16	0.70	5.58
		SA or agree	0.250	Reference		
17	Accountability to strengthen HMIS	SD or disagree	0.120	1.34	0.11	1.28
		Neutral	0.370	0.93	0.03	3.62
		SA or agree	0.280	Reference		
18	Adequate budget	SD or disagree	0.440	6.26	0.28	9.04
		Neutral	0.140	21.08	0.50	1.22
		SA or agree	0.330	Reference		
19	Involvement in data management tasks	SD or disagree	0.030	0.42	0.16	0.18
		Neutral	0.510	3.18	0.32	4.82
		SA or agree	0.240	Reference		
20	Knowledge to manage data	SD or disagree	0.030	0.35	0.47	0.53

		Neutral	0.330	3.32	0.17	2.87
		SA or agree	0.070	Reference		
21	Confident to manage data	SD or disagree	0.010	0.44	0.80	0.85
		Neutral	0.250	1.25	0.27	4.59
		SA or agree	0.200	Reference		
22	Competent in data process	SD or disagree	0.010	0.41	0.40	0.70
		Neutral	0.070	0.25	0.64	1.19
		SA or agree	0.140	Reference		
23	Behavioural determinants of data management	SD or disagree	0.020	0.32	0.51	0.60
		Neutral	0.830	3.59	0.11	16.01
		SA or agree	0.120	Reference		
	Constant		0.000			

Note: SD means strongly disagree; SA means strongly agree.

4.4.3.4.1 Socio-demographic factors associated with the data management process

Key findings of the multivariate logistic regression analysis in Table 4.43 show that age, years of experience, and work position were found to be strongly associated with the practice of the data management process. More specifically, healthcare providers of the public healthcare centres who are between 20-33 years old were 3.10 times more likely to have indicated that they indulge in the practice of data management processing than those who were 48-61 years old when the other independent variables are controlled or fixed [OR=3.10, P=0.030, 95%CI: (1.29, 7.94)]. In addition, healthcare providers who have experience of between 6-10 years in their present positions were 3.04 times more likely to engage in the data management process when compared to those who were >=11 years experienced when the other independent variables are controlled or fixed [OR=3.04, P=0.020, 95%CI: (1.34, 2.40)]. Moreover, core process heads of the public health centres were 3.21 times more likely to be associated with the practices of the data management process than those who are HMIS/HIT officers of the public healthcare centres when the other independent variables are controlled or fixed [OR=3.21, P=0.010, 95%CI: (2.16, 4.88)]. On the other hand, sex and all levels of education were not found to be statistically significant contributors for the practices of data management processes in both the binary and multivariate logistic regression analysis.

4.4.3.4.2 Technical determinants associated with the data management process

Findings documented in Table 4.43 reveal that computer skills to manage data, average availability of HMIS tools, average knowledge of HMIS tools, and average user-friendliness of HMIS tools were found to be more closely linked with the practice of data management processes. Hence, study participants who did not have basic computer skills to manage data were 67% less likely to be associated with the practice of the data management process than those who had computer skills when the other independent variables are controlled or fixed [OR=0.33, P=0.000, 95%CI: (0.30, 0.38)]. Similarly, participants who either strongly disagreed or disagreed about the availability of HMIS tools (registers, tally sheets, reporting forms, and HMIS manuals) were 51% less likely to be associated with the practice of the data management process than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.49, P=0.000, 95%CI: (0.62, 0.65)].

Moreover, participants who did not have an average knowledge of the health management information system (HMIS) tools (manuals, indicators, registers, tallies, and reporting formats) were 56% less likely to be associated with the practice of data management processing than those who knew the HMIS tools when the other independent variables are controlled or fixed [OR=0.44, P=0.000, 95%CI: (0.59, 0.67)]. Likewise, participants who either strongly disagreed or disagreed about the user-friendliness of HMIS tools (including the time taken to complete data in registers, easiness of HMIS tools, organizational practicality of HMIS tools, feeling comfortable with the HMIS tools, and satisfaction with HMIS tools) were 43% less likely to be involved with the practice of data management processing than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.57, P=0.020, 95%CI: (0.63, 0.74)].

4.4.3.4.3 Organizational determinants associated with the data management process

Several factors play a role in determining the practice of data management processing. In this case, the core finding identified in Table 4.43 confirms that the availability of a written data management strategy, the availability of a written information use strategy, the culture of information use, and the availability of motivation to strengthen HMIS were identified to be associated more strongly with the practice of data management processing. As a result, study participants who either strongly disagreed or disagreed about the availability of a written data management strategy at the level of public health centres were 75% less likely to be associated with the practice of data management processing than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.25, P=0.001, 95%CI: (0.79, 0.84)]. Similarly, participants who either strongly disagreed or disagreed about the availability of written information use strategy at the level of public health centres were 73% less likely to be associated with the practice of data management processing than those who either strongly agreed or agreed when the other independent variables are controlled [OR=0.27, P=0.000, 95%CI: (0.64, 0.75)].

Proper promotion of the culture of information use is one of many factors that helps to determine the quality of the data management processes in public health centres. Participants who either strongly disagreed or disagreed about the promotion of a culture of information use at the level of public health centres were 65% less likely to be linked to the practice of data management processing than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.35, P=0.000, 95%CI: (0.50, 0.53)]. Several factors are known to influence the data management processes. In this study, participants who either strongly disagreed or disagreed about the availability of a separate HMIS plan at the level of public healthcare centres were 59% less likely to be associated with the practice of data management processing as compared with those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.41, P=0.000, 95%CI: (0.32, 0.37)]. Furthermore, motivation to strengthen the HMIS was found to be a significant contributory factor to having a positive influence on the practices of data management processing. As a result, the main finding identified in Table 4.43 confirms that study participants who either strongly disagreed or disagreed about the availability of motivation to strengthen the HMIS at the level of public healthcare centres were 66% less likely to be associated with the practice of data management processing than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.34, P=0.000, 95%CI: (0.44, 0.50)]. In contrast, staff encouragement to make evidence-based decisions, the promotion of accountability to strengthen the HMIS, and yearly adequate budget allocation were not found to be significant statistical contributors to the practices of data management processing.

4.4.3.4.4 Behavioural determinants associated with the data management process

The active involvement of healthcare providers in data management tasks to optimize information use is an essential driving effect on the practices of data management processes. A significant finding reported in Table 4.43 shows that involvement in data management tasks, knowledge of how to manage data, confidence to manage data, competence in data management processing, and average behavioural determinants of data management processes were identified to be statistically associated with the practice of data management processing. For example, participants who did not engage in data management tasks to optimize information use were 58% less likely to be associated with the practice of data management processing than those who did engage in data management tasks to optimize information use when the other independent variables are controlled or fixed [OR=0.42, P=0.030, 95%CI: (0.16, 0.18)]. In addition, this investigation has revealed that several factors are statistically associated with the practice of data management processing. Participants who did not know how to manage data process activities were statistically 65% less likely to be associated with the practice of data management processing than those who had adequate knowledge when the other independent variables are controlled or fixed [OR=0.35, P=0.030, 95%CI: (0.47, 0.53)].

Similarly, participants who did not have the confidence to manage data process activities were statistically 56% less likely to be associated with the practices of data management processes than those who had confidence when the other independent variables were controlled or fixed [OR=0.44, P=0.010, 95%CI: (0.80, 0.85)]. In the same way, participants who did not engage in the data process activities were statistically 59% less likely to be associated with the practice of data management processing than those who were competent when the other independent variables were controlled or fixed [OR=0.41, P=0.010, 95%CI: (0.40, 0.70)].

In general, behavioural determinants of data management processes, including involvement, knowledge, confidence, and competency, were found to be significant determinants for the data management processes. It was found that, on average, participants who did not engage and did not have the necessary knowledge, confidence, and competency to manage data process activities were statistically 68% less likely to be associated with the practice of data management processing than those who did involve, have the knowledge, confidence, and competency to manage data process activities when the other independent variables are controlled or fixed [OR=0.32, P=0.020, 95%CI: (0.51, 0.60)].

4.4.3.5 Determinants of information use (multivariate logistic regression)

4.4.3.5.1 Socio-demographic factors associated with the information use

Among the socio-demographic factors, age, years of experience in the present position, and work position were identified to be statistically associated with the practice of information use at the level of public health centres.

Table 4.44: Determinants of information use in multivariate logistic regression (n=561)

SN	Variables in the Equation	Response level/category	Multivariate logistic regression			
			Sig.	Adjusted Odds Ratio (AOR) of Exp (B)	95% C.I. for EXP(B)	
					Lower	Upper
1	Age Groups	20-33	0.020	2.72	4.48	10.01
		34-47	0.200	3.05	0.49	4.56
		48-61	0.400	Reference		
2	Sex	M	0.820	3.02	0.43	2.88

		F	0.520	Reference		
3	Years of experience	1-5 years	0.810	3.24	0.27	5.24
		6-10 years	0.020	3.07	1.07	2.09
		>=11 years	0.430	Reference		
4	Work position	Healthcare provider	0.080	4.95	1.39	4.10
		Case team head	0.070	3.81	0.72	9.31
		Core process head	0.000	3.59	12.7	16.31
		Medical director	0.070	4.32	1.62	9.58
		HMIS/HIT officer	0.070	Reference		
5	Level of Education	Diploma	0.460	6.77	0.22	8.59
		Degree	0.650	4.68	0.16	8.38
		Master & above	0.640	Reference		
6	Computer skill to manage data	SD or disagree	0.000	0.33	0.31	0.49
		SA or agree	0.060	Reference		
7	Average availability of HMIS tools	SD or disagree	0.000	0.6	0.75	0.85
		Neutral	0.080	4.11	0.26	4.64
		SA or agree	0.120	Reference		
8	Average knowledge on HMIS tools	SD or disagree	0.000	0.41	0.56	0.67
		Neutral	0.292	0.27	0.02	6.78
		SA or agree	0.230	Reference		
9	Average User-friendliness of HMIS tools	SD or disagree	0.010	0.35	0.77	0.86
		Neutral	0.034	0.27	0.01	0.84
		SA or agree	0.106	Reference		
10	Availability of data management strategy	SD or disagree	0.000	0.23	0.02	0.04
		Neutral	0.058	2.77	0.78	1.89
		SA or agree	0.240	Reference		
11	Availability of information use strategy	SD or disagree	0.000	0.20	0.74	0.76
		Neutral	0.090	0.35	0.93	1.77
		SA or agree	0.321	Reference		
12	Culture of information use	SD or disagree	0.010	0.41	0.72	0.75
		Neutral	0.090	3.18	0.73	1.39
		SA or agree	0.130	Reference		
13	Availability of separate HMIS plan	SD or disagree	0.010	0.46	0.35	0.37
		Neutral	0.110	0.14	0.02	1.902
		SA or agree	0.230	Reference		

SN	Variables in the Equation	Response level/category	Multivariate logistic regression			
			Sig.	Adjusted Odds Ratio (AOR) of Exp (B)	95% C.I. for EXP(B)	
					Lower	Upper
14	Monthly internal supervision	SD or disagree	0.970	2.79	0.33	3.138
		Neutral	0.660	4.85	0.13	2.921
		SA or agree	0.890	Reference		
15	Motivation is encouraged	SD or disagree	0.000	0.33	0.23	0.24
		Neutral	0.630	1.69	0.89	4.35
		SA or agree	0.235	Reference		
16	Staff makes decisions	SD or disagree	0.130	9.19	0.71	16.19
		Neutral	0.200	13.1	0.91	1.61
		SA or agree	0.280	Reference		
17	Accountability to strengthen HMIS	SD or disagree	0.320	1.47	0.16	1.81
		Neutral	0.420	7.62	0.23	3.99

		SA or agree	0.270	Reference		
18	Adequate budget	SD or disagree	0.020	0.38	0.17	0.19
		Neutral	0.060	5.28	0.99	3.95
		SA or agree	0.250	Reference		
19	Knowledge to optimize information use	SD or disagree	0.010	0.33	0.78	0.80
		Neutral	0.070	62.9	0.78	0.86
		SA or agree	0.135	Reference		
20	Confident in information use	SD or disagree	0.030	0.52	0.75	0.76
		Neutral	0.110	0.16	0.22	1.89
		SA or agree	0.090	Reference		
21	Competent in information use	SD or disagree	0.040	0.24	0.21	0.24
		Neutral	0.990	7.62	0.23	3.99
		SA or agree	0.790	Reference		
22	Motivation to optimize information use	SD or disagree	0.010	0.46	0.41	0.52
		Neutral	0.510	2.42	0.99	1.14
		SA or agree	0.230	Reference		
23	Behavioural determinants of information use	SD or disagree	0.020	0.44	0.20	0.40
		Neutral	0.220	0.63	0.02	2.32
		SA or agree	0.310	Reference		
	Constant		0.000			

Essential findings of the multivariate logistic regression analysis in Table 4.44 show that participants of the public healthcare centres who are between 20-33 years old were statistically 2.72 times more likely to be associated with the practice of information use than those who were 48-61 years old when the other independent variables are controlled or fixed [OR=2.72, P=0.020, 95%CI: (4.48, 10.01)]. Participants who had an experience of between 6-10 years in their present positions were statistically 3.07 times more likely to be associated with the practice of information use than those who had more than or equal to eleven years of experience when the other independent variables are controlled or fixed [OR=3.07, P=0.020, 95%CI: (1.07, 2.09)]. Moreover, work position was found to provide a significant link to the practice of information use. Core process heads of the healthcare centres were 3.59 times more likely to be involved in the practice of information use than those who are HMIS/HIT officers of the healthcare centres when the other independent variables are controlled or fixed [OR=3.59, P=0.000, 95%CI: (12.74, 16.31)]. On the other hand, the sex and levels of education of the healthcare providers were not identified to be significantly liked to the practices of information use in both the binary and multivariate logistic regression analysis.

4.4.3.5.2 Technical determinants associated with the information use

In this study, the four dimensions of technical determinants, namely computer skills to manage data, the availability of HMIS tools (scale), knowledge of HMIS tools (scale), and the perceived user-friendliness of HMIS tools (scale), were identified as being closely associated with the practice of information use. The findings documented in Table 4.44 show that study participants who did not have essential computer skills to manage data were statistically 67% less likely to be associated with the practice of information use in comparison to those who had computer skills when the other independent variables are controlled or fixed [OR=0.33, P=0.000, 95%CI: (0.31, 0.49)]. Similarly, participants who either strongly disagreed or disagreed on the average availability of HMIS tools (registers, tally sheets, reporting forms, and HMIS manuals) were statistically 40% less likely to be associated with the practice of information use at the level of public health centres in comparison to those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.60, P=0.000, 95%CI: (0.75, 0.85)]. The most important finding in Table 4.44 is that study participants who did not have an average knowledge of the HMIS tools (HMIS manuals, HMIS indicators, registers, tallies, and reporting formats) were statistically 59% less likely to be associated with the practice of information use in comparison to those who had the knowledge when the other independent variables are controlled or fixed [OR=0.41, P=0.000, 95%CI: (0.56, 0.67)]. Furthermore, participants who either strongly disagreed or disagreed on the user-friendliness of HMIS tools (including the time taken to complete data in registers, easiness of HMIS tools, organisational practicality of HMIS tools, feeling comfortable with the HMIS tools, and satisfaction with HMIS tools) were 65% less likely to statistically associated with the practice of information use in comparison to those who either strongly agreed or agreed when the other independent variables are controlled [OR=0.35, P=0.010, 95%CI: (0.77, 0.86)].

4.4.3.5.3 Organizational determinants associated with information use

Many factors play a key role in determining the practices of information use. This study has shown that six of the nine organizational determinants, including the availability of a written data management strategy, the availability of a written information use strategy, a culture of information use, the availability of a separate HMIS plan, a motivation to strengthen the HMIS, and an adequate budget to strengthen the HMIS were statistically associated with the practice of information use. For example, Table 4.44 confirms that participants who either strongly disagreed or disagreed about the availability of a written data management strategy at the level of public health centres were statistically 77% less likely to be associated with the practice of information use at the level of public healthcare centres in comparison to those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.23, P=0.000, 95%CI: (0.02, 0.04)].

As indicated in Table 4.44, study participants who either strongly disagreed or disagreed about the availability of written information on the use strategy at the level of public health centres were statistically 80% less likely to be associated with the practice of information use than those who either strongly agreed or agreed about the availability of written information on the use strategy when the other independent variables are controlled or fixed [OR=0.20, P=0.000, 95%CI: (0.74, 0.76)].

Furthermore, promoting the culture of information use is one of the key factors that help define the quality and practice of information use in public healthcare centres. Given that, participants who either strongly disagreed or disagreed about the promotion of a culture of information use at the level of public health centres were statistically 59% less likely to be associated with the practice of information use than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.41, P=0.010, 95%CI: (0.72, 0.75)]. Several factors are known to be statistically associated with the practice of information use. Participants who either strongly disagreed or disagreed about the availability of a separate HMIS plan at the level of public health centres were statistically 54% less likely to be associated with the practice of information use in comparison to those who either strongly agreed or agreed when the other independent variables are controlled [OR=0.46, P=0.010, 95%CI: (0.35, 0.37)]. Likewise, motivation to strengthen the HMIS is a significant contributory factor for engaging in information use practices. The main finding identified in Table 4.14 is that healthcare providers who either strongly disagreed or disagreed about the availability of motivation to strengthen the HMIS at the level of public healthcare centres were statistically 67% less likely to be associated with the practice of information use than those who either strongly agreed or agreed when the other independent variables are controlled or fixed [OR=0.33, P=0.000, 95%CI: (0.23, 0.24)].

Moreover, the yearly allocation of an adequate budget to strengthen the HMIS was identified to be statistically associated with the practices of information use at the level of public healthcare centres. In this study, participants who either strongly disagreed or disagreed about the allocation of an adequate yearly budget to strengthen the HMIS at the level of public healthcare centres were statistically 62% less likely to be associated with the practices of information use than those who either strongly agreed or agreed when the other independent variables are controlled [OR=0.38, P=0.020, 95%CI: (0.17, 0.19)]. In contrast, agreement about the provision of monthly internal supervision to strengthen the HMIS, staff encouragement to make evidence-based decisions, and promotion of accountability to strengthen the HMIS were not found to be statistically associated with the practice of information use.

4.4.3.5.4 Behavioural determinants associated with the information use

Several factors are known to be associated with the practices of information use. The findings of this study provide evidence that five of the behavioural determinants, including knowledge to optimize information use, confidence in information use, being competent in information use, and motivation to optimize information use, as well as the average of behavioural determinants of information use are strongly associated with the practice of information use. For example, a significant finding demonstrated in Table 4.44 is that participants who did not have sufficient knowledge of how to optimize information use were statistically 67% less likely to be associated with the practice of information use than those who had enough knowledge when the other independent variables are controlled or fixed [OR=0.33, P=0.010, 95%CI: (0.78, 0.80)]. Several factors are statistically associated with the practice of information use. Participants who did not have confidence in information use were statistically 48% less likely to be associated with the practice of information use than those who had confidence when the other independent variables were controlled or fixed [OR=.52, P=0.030, 95%CI: (0.75, 0.76)]. Moreover, participants who did not have competency in information use were statistically 76% less likely to be associated with the practice of information use at the level of public healthcare centres than those who had competency when the other independent variables are controlled [OR=0.24, P=0.040, 95%CI: (0.21, 0.24)]. Similarly, participants who did not have any motivation to optimize information use were statistically 54% less likely to be associated with the practice of information use than those who were competent when the other independent variables are controlled or fixed [OR=0.46, P=0.010, 95%CI: (0.41, 0.52)].

In general, behavioural determinants of information use were found to be statistically significant determinants in information use practices. In this case, on average, participants who did not have the knowledge, confidence, competency, or motivation to optimize information use were statistically 56% less likely to be associated with the practice of information use than those who had knowledge, confidence, competency, and motivation to optimize information use when the other independent variables are controlled or fixed [OR=0.44, P=0.020, 95%CI: (0.20, 0.40)].

4.4.3.6 Evaluating the performance of the statistical models

Evaluating the performance of the model is important in a given statistical analysis. Several statistics can be used to evaluate the performance of a single model using the model chi-Square, percent correct predictions, and pseudo-R^2.

First, the chi-Square (x^2) statistic was used to determine if the overall model is statistically significant. The maximum likelihood ratio (MLR) statistic has a chi-square distribution with a given degree of freedom, where the number of independent variables represents the degree of freedom entered into the statistical model. In this study, two separate analyses were done, and two models were produced to evaluate the practices of data management processes and practices of information use separately. As a result, the overall model performance used to measure the practices of data management processes and practices of information use were statistically significant at (X^2=38.39, P=0.001) and (X^2=23.78, P=0.000), respectively.

Second, the percent correct prediction was used to evaluate the statistical model adequacy. Classifications of tables were used to evaluate the models. This method is used to measure the probability of correct classification of the study participants' responses to either positive responses (yes=1) or negative responses (no=0). The final classification table of the SPSS outputs indicates how well the overall combination of the independent variables explained the practices of data management processes and the practices of information use. Overall, 91.1% and 92.9% of the study participants were measured and classified correctly concerning the practices of data management processes and information use, respectively.

Third, logistic regression models are fitted using the method of maximum likelihood ratio – that is, the parameter estimates are those values which have been observed. The proportion of variance (%) in the dependent variables (practices of data management processes and practices of information use) that can be explained by the independent variables; and then if R-squared (r^2) value is >0.7, this value is generally considered as evidence to have a substantial effect on the dependent variables (practices of data management processes and practices of information use). In this study, the goodness of fit was checked by the -2Log likelihood test using the coefficient of “pseudo" R^2. The Nagelkerke’s-R^2 showed that approximately 86.6% and 88.7% of the practices of data management processes and practices of information use are explained by the effect of the 23 independent variables that have been used in the multivariate logistic regression models, respectively.

CHAPTER FIVE

INTEGRATION AND INTERPRETATION

5.1 INTRODUCTION

Chapter Five presents the integration, interpretation and discussion of the combined findings of the quantitative document review and the quantitative cross-sectional survey of the study. The study objectives were to assess the accuracy, completeness and timeliness of maternal health data generated; to investigate the influence of technical, behavioural and organizational factors on data management; and to determine the extent of health information use. The PRISM conceptual framework is used to guide the integration and interpretation of results.

5.2 PRESENTATION OF INTEGRATED FINDINGS

5.2.1 Integration Processes

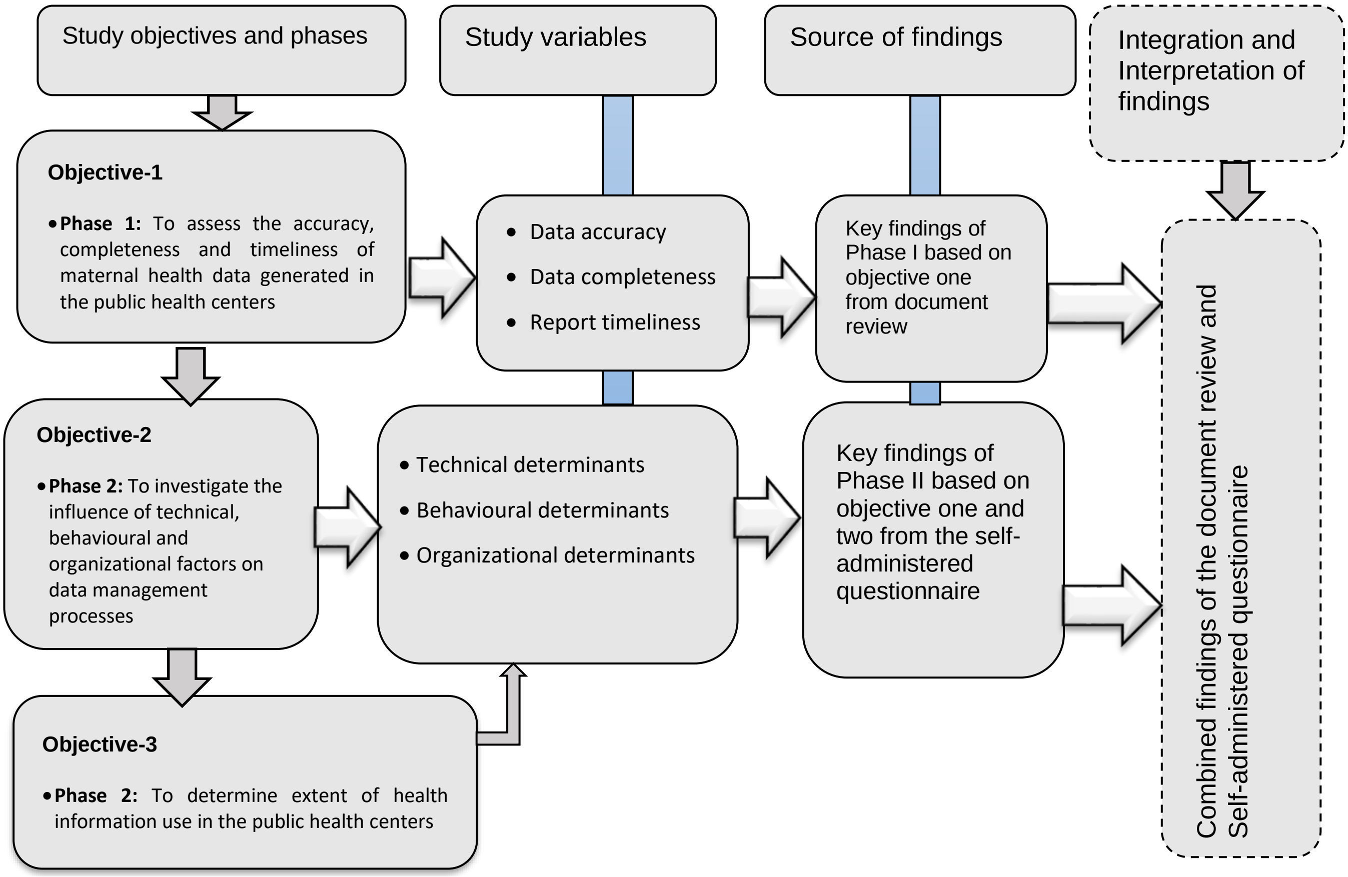

Figure 5.1: Integration processes of the key finding from phases one and two

5.2.2 Data Quality in healthcare facilities

The primary objective of this study was to determine the level of maternal data quality in relation to data accuracy, completeness, and timeliness. Maternal health registers; tally sheets; reporting forms, data quality monitoring logbooks, and the DHIS2 database were used as the data sources for a document review. Alipour and Ahmadi (2017:2) confirm the value of high-quality data in achieving organizational objectives, optimizing the decision-making processes, and improving the quality of healthcare utilization.

The findings of the review showed that all the reviewed indicators (n=8) and data elements (n=8) were neither accurate nor consistent, except for the maternal death indicator. This applies to all the healthcare centres from April to September 2019. A significant number of the participants indicated that the value of data accuracy, including the reporting timeliness and content completeness, was not emphasised. On average, 80% (n=472) of the participants reported that they lacked adequate knowledge of the HMIS manuals to manage data quality. Also, 72% of the participants did not have the competency to manage and improve the dimensions of data quality, including accuracy, completeness and timeliness. This seems to indicate an absence of regular mechanisms of data control monitoring on a weekly and monthly basis. The findings suggest that data were collected without proper validation processes. A study in Zimbabwe shows that the overall quality of data for healthcare facilities has significantly improved through regular data review and control mechanisms (Xiao et al. 2017:3).

High data inconsistency was identified between registers and tally sheets, indicating that significant data were lost. For example, on average, 23% (n=1133) of new family planning users, 43% (n=3297) of the ANC first visit users, 57% (n=4355) of the syphilis total tested, and 58% (n=4373) of the hepatitis total tested mothers were not reported in the tally sheets in all of the public healthcare centres. On the other hand, 79.7% (n=470) of the participants indicated that they did not feel comfortable using HMIS tools to manage data quality. 81% (n=477) of the study participants indicated that a motivational strategy had not been developed to improve data accuracy, including an emphasis on content completeness and timeliness in healthcare facilities. Meanwhile, 74.1% (n=437) of participants confirmed that each healthcare provider did not have institutional accountability with defined job descriptions for data management tasks. There appears to be little satisfaction with HMIS tools. In addition, motivation from management and clearly stipulated accountability expectations were not promoted. This study assumes that job descriptions are important in getting people motivated as they will be aware of what is expected of them and the roles they need to perform. Findings show that there will be fewer data losses and inconsistencies between data sources such as registers and tally sheets if staff are motivated and have the required skills. These gaps could have a direct effect on the decision-making processes of healthcare facilities. The findings are supported by a recent study in Tanzania which showed inconsistencies between registers and reporting formats; and between the data in the tally sheets with the registers (Anasel et al. 2019:18). Also, in Ethiopia, 52% of public healthcare centres in western Ethiopia did not regularly check the accuracy of data elements and indicators against the national pre-defined standard (Yarinbab & Assefa 2018:7).

The timeliness of reporting is one of the dimensions of data quality. It is fundamental to ensure decisions in the healthcare system are made timely to have maximum impact on health outcomes. However, 70% of the reports sent from case teams to healthcare centres did not document their received date in the data quality monitoring logbook. 81.5%, 84.6% and 86.9% of participants in healthcare centres, core processes, and case teams, respectively, did not understand the value of timely reporting in improving data quality to support decision-making. This has shown a variation between the levels with declining trends from the healthcare centre to the following two consecutive levels. Monthly reports sent by each case team were not documented in the health centres' data quality monitoring logbook to track their timeliness. This may be linked to the fact that 77.3% of the participants reported that there was no onsite training to increase the level of understanding of the importance of report timeliness. On average, 84.3% of the participants reported that there was no written data management strategy at healthcare centres, core processes and case teams. Moreover, the level of monthly internal supervision to improve the HMIS has shown considerable variations across the levels. For example, 83.9%, 80%, and 76.1% of the participants either strongly disagreed or disagreed with the provision of internal supervision at the level of case teams, core processes and healthcare centres, respectively. Timeliness appears to be a challenge and is linked to organizational factors such as training, data management strategy and internal supervision. Also, there seems to be little understanding of the importance of timely documentation for improving data quality, as well as case teams receiving minimum HIS-related internal support, followed by core processes relative to healthcare centres. Hence, there is a need to improve the practice of timely documentation in healthcare facilities. Studies in Rwanda and Nigeria showed that healthcare facilities that tracked the report's timeliness before it was sent to the next level have improved data quality (Innocent et al. 2016:5; Bhattacharya et al. 2019:7).

Content completeness is another dimension of data quality. It is useful to determine the missing data values in registers and whether omissions are acceptable to conduct evidence-based decision processes. Data can only influence many decisions at the level of policy-makers and patient care management if they are complete. In this study, seventeen data elements were used as criteria to assess the completeness of indicators. On average, the data values for 21% of mothers were found to be incomplete, not showing any counselling on infant feeding, identifying danger signs, using family planning and maternal nutrition at the time of the ANC first visit during the six months. Similarly, 82% and 67% of the data values for early postnatal care and family planning visits were found to be incomplete, respectively. This could be linked to the fact that more than 50% of the participants did not have adequate knowledge of how to collect complete data using the HMIS registers. Also, 75% of the study participants indicated that the time needed to complete the day-to-day data collection activities was too long and regarded as a burden in healthcare facilities, particularly at the level of case teams. On average, 80% of the participants did not feel comfortable managing and improving data completeness using HMIS tools. Moreover, more than 80% of the participants have not been motivated or encouraged to produce complete data routinely. These findings appear to indicate that technical issues related to reporting structures, low confidence in the use of HMIS tools, low levels of knowledge on the importance of quality data, and inadequate institutional support for improving data management have had an impact on data quality. Adejumo (2017:38) identified challenges related to the level of confidence and knowledge of general data management processes that could directly affect the completeness of the reports. In Ethiopia, 71% of public healthcare centres did not complete the data in registers, tally sheets and reporting forms, and 22% of the monthly data elements and indicators were incomplete due to a lack of adequate knowledge and confidence in the data management tasks (Yarinbab & Assefa 2018:7; Teklegiorgis et al. 2016:7-8).

Findings of the document review indicate that, on average, 50% of the public healthcare centres did not conduct a lot quality assurance sampling (LQAS) technique during the six months under review. This may be linked to the fact that 78% of healthcare providers reported that LQAS self-assessment was not conducted in healthcare facilities to optimize data quality. Also, 90% of the public healthcare centres did not conduct routine data quality assurance (RDQA) techniques in the six months under review. As much as 90% of the participants could explain the importance of routine data quality assurance (RDQA) in improving data management practices. But actions taken to improve data quality were not documented in 90% of the public healthcare centres under review. Also, 85.1% of the participants indicated that an evidence-based action plan had not been prepared and continuously monitored. These facts suggest that healthcare facilities do not fully practice the core functions of HMIS to fix potential causes of data inconsistencies, incompleteness, and untimeliness regularly. This finding is supported by a similar study conducted in the Southern part of Ethiopia, which revealed that most of the healthcare centres did not perform the LQAS self-assessment to strengthen the practices of data management and information use (Endriyas et al. 2019:7). Also, a study by the University of Iran showed that, on average, 62% of data elements and indicators were not properly recorded in various data sources (Asghari, Mardanshahi, Farahabadi, Siamian, Gorji, Saravi, Rezazadeh & Paymard 2016:2).

5.2.3 Data management in healthcare facilities

5.2.3.1 Data management processes

Processes of data management in this study refer to data collection, data compilation processes, knowledge and skills to analyze data, support for data analysis, skills to display data using different charts, and data presentation.

Data collection is the first and most important step in the data management process. However, the data quality monitoring logbook indicates that all the indicators and data elements did not meet the required standards across HMIS data sources during the period under review. This could be associated with the fact that more than 86% of participants suggested that the importance of quality data collection is not well-known to optimize the practice of data management processes. The value of quality data collection has shown considerable variance between the three levels. For example, at the level of the case teams, the value of data collection is significantly lower relative to the other levels, followed by core processes and then health centres. In addition, 72% of the participants were not competent in data collection processes. 75% of the study participants expressed the perception that HMIS tools were not user-friendly. It would appear that a regular conversation about data quality is not a priority agenda for healthcare facilities. This could also suggest a low level of commitment to reporting requirements. Data quality discussions are not conducted as per standard in low- and middle-income countries, resulting in poor quality data at the level of healthcare facilities due to a lack of leadership (Akhlaq et al. 2016:6; Measure Evaluation 2018:9).

Data collation/compilation is the second key step in data management. It involves aggregating data elements and indicators from the register into tally sheets and from tally sheets to reporting formats. On average, 57% of the total syphilis-tested patients and 59% of the hepatitis non-reactive mothers were not aggregated from registers to tally sheets. In addition, the number of safe abortion users in the reporting forms was found to be 30% lesser compared to the registers. Early postnatal care users in reporting forms and DHIS2.3 were17% and 48% higher, respectively, compared to registers. At the same time, repeat contraceptive users by age were 25% higher in DHIS2 than in registers. Overall, 43% of mothers were not collated in the tally sheets. 83% of the participants indicated that the data compilation processes were often rushed. The practice of compiling/collating data to meet the quality of data management standards has shown a significant variance across levels. For example, data compilation practice is lower at the case team level, followed by the core processes and then the public healthcare centres. On average, 90% of the participants did not have adequate knowledge of how to compile data elements and indicators. Also, 70% of the participants did not have the confidence to compile and process data. 74% of the participants were not satisfied with the design of HMIS tools for compiling or collating data. This would result in substantial indicators compiled below average. Findings suggest that data completion from registers to tally sheets would be inaccurate if healthcare providers are unaware, lack confidence, or are not satisfied with the HMIS tools. A similar finding from Tanzania shows that the practices of data compilation at the level of healthcare facilities are often rushed when reporting deadlines arrive, resulting in data backlogs and limited time for ensuring data quality (Bhatia et al. 2016:5). Also, in South Africa, Nicol et al. (2017:10) showed that most health professionals were unable to compile data adequately at the level of health facilities due to lack of confidence, little satisfaction and lack of understanding of indicators, data elements and reporting formats.

Data analysis is the third key step in the process of data management. Data from different sources are collected, collated and then analysed in order to form some sort of conclusion and justification. The findings of the document review showed that 90% (n=9) of the public healthcare centres had no documented discussions and the main challenges of data analysis. As a result, health problems were not prioritized based on magnitude, community concern, seriousness, and feasibility of the intervention, by the performance review team, in 70% of the public healthcare centres. This may be linked to the fact that, on average, 93% of the participants did not have the appropriate skills to analyse the data. For example, the practice of data analysis is significantly limited at the level of the case teams relative to the other levels. Findings showed that, on average, 80% of the participants did not receive technical support routinely to improve data analysis tasks. These healthcare centres failed to plan action points that could help strengthen data analysis tasks. More than 84% of the study participants did not report having basic computer skills to perform data management tasks, including data analysis. More than 66% of the study participants did not understand the detailed definitions of HMIS indicators and data elements that support skills for data analysis. 72% of the participants did not report having basic competence to conduct data analysis tasks. More than 77% of the study participants did not receive on-site training to improve HMIS tasks, including routine data analysis. These facts seem to have impacted the quality of data analysis. This may lead to shelved unprocessed data. The absence of written HMIS plans to provide strategies and to ensure data quality at healthcare facilities showed a negative impact on the data analysis skills of healthcare providers. This will harm measures to determine the performance, efficiency and resources management. A comparable study in North-West Ethiopia indicates that, on average, 76% of healthcare providers did not receive data analysis training and technical support in healthcare facilities (Dagnew et al. 2018:5). Also, lower-level healthcare providers often see and consider themselves as data collectors, they believe that data analysis and interpretation is not their responsibility due to lack of knowledge, confidence and basic computer skills (Measure Evaluation 2018:17).

Presentation of data is the fourth important step in the process of data management. The collected, compiled, and analysed data should be presented to users in a logical order and statistical detail to support decisions at all levels of the healthcare system (In & Lee 2017:8; Measure Evaluation 2019:31). The findings of the document review show that 60% of public health centres did not document all the expected and reported data elements of the case teams in the data quality monitoring logbook during the six months under review. At the same time, 60% and 70% of these healthcare facilities have been unable to perform LQAS for outpatient and inpatient data, respectively, to promote data presentation practice routinely. This could be directly associated with the fact that, on average, more than 92% of the participants did not have the skills to display data using different charts/graphs at all levels. On average, 83% of the participants indicated that data presentation was not visible. For example, at the level of case teams, data presentation visibility is almost non-existent compared to healthcare centres followed by core processes. In addition, most participants expressed that there was no motivation or encouragement for healthcare providers to make evidence-based decisions through monthly performance reviews and weekly data presentations. On average, more than 73% of the participants did not know how to display data to support evidence-based decisions. Routine quality monitoring activities did not appear to be performed according to the standard and had a negative impact on the quality data presentation practice. It can be assumed that where healthcare providers lack data analysis skills, motivation and knowledge, data presentation practice is severely negatively affected in healthcare facilities. In Western Ethiopia, a similar study showed that only 7.2% of the public healthcare centres presented monthly data using charts and tables due to a lack of skills and knowledge (Asemahagn 2017:9). Another finding from North-West Ethiopia indicated that only 24% of healthcare providers presented their monthly data using charts due to a lack of motivating mechanisms for healthcare providers (Dagnew et al. 2018:5).

This study assumes that in the absence of specific efforts to develop strategies for the practices of data management, as shown in the document review and survey data, there will be no incentive or opportunity to learn the skills and best practices of data management. This suggests that healthcare providers do not recognize or internalize the value of data management or do not take data management as part of their clinical tasks; this may be due to a lack of defined roles, responsibilities and institutional accountability for data management. These defined gaps need to be addressed through the development of practical strategies.

5.2.3.2 Factors associated with data management

Data management processes are essential in producing quality data to facilitate and ensure evidence-based decision-making. A significant amount of poor data quality concerning accuracy, completeness, and timeliness found in the document review, as well as significant challenges expressed by the survey participants, could suggest that the implementation plan for HMIS is not well-established across all levels, which could be significantly related to technical, organizational and behavioural determinants. This further strengthens the assumption that there needs to be a symbiotic relationship between guidelines, implementation plans and measures to build the capacity of the HIS in data management.

Technical Determinants are defined in this study concerning computer literacy, the availability of HMIS tools (registers, tally sheets, report formats, and HMIS manuals), and perceptions of user-friendliness of HMIS tools to manage data in health centres. The logistic regression revealed that participants who reported not having basic computer skills to manage data were 67% less likely to practice data management processes than those who had computer skills [OR=0.33, P=0.000, 95%CI: (0.30, 0.38)]. Also, study participants who either strongly disagreed or disagreed about the user-friendliness of HMIS tools (including the time taken to complete data in registers, easiness of HMIS tools, organization practicality of HMIS tools, feeling comfortable with the HMIS tools, and satisfaction with HMIS tools) were 43% less likely to properly conduct the practices of data management processes than those who either strongly agreed or agreed [OR=0.57, P=0.020, 95%CI: (0.63, 0.74)]. It seems that there is a strong relationship between the design of the HMIS tools and the likelihood of effective engagement with data management processes to ensure quality. In other words, these findings suggest that where healthcare providers lack basic computer skills and are less satisfied with HMIS tools, the practice of data management is adversely affected. Similarly, different studies in Kenya show that in 2015, 48% and in 2018, more than 36% of health workers without computer skills were less likely to manage data in healthcare facilities than those with computer skills (Kiilu et al. 2015:3; Nandikove et al. 2017:6), respectively. In addition, healthcare providers who considered the HMIS tools as not user-friendly were not adequately involved in data management tasks in Kenya's healthcare facilities (Kirimi 2017:36).

Organizational Determinants are defined concerning the availability of written data management and information use strategies; the culture of information use; availability of a separate HMIS plan, provision of internal supervision to strengthen HMIS, motivation to strengthen HMIS, staff empowerment, onsite training, accountability, and budget allocation to strengthen the HMIS at the level of public healthcare centres. In this study, participants who either strongly disagreed or disagreed about the availability of a written data management strategy at the level of public healthcare centres were 75% less likely to engage effectively with the practices of data management processes than those who either strongly agreed or agreed [OR=0.25, P=0.001, 95%CI: (0.79, 0.84)]. Participants who either strongly disagreed or disagreed about the promotion of information use culture in healthcare centres were 65% less likely to effectively perform the tasks of data management processes than those who either strongly agreed or agreed [OR=0.35, P=0.000, 95%CI: (0.50, 0.53)]. Also, participants who either strongly disagreed or disagreed about the availability of a separate HMIS plan at the level of healthcare centres were 59% less likely to engage in data management processes as compared with those who either strongly agreed or agreed [OR=0.41, P=0.000, 95%CI: (0.32, 0.37)]. These facts indicate the need for a data management strategy to guide, facilitate and encourage the HIS implementation. It may also mean that when an information use culture is properly promoted and a separate HMIS plan is prepared and implemented, these strategies will enable HIS tasks to be carried out. A similar study indicates that the existence of a data management strategy, strong HIS leadership, and ongoing technical support are widely seen as good opportunities and motivating factors to strengthen the practices of data management processes across healthcare facilities (PAHO & WHO 2019:36). A systematic review carried out in low and middle-income countries have shown those healthcare facilities without a HIS plans are less likely to practice data management tasks (Akhlaq et al. 2017:13).

Behavioural Determinants are defined in this study as the knowledge to optimize information use; the knowledge to manage data process activities, knowledge of the HMIS tools, confidence and competence in information use, motivation to optimize information use, and the level of involvement in data management tasks to optimize information use in public healthcare centres. Overall, behavioural determinants of information use and data management practices were found to be statistically linked in a significant way in the multivariate logistic regression analyses.

Key findings showed that, on average, study participants who did not engage in data processing, did not have knowledge in this regard, and lacked the confidence and competency to manage data processing tasks, were 68% less likely to be effectively involved in the data management processes than those who did [OR=0.32, P=0.020, 95%CI: (0.51, 0.60)]. Participants who did not have the knowledge to optimize data management practice were 65% less likely to practice correct data management processes [OR=0.35, P=0.030, 95%CI: (0.47, 0.53)]. Also, participants who did not have average knowledge of the HMIS tools were 59% less likely to perform the data management tasks [OR=0.41, P=0.000, 95%CI: (0.56, 0.67)]. In addition, participants who were not confident were 56% less likely to manage data [OR=.52, P=0.030, 95%CI: (0.75, 0.76). Also, the participants who reported low competence were 59% less likely to practice data management competently [OR=0.41, P=0.010, 95%CI: (0.40, 0.70)]. Participants not engaged in data tasks were 58% less likely to optimize data quality [OR=0.42, P=0.030, 95%CI: (0.16, 0.18)]. These facts imply that data management practice is significantly dependent on adequate knowledge, a high level of confidence, and competence to strengthen the functionality of HMIS tasks. Behavioural determinants appear to impact the achievement of HMIS tasks significantly. A study from Kenya and Uganda also showed that healthcare providers who did not have the confidence or were not competent were less likely to improve data management processes (Mucee et al. 2016:8; Muhindo & Joloba 2016:3).

5.2.4 Information use in healthcare facilities

5.2.4.1 Practice of information use

The quantitative cross-sectional survey's third objective was to investigate the influence of technical, behavioural and organizational factors on the extent of health information use in public health centres. This study defines information use as the level of information re-packaging and disseminating, analytical report production, action plan preparation and monitoring, a culture of written feedback provision, and information use dimensions to strengthen the HMIS.

Information repackaging focuses on organising analysed data or information in appropriate and usable ways. This practice is important to interpret and convert information into a form that can be easily understood and usable by users (Radhakrishnan & Francis 2018:4).

The mean average variations in the rate of repeat contraceptive users and the ANC fourth visits across HMIS tools were 6% and 22%, respectively. Moreover, the maximum data variation between registers and DHIS2 for syphilis test reactive was 100%. This means that 100% of the reactive mothers tested for syphilis were reported in the DHIS2 but not on registers, potentially affecting the quality of the information repackaged. Similarly, for two data elements, such as the HIV test and population code, 21% and 100% of the ANC first and early postnatal service mothers were found to be incomplete in the registers. These could be linked to the fact that, on average, 88% of the participants indicated that information was not repackaged. 87% of the participants reported that the culture of information use was not promoted well enough to enable them to acquire the skills to repackage information. These findings mean that if data are significantly varied across HMIS data sources and if indicators are found to be incomplete, this will have a significant impact on the repackaging of information. This could be associated with low computer skills, a lack of a strategy for the use of information, and a lack of culture for the use of information. The lack of computer skills and a poor information culture in Tanzania have been identified as a challenge in repackaging information such as guidelines, technical reports, leaflets, and booklets (Chipungahelo et al. 2015:3).

Information dissemination: The repackaged information is routinely disseminated to staff and the communities. In this document review, mean data variations across four HMIS data sources (including registers, tallies, reporting forms, and DHIS2) for non-reactive and reactive-identified hepatitis-tested mothers have been found to be 21% and 25%, respectively. Also, 95% of the data about immediate postpartum family planning were found to be incomplete. These differences may be linked to the finding that 85% of the participants indicated that information dissemination is not well practiced with no dissemination of information in case teams compared to the other levels. There was a substantial difference between the three levels in displaying analytical reports using charts/graphs. Nearly no analytical reports were displayed at the case team level compared to public healthcare centres, followed by core processes. These facts appear to indicate that the importance of data quality and information needs was not recognized, particularly at the level of case teams. Comparable research in South Africa has shown that health information has not been repackaged and disseminated in healthcare facilities as expected due to a lack of understanding of the importance of information dissemination and use (Nicol et al. 2017:7) and lack of skills for information dissemination (Ugwuogu 2015:6).

Performance review is a significant component of the information use that is aimed at addressing quality-related data gaps in planning, implementing and monitoring. A finding of the document review shows that 80% of public healthcare centres did not identify, review and document any inconsistent data elements, possible causes, and actions taken as part of the performance review. This might be related to the fact that more than 88% of the participants reported that evidence-based action plans were not prepared to improve data quality. Also, the practice of developing the action plan is considerably lower at the individual level relative to the healthcare centres, followed by case teams and core processes, respectively. On average, 80% of the participants reported not having adequate knowledge at all levels to optimize information use through performance review activities. 84.9% of the participants strongly disagreed or disagreed about the adequacy of the budget allocation to strengthen the HMIS. This indicates that HIS challenges are increased significantly from top to bottom levels, possibly due to a lack of well-established HMIS performance and data quality review teams at the three levels. Comparable studies conducted by O'Hagan et al. (2017:11) and Teklegiorgis et al. (2016:6-9) show that healthcare providers in healthcare facilities with adequate knowledge and a sufficient budget are more likely to conduct performance reviews and monitor data quality.

Written feedback is an important component of the cycle of information use practices, facilitating effective communication and encouraging discussion on data-related issues. This fact is supported by a study from the USA, which shows that peer learning and written feedback can enable health workers to share health information; discuss data quality activities; and address data-related challenges effectively (PAHO & WHO 2019:48). The finding of the document review indicated that, on average, 70% of the HMIS units in public healthcare centres were not provided with written feedback on data quality every month. At the same time, the findings of the survey were that more than 84% of the participants expressed the view that HMIS-related written feedback was not circulated monthly from the governing board of healthcare centres to respective healthcare centres, from healthcare centres to core processes, from core processes to case teams, and from case teams to individuals. On average, 81% of the participants indicated that encouragement to implement and improve the key functions of the HMIS, including circulating written feedback, is not always done in healthcare facilities. It appears that the impact of written feedback on improving the quality of data and the use of information has not been generally recognized from top to bottom, particularly at the level of case teams. Written feedback was given to healthcare facilities in Kenya to improve data quality and information use (Mucee et al. 2016:41-49). A related study from Ethiopia shows that data quality was 3.5 times higher for healthcare centres that received feedback from their supervisors (Teklegiorgis et al. 2016:6-9). In developing countries, healthcare providers rarely get written feedback on the HMIS, a practice which is unconstructive, outdated and unproductive (Dehnavieh et al. 2019:2).

Evidence-based decision-making is vital across a range of healthcare system activities to promote and maintain the quality of healthcare systems. Healthcare managers, policymakers, and various information users often need high-quality data and information for evidence-based decision-making processes to improve the healthcare infrastructure and healthcare services and serve various community needs (Measure Evaluation 2015:6). In this study, the data quality monitoring logbook did not show any evidence of recorded discussions and decisions on the monthly reviews about data accuracy, completeness and timeliness in 60% (n=6) of the healthcare centres. This may be linked to the fact that, on average, 84% of participants indicated that information was not used for making decisions, such as updating implementation strategies, introducing new strategies, revising annual plans, tracking day-to-day activities, responding to priority health service needs, and connecting decisions with evidence at the level of healthcare facilities. Over 72% of the participants reported that healthcare providers are not encouraged to make evidence-based decisions. These findings indicate that decisions were taken without adequate evidence, which may be due to a lack of information platforms, such as weekly case presentations focusing on data quality and performance reviews. More or less similar study findings from Tanzania confirm that data use for decision-making is minimal, particularly in lower levels of healthcare facilities, due to limited knowledge of data interpretation. It was also noted that there was no forum in healthcare facilities between healthcare providers to share and discuss data-related issues (Somi et al. 2017:6). The same can be said about Ethiopia; for example, policy-making decisions are fragmented and disorganized due to conflicting interests of different users and agencies. Consequently, valuable and substantial health data resources remain unused to improve organizational effectiveness and community health needs (Dagnew et al. 2018: 5-8; Yarinbab & Assefa 2018:7; Abera et al. 2016:10). A related study conducted by Measure Evaluation (2018:15) suggested that health information is often not used in various decision-making processes to allocate resources and guide interventions. On the other hand, findings in Tanzania and Morocco show that evidence has been used to assess healthcare system performance and to set the priority needs of the community (Anasel et al. 2019:28). Also, in South Africa, 46% of healthcare centres have used data and information to take decisions on planning, budgeting and progress tracking (Nicol et al. 2017:4) in comparison with 38.4% of public healthcare centres in Ethiopia (Asemahagn 2017:8).

5.2.4.2 Factors associated with information use

The practice of information use is essential to ensure evidence-based decision-making processes at the level of public healthcare centres, core processes, and case teams. The third objective of this study is focused on determining the extent of health information use for various decision-making processes at the level of healthcare centres. Evidence-based decision-making processes are crucial for healthcare facilities globally to improve the overall healthcare service quality, patient care management and client satisfaction, while evidence-based decisions are poorly practised and utilized in developing countries like Ethiopia.

5.2.4.2.1 Technical determinants

Findings of the document review indicate that challenges to data quality have not been identified and the root causes of the challenges have not been analyzed; discussions on data quality have not been conducted on a monthly and routine basis, gaps have not been prioritized based on root cause analysis, and action points have not been prepared. Monthly feedback was not provided adequately. These gaps identified from the document review could be linked to technical, organizational and behavioural factors.

Multivariate logistic regression results show that healthcare providers who are more likely to use information are those who have computer skills to perform data analysis, who have knowledge of HMIS tools to improve the use of information, and who are well aware of HMIS tools as being user-friendly to perform HIS tasks properly. A similar study in Kenya and Ethiopia indicates that healthcare providers with computer skills are more likely to increase information use than those who do not have computer skills (Nandikove et al. 2017:6; Teklegiorgis et al. 2016:6-9).

5.2.4.2.2 Organizational Determinants

Findings from the multivariate logistic regression analysis show that involvement of healthcare providers in information-use tasks is likely where the information-use strategy is readily available and accessible to guide, monitor and evaluate HIS implementation, where a separate and written HMIS plan is well-prepared and institutionally practised, and where the promotion of information use is well-established. A similar study conducted in the Southern part of Ethiopia indicates that information has not been used enough at the level of healthcare facilities due to a lack of a written health information system strategy to guide and track information use for different decisions (Endriyas et al. 2019:5). Written information use strategy is usually valued as an opportunity to improve the practices of information use in health facilities. Also, the HMIS needs to be supported by a written strategy and effective leadership to ensure the maximum use of information in healthcare facilities (PAHO & WHO 2019:36).

5.2.4.2.3 Behavioural determinants

Findings reveal that the use of healthcare information is dependent on behavioural factors that include adequate knowledge, a high level of confidence, competence and motivation to achieve the goals of the HIS. A related study has shown that healthcare providers who do not realise the importance of information and are incompetent in performing data management tasks are less likely to use the information for different decision-making processes (Akhlaq et al. 2016:2-6). Another study in Ethiopia indicated that 40% of healthcare providers who reported not having knowledge of the value of health information were less likely to endorse their decisions with evidence (Dufera et al. 2018:5).

Overall, the most crucial facts extracted and combined from the two phases are that, first of all, the key challenge is a lack of understanding and internalizing the importance of evidence-based decision-making across all health system levels. The second challenge is the lack of skills, motivation, and competence to strengthen the core functions of the HMIS and to improve healthcare service utilization. Third, identified gaps are directly linked to organizational determinants. Among those are a lack of established accountability, including defined roles and responsibilities for data management; a lack of motivation and incentives; a lack of a written HIS strategy and an HMIS plan; the poor practice of little written feedback provision; and, finally, a lack of HIS capacity-building and internal technical support.

CHAPTER SIX

STRATEGY DEVELOPMENT, VALIDATION AND DISCUSSION

6.1 INTRODUCTION

Chapter six presents the development and validation of strategies using the Delphi technique. The study's objective was to develop strategies for data management and information use in public healthcare centres. Significant gaps associated with data quality, data management, and information use have been identified from the document review and quantitative survey in two separate, consecutive study phases. The key findings were combined and interpreted accordingly.

6.2 STRATEGY DEVELOPMENT

In Chapter Five, the PRISM theoretical framework was used to guide the integration and interpretation of pertinent and critical results. The key findings of the document review and the quantitative survey were combined to extract new meaning/meta-inferences from the two data sets in the areas of data quality, data management, and information use, allowing for the development of validated HIS strategies. Initially, twenty-five strategies were proposed, with ten focusing on data quality, seven on data management, and eight on improving information use. In addition, refined action plans to implement proposed strategies, indicators of success for proposed strategies, a time frame for evaluating strategy implementation, and a responsible body to support, guide, and implement the proposed strategies, are defined and documented, as shown in Annexure 8.

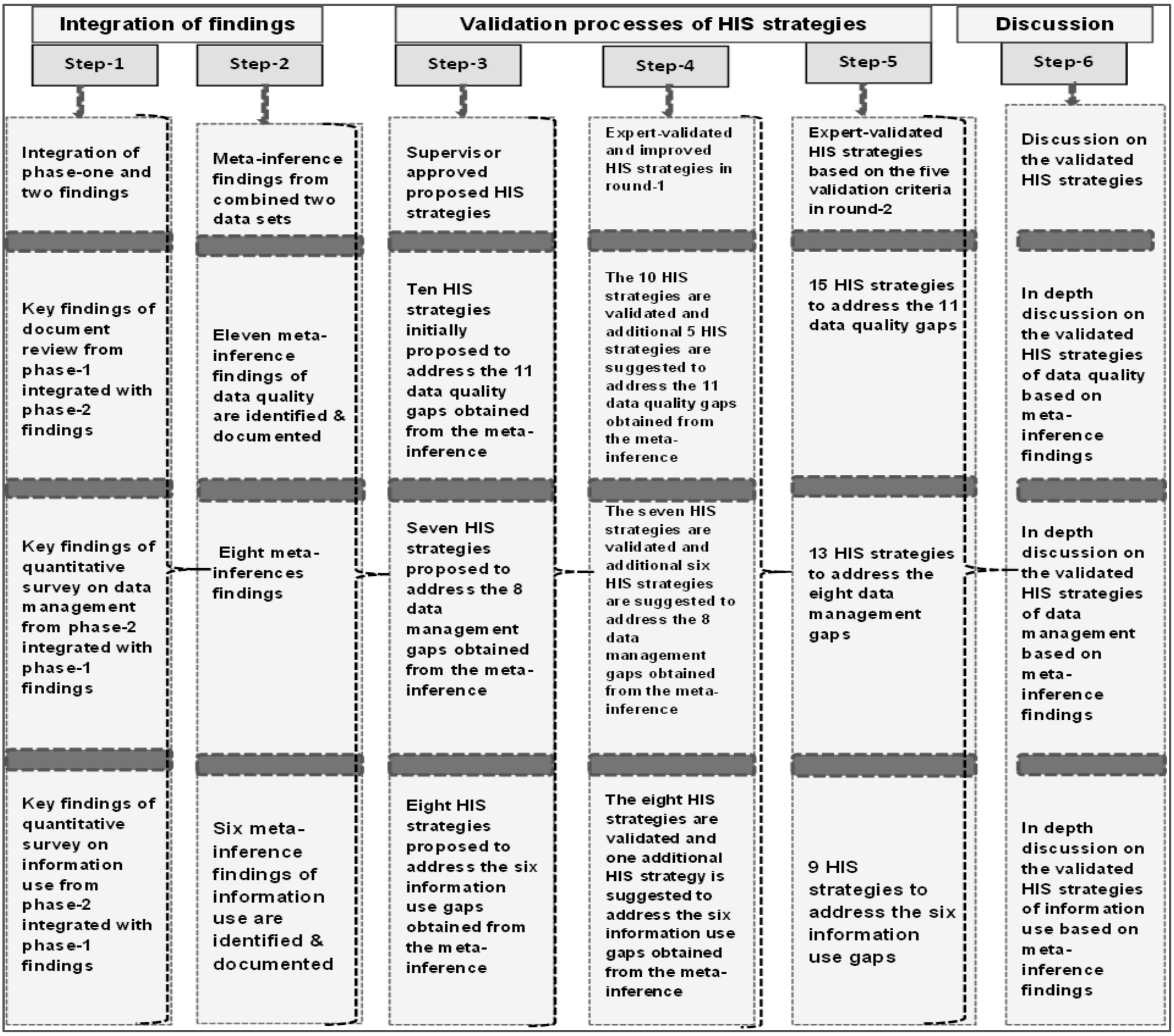

Figure 6.1: The logical flow of findings integration, validation processes of his strategies and discussions

6.3 VALIDATION OF THE STRATEGIES

The study applied the Delphi technique to validate and obtain consensus on strategies to help healthcare facilities improve their data management and information use practices. The Delphi technique is essential to determine the extent to which experts agree on a given issue and to reach a consensus in areas where they disagree. It is commonly used in healthcare facilities to validate proposed strategies using expert consensus (Stewart 2017:3). The Delphi technique has been used in healthcare studies to gather and validate expert opinions on an individual basis in order to develop feasible interventions with a high level of consensus to address certain gaps (Ab-Latif, Dahlan, Ab Mulud & Mat-Nor 2017:2). This method is widely used to gather data from a group of experts in order to develop interventions for a specific real-world problem by reaching a consensus through rounds of review (Avella 2016:2). In addition, anonymity, inclusion and exclusion criteria, and an average of expert responses based on the Likert scale are all used in this technique to ensure high research quality (Avella 2016:5). The purpose of group consensus is to determine the level of agreement among a group of healthcare information systems experts on the proposed data quality; data management and information use strategies for the HIS. Moreover, this technique allows experts to reconsider their initial responses based on previous round feedback; and in this study, the following three phases were followed:

6.3.1 Preparation phase: Recruitment of experts

A set of criteria for inclusion was developed. Potential experts were identified and defined as individuals with sufficient knowledge of the healthcare information system. A master's degree, at least five years of work experience in the field, and the ability to influence policy were set as criteria. Hereafter, 21 experts were purposefully chosen based on the inclusion criteria listed above. This procedure is justified further by the fact that a purposive sampling technique was required to reach a consensus, in which the sample was selected not to represent the general population but rather their expert ability to answer the properly defined research questions (Avella 2016:2). Selected experts were invited through a phone call and an invitation letter. The consent form was included in the package. The proposed strategy and consent form were privately emailed to each expert, and they were given one week to review the strategies and respond via email.

6.3.2 Socio-demographic data of experts

Table 6.1: Socio-demographic data (n=21)

SN	Expert position		Years of experience		Education	Gender
	Expert participated in the validation	Numbers of experts	Numbers of years	Numbers of experts		
1	M&E expert	5	5 years	5	Master's degree=21	Male=19 Female=2
2	HIS Expert	10	6 years	2		
3	Planning, and M&E Director	1	7 years	3		
4	HIS implementation supervisor	1	8 years	2		
5	HIS implementation manager	1	10 years	3		
6	Senior HIS advisor	2	11 years	3		
7	HMIS Advisor	1	12 years	1		
8	Total	21	14 years	1		
			20 years	1		
			Total	21		

Table 6.1 provides a summary of the socio-demographic data of experts. In this study, 21 of the 25 invited experts accepted and participated in the validation processes. The response rate was 100% (n=21). The mean age of the experts was 37.6 years. They had an average of 8.6 years of work experience in their current position. Each expert possessed a master's degree in education. The majority (90.5%, n=19) of them were males.

6.3.3 Implementation phase

Round 1: Sending the proposed strategies to each expert via email: The proposed strategies were sent through email to each expert separately with a consent form which was followed by phone calls and text messages. The expected date of return of the reviewed strategies was agreed with each expert; and a phone call was made to remind them. In this study, experts were asked to rate their level of agreement or disagreement with each proposed strategy using a three-point Likert scale with the options “strongly disagree/disagree”, “neutral”, and “agree/strongly agree”. Moreover, clear instructions were given at the top of each page of the proposed strategies on how to assign a code to each proposed strategy based on their level of agreement or consensus. In this case, the instruction was code=3 for experts who strongly agreed or agreed; code=2 for neutral; and code=1 for those who disagreed or strongly disagreed.

Determining consensus: Several methods for determining the point of consensus are described in the literature, including a predetermined number of rounds; a specific level of agreement; and an average per cent of majority opinions of cut-off rate (Avella 2016:2-3). While there is no agreement on the best approach, the phrase "certain level of agreement" is the most commonly used. In addition, there is no accepted set of standards for the target percentage of agreement, even though greater or equal to 70% is commonly reported in the literature (Stewart et al. 2017:4; Keeney et al. 2011:53). In this study, it was assumed that if the level of agreement among experts reached a value equal to or greater than 70% in the first round, experts were only asked to put their general validation agreement based on the five newly designed validation criteria in the second round; and then the validation process would be completed. However, if the level of agreement did not meet the cut point in the first round, the second round was continued for review, and then experts were asked to put their general validation agreement based on the five newly designed validation criteria in the third round.

Collecting and analyzing the responses: In this study, to measure the level of expert consensus on the proposed strategies, the table below was used as a guide to determine the level of agreement among experts. This result was also analyzed using descriptive statistics, including the mean, response frequency and percentage.

Table 6.2: Interpretation for the level of agreement/consensus

Cut points	Interpretation
If the average expert agreement/consensus is <70%	Weak agreement/consensus
If the average expert agreement/consensus is ≥70%	Strong agreement/consensus

According to Table 6.2, the predetermined cut point for the level of agreement was set at "strong agreement" (if the cut point was ≥70%). Therefore, the researcher collected, aggregated, and summarized the average level of agreement among experts for each round. The process was terminated based on the final average score and a predetermined stop criterion (e.g. the level of consensus and response stability).

6.3.4 Findings of the proposed HIS strategies in Round One

Table 6.3: Findings on strategies to strengthen data quality in round one (n=21)

	Meta-inferences from combined data sets	Proposed strategies	Level of agreement/disagreement		
			Strongly disagree/ disagree (code=1)	Neutral (code=2)	Strongly agree/agree (code=3)
1	**A.** Absence of regular mechanisms for data quality monitoring	**1.** Develop and implement a data quality assurance plan	10% (n=2)	0% (n=0)	90% (n=19)
2	**B.** Lack of a well-established HMIS performance and data quality review mechanisms	**2.** Establish performance and data quality review teams with a standard term of reference at all levels	14% (n=3)	10% (n=2)	76% (n=16)
		3. Establish HIS accountability within the framework of data governance at all levels	0% (n=0)	0% (n=0)	100% (n=21)
3	**C.** Less satisfaction with HMIS tools	**4.** Revise and improve the interface of the HMIS system	5% (n=1)	14% (n=3)	81% (n=17)
4	**D.** Job descriptions of healthcare providers on data management are not defined	**5.** Develop job descriptions with roles and responsibilities clearly differentiated	0% (n=0)	5% (n=3)	95% (n=20)
5	**E.** Little understanding of the importance of timely documentation and reporting	**6.** HIS training to improve ▶ The level of understanding of timely documentation and reporting ▶ The quality of key data management components such as data collection, compilation, analysis, problem identification, and action plan development	14% (n=3)	10% (n=2)	76% (n=16)
6	**F.** The quality of key data management components did not meet expectations				

7	**G.** Low level of knowledge of the importance of quality data	**7.** HIS training focusing on knowledge to boost confidence in the use of HMIS tools	5% (n=1)	9% (n=2)	86% (n=18)
8	**H.** Low confidence in the use of HMIS tools				
9	**I**. Healthcare facilities do not fully practise the core functions of HMIS to address causes of data inconsistencies	**8.** Keeping and using a data quality monitoring logbook	0% (n=0)	10% (n=2)	90% (n=19)
		9. HMIS mentorship at (HC, CP, CT and Individual)	0% (n=0)	0% (n=0)	100% (n=21)
10	**J**. Case teams received minimum HIS internal support	**10.** HIS internal supportive supervision with a special focus on lower levels such as case teams	5% (n=1)	5% (n=1)	90% (n=19)
Average			5% (n=1.1)	6% (n=1.2)	90% (n=18.6)

Table 6.3 provides a summary of validated HIS strategies to strengthen the level of data quality. In this table, ten proposed HIS strategies were reviewed by the research supervisor and validated by HIS experts. In the first round, the highest and lowest levels of agreement for a single proposed strategy were reported to be 100% (n=21) and 76.2% (n=16), respectively. The average level of agreement for the ten proposed HIS strategies to improve data quality was found to be 90% (n=18.6).

Table 6.4: Strategies to strengthen data management in round one (n=21)

	Meta-inferences from combined data sets	Proposed strategies	Level of agreement or disagreement		
			Strongly disagree/ disagree (code=1)	Neutral (code=2)	Strongly agree/ agree (code=3)
1	**A.** Low commitment to reporting requirements	**1**. Providing training for technical leaders to improve • the level of understanding of data quality as priority agenda • information use at all levels	5% (n=1)	19% (n=4)	76% (n=16)

2	**B**. Shelved unprocessed data due to low data analysis skills	**2**. Data analysis training to improve the percentage of processed data	0% (n=0)	0% (n=0)	100% (n=21)
3	**C.** Routine quality monitoring activities did not appear to be performed according to the standard	**3**. Establish peer learning networks through WhatsApp/ telegram to monitor routine data	5% (n=1)	0% (n=0)	95% (n=20)
4	**D.** Substantial indicators compiled below average.	**4**. Skill-based HIS training • to ensure the maximum level of data compilation; • to improve data accuracy across the data sources by avoiding missed outliers and incorrect data values	5% (n=1)	0% (n=0)	95% (n=20)
5	**E.** Data from key data sources were significantly inaccurate				
6	F. Data presentation was significantly inadequate at all levels	**5**. Data presentation training to improve skills in how to present data at all the levels	10% (n=2)	10% (n=2)	80% (n=17)
7	G. Absence of written HMIS plans to improve • Data quality • Healthcare performance; • Resource management	**6.** Preparing separate and written HMIS plan to support data management tasks at all levels	0% (n=0)	5% (n=1)	95% (n=20)
8	H. There is no data management strategy to guide, facilitate and support HIS implementation.	**7**. Developing a data management strategy to guide, facilitate and encourage HIS implementation at all levels	0% (n=0)	0% (n=0)	100% (n=21)
Average			3% (n=0.72)	7% (n=1.4)	90% (n=18.6)

Table 6.4 provides a summary of validated HIS strategies to strengthen data management. In this case, eight proposed HIS strategies were reviewed and validated by the HIS experts. The highest and lowest levels of agreement for a single proposed strategy were reported to be 100% (n=21) and 76.2% (n=16), respectively. The

average level of agreement for the eight proposed HIS strategies to improve data management was found to be 90% (n=18.6).

Table 6.5: Strategies to strengthen information use in round one (n=21)

	Meta-inferences from combined data sets	Proposed strategies	Level of agreement or disagreement		
			Strongly disagree/disagree (code=1)	Neutral (code=2)	Strongly agree/agree (code=3)
1	**A**. Data are significantly varied across HMIS data sources to repackage information **B**. lack of culture for information repackaging	**1**. Advanced training in information repackaging and dissemination	0% (n=0)	10% (n=2)	90% (n=19)
3	**C**. The importance of information needs has not been recognized, particularly at case teams	**2**. Establishing term of reference to guide information repackaging and disseminating	0% (n=0)	0% (n=0)	100% (n=21)
4	**D**. Decisions in healthcare facilities were made without sufficient evidence	**3**. Develop an incentives system to: (a) encourage information use; (b) create opportunities for learning and sharing best practices; (c) build data ownership; (d) promote evidence-based decision-making as a means of providing opportunities for staff development	0% (n=0)	0% (n=0)	100% (n=21)
5	**E**. There is limited of information use and a lack of a culture that promotes information use	**4**. Establishing information use audits at all levels	0% (n=0)	0% (n=0)	100% (n=21)
		5. Creating data learning and sharing forums at inter- and intra-healthcare facilities	0% (n=0)	0% (n=0)	100% (n=21)
		6. Publishing brochures or newsletters at healthcare facilities	0% (n=0)	5% (n=1)	95% (n=20)
6	**F**. Insufficient budget for implementation of HMIS	**7**. Assigning budget for strengthening and implementing HIS	10% (n=2)	5% (n=1)	100% (n=18)

7	**G**. HIS written feedback was not provided, particularly at the level of the case teams	**8**. Establishing feedback delivery, control and tracking log book/electronic system after a performance review meeting	0% (n=0)	0% (n=0)	100% (n=21)
		Average	1% (n=0.2)	2% (n=0.5)	97% (n=20.3)

Table 6.5 provides a summary of validated HIS strategies to strengthen information use. Seven proposed HIS strategies were reviewed and validated by HIS experts. The highest and lowest levels of agreement for a single proposed strategy were reported to be 100% (n=21) and 76.2% (n=16), respectively. The average level of agreement for the seven proposed HIS strategies to improve information use was 97% (n=20.3).

6.3.5 Final phase of the Delphi technique

The response rate as well as the level of agreement or disagreement reached for each proposal and overall for the proposed strategies, were briefly summarized and reported during this phase. Modified and newly added strategies were documented and reported as well.

Round 2: Validating the improved and updated HIS strategies

In the first round, twenty-five proposed HIS strategies were sent to HIS experts for review, and on average, 91% (n=19.17) of the experts strongly agreed with the proposed strategies, while around ten experts suggested twelve complementary strategies in the comment section to strengthen the proposed strategies. All comments and suggestions were incorporated into the final strategies. As a result, the improved and reviewed HIS strategies were sent through email to the 21 experts who had participated in the first round. In this round, the experts were asked to rate their level of agreement or disagreement with the improved strategies using a three-point Likert scale with “strongly disagree/disagree”, “neutral”, and “agree/strongly agree” as options. The final HIS strategies were thus validated in the second round by the same experts who participated in round one, based on the five key validation criteria, as shown in Table 6.6 below. The criteria were scope and purpose, clarity and simplicity, feasibility, importance, and content quality.

6.3.6 Presentation of final strategies

Table 6.6: Strategies to strengthen the level of data quality (n=21)

Meta-inferences from combined data sets	**Proposed strategies**
A. Absence of regular mechanisms for data quality monitoring. **B.** Lack of well-established HMIS performance and data quality review mechanisms. **C.** Data are significantly varied across HMIS data sources.	**1.** Develop, implement and measure data quality assurance plan regularly. **2.** Strengthening existing performance and data quality review teams at the health centre level. **3.** Establish new performance and data quality review teams at the core process and case team levels.
	4. Establish HIS accountability within the framework of data governance at all levels.
D. Less satisfaction with HMIS tools.	**5.** Revise and improve the HMIS system's interface, both paper and computer-based.
E. Job descriptions of healthcare providers on data management are not defined.	**6.** Develop job descriptions with roles and responsibilities clearly differentiated.
F. Little understanding of the importance of timely documentation and reporting. **G.** The quality of key data management components did not meet expectations.	**7.** Regular on-the-job training, followed by ongoing HIS advocacy to improve the level of understanding on timely documentation and reporting the quality of key data management components such as data collection, compilation, analysis, problem identification, and action plan development. **8.** Post-training follow-up and HIS experience sharing. **9.** Appointing official case team leaders to facilitate and coordinate both data management and clinical tasks.
H. Low level of knowledge of the importance of quality data. **I.** Low level of confidence in the use of HMIS tools.	**10.** On-job training focusing on knowledge, skill and practice to boost confidence in the use of HMIS tools. **11.** Advocate and design policy to give attention to HIS to assign a highly qualified professional to manage data system at the healthcare centre level.
J. Healthcare facilities do not fully practice the core functions of HMIS to address causes of data inconsistencies.	**12.** Updating, maintaining, and using a paper and computer-based data quality monitoring logbook.
	13. HMIS mentorship at • Healthcare centre; Core process; Case team & Individual.

K. Case teams received minimum HIS internal support.	**14.** HIS internal supportive supervision with a special focus on lower levels, such as case teams. **15.** Building HMIS officers' capacity to provide technical support and guidance to case teams at the facility level in order to improve HIS implementation.

S*trategies* to strengthen data quality: Table 6.6 provides a summary of validated and updated HIS strategies for improving data quality. Initially, ten HIS strategies were proposed in order to improve data quality. In the first round, on average, 90 % (n=18.6) of field experts accepted the proposed HIS strategies, with suggestions for modification and the addition of new strategies to reshape and update the proposed HIS strategies. In this case, seven of the ten proposed HIS strategies for improving data quality were modified, and five new strategies were proposed, bringing the total to fifteen. In addition, based on the experts' suggestions and comments, some of the pre-defined timelines for evaluating HIS strategies, the proposed indicators for measuring success, and the listed action plans have been updated and improved as indicated in Annexure 8.

Table 6.7: Strategies to strengthen data management (n=21)

Meta-inferences from combined data sets	**Proposed strategies**
A. Low commitment to reporting requirements. **B.** Shelved unprocessed data due to low data analysis skills. **C.** Routine quality monitoring activities did not appear to be performed according to the standard.	**1.** HIS advocacy to facility leaders to create understanding and make data quality a priority agenda. **2.** Prepare and implement standard operating procedures (SOP) to guide data quality and use.
	3. Role-based on-job data analysis training for technical staff, followed by post-training follow-up and support.
	4. Establish a peer learning network through WhatsApp/ telegram to discuss and improve overall data quality.
D. Substantial indicators compiled below average. **E.** Data from key data sources were significantly inaccurate.	**5.** Encourage leaders to commit to regular follow-up and support for data management tasks at all levels. **6.** Negotiating with the administrative wing on how to internalize and reduce the workload of healthcare workers to improve data quality. **7.** Provide pre and in-service training on HIS for HMIS officers and healthcare workers prior to assignment to the facility to familiarize with the practical environment, as well as yearly refresher training.

F. Data presentation was significantly inadequate at all levels.	**8.** Data visualization training integrated with advocacy to improve skills in how to present data in tables, graphs and different charts at all levels. **9.** Data visualization incentives: Employees will be more motivated to exercise and improve their skills if performance evaluations and other benefits are based on data. **10.** Provide pinboards and/or data display technology for data presentation.
G. The absence of written HMIS plans to improve • Data quality • Healthcare performance • Resource management	**11.** Prepare a separate and written HMIS plan to support data management tasks at all levels
H. There is no data management strategy to guide, facilitate and support HIS implementation.	**12.** Develop and customize a data management strategy to guide, facilitate and encourage HIS implementation at all levels **13.** Establish and implement an HIS governance structure with a legal framework

S*trategies* to strengthen data management: Table 6.7 shows a summary of validated and updated HIS strategies for strengthening data management. Primarily, seven HIS strategies were proposed to improve data management. In the first round, on average, 90 % (n=18.6) of field experts accepted the proposed HIS strategies, with substantial suggestions for modification and the addition of new strategies to improve the strategies. Thus, five of the eight original HIS strategies for improving data management were modified, and six new strategies were proposed, bringing the total to thirteen. Moreover, based on the experts' comments, some of the pre-defined timelines for evaluating strategies, the proposed indicators for measuring success, and the listed action plans were updated as indicated in Annexure 8.

Table 6.8: Strategies to strengthen information use (n=21)

Meta-inferences from combined data sets	Proposed strategies
A. lack of culture for information repackaging. **B.** The importance of information needs has not been recognized, particularly in case teams.	**1.** Advanced training and practical exercises on • information repackaging, • information dissemination. **2.** Creating and recognizing individual and team role models to encourage information repackaging and dissemination at all levels.
	3. Establishing terms of reference to guide information repackaging and disseminating
C. Decisions in healthcare facilities were made without sufficient evidence.	**4.** Develop a cross-cutting incentives system to • encourage information use, • create opportunities for learning and sharing best practices, • and build data ownership. • promote evidence-based decision-making as a means of providing opportunities for staff development. • promote leadership contribution to data management and information use.
D. There is limited information use and a lack of a culture that promotes information use.	**5.** Establishing information use audits, followed by institutional accountability at all levels.
	6. Creating data learning and sharing forums at inter- and intra-healthcare facilities.
	7. Publishing brochures or newsletters linked to key performance at healthcare facilities.
E. Insufficient budget for implementation of HMIS.	**8.** Allocating a minimum of 2 to 5 per cent of the annual budget to strengthening and implementing HIS.
F. HIS written feedback was not provided, particularly at the level of the case teams.	**9.** Establishing feedback delivery, control and tracking logbook/electronic system after a performance review meeting.

***Strategies* to strengthen information use:** Table 6.8 summarises validated and updated HIS strategies for improving information use. Initially, eight HIS strategies were proposed in order to improve the information. On average, 97 % (n=20.3) of field experts accepted the proposed HIS strategies, with one suggestion for adding a new strategy to complement the proposed HIS strategies. As a result, one new strategy was added, bringing the total to nine.

Table 6.9: Validation findings for the improved his strategies in round two (n=21)

SN	HIS strategies validation criteria	Level of agreement or disagreement		
		Disagree/strongly disagree (code=1)	Neutral (code=2)	Agree/ Strongly agree (code=3)
1	**Scope and purpose**: The scope and purpose of the proposed HIS strategies are well-defined.	0% (n=0)	4.8% (n=1)	95.2% (n=20)
2	**Clarity and simplicity:** The proposed HIS strategies are clear and simple.	0% (n=0)	4.5% (n=1)	95.5% (n=20)
3	**Feasibility**: The proposed HIS strategies are relatively cost-effective to implement.	0% (n=0)	19% (n=4)	81.0% (n=17)
4	**Importance:** The proposed HIS strategies are important to improve data management and information use.	0% (n=0)	4.8% (n=1)	95.2% (n=20)
5	**Quality content**: The proposed HIS strategies have sufficient content quality to improve data management and information use.	0% (n=0)	9.5% (n=2)	90.5% (n=19)
6	Overall validation average	0% (n=0)	10% (n=2)	90% (n=19)

In summary, the final HIS strategies were validated in the second round by the same experts who participated in the first round, based on the five key validation criteria, which are shown in Table 6.9, namely scope and purpose, clarity and simplicity, feasibility, importance, and content quality. An average of 90% (n=19) of the experts agreed or strongly agreed on the improved HIS strategies' well-defined scope and purpose, clarity and simplicity, cost-effectiveness, importance, and content quality, all of which would contribute to better data management and information use in healthcare facilities at all levels. Expressly, 95.2% (n=20) of the experts agreed or strongly agreed on the scope and purpose, clarity and simplicity, and importance of the proposed improved HIS strategies for better data management and information use. 90.5% (n=19) of the experts agreed or strongly agreed that the improved HIS strategies had a sufficient content quality to improve data management and information use. Similarly, 81.0% (n=17) of the experts agreed or strongly agreed that the improved HIS strategies are relatively inexpensive or feasible to implement in healthcare facilities. This means that four experts were neutral on the strategies' feasibility but did not provide any explanations.

6.3.7 Summary of the final HIS strategies

Table 6.10A1: strategies to strengthen the level of data quality

Meta-inferences from combined data sets	Proposed strategies	Action plans	Responsible body	Indicator of success	Time
A. Absence of regular mechanisms for data quality monitoring **B.** Lack of well-established HMIS performance and data quality review mechanisms **C.** Data are significantly varied across HMIS data sources	**1.** Develop, implement and measure data quality assurance plan regularly **2.** Strengthening existing performance and data quality review teams at the health centre level **3.** Establish new performance and data quality review teams at the core process and case team levels	• Provide financial support to monitor data quality • Support to ensure consistency and sustainability	• FMOH-PPMED and RHB-PMED	• Assessed indicators score data accuracy verification factor of between 90% and 110% • There is evidence of review teams' roles and performed tasks across the levels	Every quarter
		• processes on a regular basis using a checklist • Compare data values across data sources • Identify and measure errors in data management • Review performance and data quality based on the data quality plan and terms of reference • Cross-check the data collection, recording, compilation, analysis, and documentation • Share written feedback and lesson learning routinely • Monitor systematically the performance review team activity based on the given standard	SCHOH, PHC-MD, CPH, and CTH FMOH-PPMED, RHB-PMED and SCHOH		

	4. Establish HIS accountability within the framework of data governance at all levels	• Set clear HIS performance and data quality expectations • set measurements or a HIS code of conduct • Implement accountability conversations on ✓ repeated commitment failures on data quality and use ✓ HMIS performance and data quality review ✓ Poor data management and data use culture • Monitor individual and team progress	• FMOH-PPMED, RHB-PMED • SCHOH • Governing board of the healthcare facilities	• HIS accountability is established and operated within the framework of data governance at all levels	Every quarter
D. Less satisfaction with HMIS tools	**5.** Revise and improve the HMIS system's interface, both paper and computer-based.	• Review the existing system prior to revision • Define data needs of relevant healthcare units • Determine an appropriate and effective data flow • Involve healthcare providers in the revision, design and development process to address their real concern • Develop the procedures for data processing • Pre-test the new HMIS tools to incorporate feedback • Provide training for data providers and data users • Monitor and evaluate the system • Develop effective feedback mechanisms	• FMOH-PPMED, • RHB-PMED • SCHOH	• The satisfaction level of healthcare providers with HMIS tools ranges from 90% to 100% at healthcare centres, core processes and case teams	Yearly

Note: FMOH-PPMED (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres).

Table 6.11A2: strategies to strengthen the level of data quality

Meta-inferences from combined data sets	Proposed strategies	Action plans	Responsible body	Indicator of success	Time
E. Job descriptions of healthcare providers on data management are not defined	**6.** Develop job descriptions with roles and responsibilities clearly differentiated	Define job descriptions to be applicable at all levels • Perform a job analysis • Identify and include a summary objective of the level • List job duties and responsibilities • Identify the skill sets to perform the job task • Set reporting and supervision plan (who does this employee report to?) • Set performance measurement • Monitor and evaluate implementation regularly • Communicate implementation via written feedback	• FMOH-PPMED • RHB_PMED • SCHOH	• Every position has a clearly defined job description and reporting mechanism	Quarterly
F. Little understanding of the importance of timely documentation and reporting	**7.** Regular on-the-job training, followed by ongoing HIS advocacy to improve • level of understanding on timely documentation and reporting	• Set organizational training objectives • Identify and recruit certified trainers • Select a training approach (video, semi and fully interactive) • Prepare a budget for training • Evaluate training output (pre- and post-training tests)	• FMOH-PPMED RHB-PMED • SCHOH	• Improve the level of understanding of the components of data management ranges from 90%	Quarterly

G. The quality of key data management components did not meet expectations	• the quality of key data management components such as data collection, compilation, analysis, problem identification, and action plan development **8.** Post-training follow-up and HIS experience sharing **9.** Appointing official case team leaders to facilitate and coordinate both data management and clinical tasks	• Perform post-training follow-up, support and experience sharing on ✓ the practice of timely documentation ✓ the implementation of data management components	• PHC-MD, CPH & CTH	to 100% at all levels • Improved knowledge of the importance of quality data • Improved confidence in the use of HMIS tools	
H. low level of knowledge on the importance of quality data **I.** low confidence in the use of HMIS tools	**10.** On-job training focusing on knowledge, skill and practice to boost confidence in the use of HMIS tools **11.** Advocate and design policy to give attention to HIS to assign a highly qualified professional to manage data system at the healthcare centre level	• Monitor and provide written feedback to improve timely reporting and data documentation as per the standard • Assess post-training implementation	• FMOH-PPMED RHB-PMED • SCHOH		
		• Document implementation success, lesson learning and key challenges	• PHC-MD, CPH & CTH		

Note: FMOH-PPMED (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres).

Table 6.12A3: strategies to strengthen the level of data quality

Meta-inferences from combined data sets	Proposed strategies	Action plans	Responsible body	Indicator of success	Time
J. Healthcare facilities do not fully practice the core functions of HMIS to address causes of data inconsistencies	**12.** Updating, maintaining, and using a paper and computer-based data quality monitoring log-book	• Prepare and use standard data quality monitoring logbook at PHC, CP and CT levels	• FMOH-PPMED, RHB_PMED, and SCHOH	• The rate of the functionality of the data quality monitoring logbook to track reporting timeliness, completeness, consistency, and accuracy ranges from 90% to 100% at all levels	Monthly
		• Monitor implementation using a checklist • Provide written feedback for all levels			
		• Prepare action points on the status of the data quality monitoring logbook to improve data consistency in accordance with the standard at all levels	• PHC-MD, CPH & CTH		
	13. HMIS mentorship at • Healthcare centre • Core Process • Case team • Individual	• Prepare mentorship guide • Prepare a standard checklist for HMIS mentorship • Provide budget support for mentoring	• FMOH-PPMED, RHB-PMED, and SCHOH	• There is a mentorship plan and evidence of implementation according to the standard	Monthly
		• Prepare and implement mentorship action points at levels	• SCHOH and RHB-PMED to health centres • PHCMD to core processes		
K. Case teams received	**14.** HIS internal supportive supervision with a	• Prepare a checklist for healthcare facilities, including the three levels • Conduct HIS supervision		• HIS supervision is provided and documented as	Quarterly Monthly Bimonthly

minimum HIS internal support	special focus on lower levels, such as case teams **15.** Building HMIS officers' capacity to provide technical support and guidance to case teams at the facility level in order to improve HIS implementation	• Provide written feedback • Prepare and implement an action plan • Follow-up the implementation of the action plan	• CPH to case teams • CTH to individual	evidence at health centres, core processes, case teams and individual levels	Weekly

Note: FMOH-PPMED (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres).

Table 6.13B1: Strategies to strengthen data management

Meta-inferences from combined data sets	Proposed strategies	Action plans	Responsible body	Indicator of success	Time
A. Low commitment to reporting requirements **B.** Shelved unprocessed data due to low data analysis skills **C.** Routine quality monitoring activities did not appear to be performed according to the standard	1. HIS advocacy to facility leaders to create understanding and improve data quality as a priority agenda 2. Prepare and implement standard operating procedure (SOP) to guide data quality and use	Providing training for technical leaders on how to: • Increase data ownership at all levels • Prioritize data quality gaps with evidence • Lead and decide routinely with evidence • Motivate health workers to use data • Share lessons and feedback on data quality • Assess, monitor and evaluate periodically to verify if major decisions are made based on available data	• FMOH-PPMED • RHB-PMED • SCHOH	• All professionals have advanced understanding of the importance of data quality • The percentage of analysed data according to the standard ranges from 90% to 100%	Quarterly
	3. Role-based on-job data analysis training for technical staff, followed by post-training follow-up and support	Providing training on data analysis and how to: • Understand simple data analysis • Practice and improve data analysis • Organize and analyze data routinely • Justify and interpret analyzed data • Report analyzed data to users			
		• Perform post-training tasks, including ✓ conversation on data quality ✓ compiling and analysing data on a regular basis	• PHC-MD, CPH, and CTH		Monthly
		• Assess post-training implementation • Monitor and provide written feedback on the leadership roles, commitment and ownership of data to improve data quality as per standard at all levels	• FMOH-PPMED • RHB-PMED • SCHOH		

	4. Establish a peer learning network through WhatsApp/ telegram to discuss and improve overall data quality	• Establish peer learning networks to monitor data regularly	• FMOH, RHB and SCHO		Monthly
		• Capacitate peer learning network facilitators at all levels			
		• Monitor peer learning networks on a regular basis • Share lessons of peer learning networks • Provide feedback on peer learning networks	• FMOH, RHB and SCHO		
D. Substantial indicators compiled below average. **E.** Data from key data sources were significantly inaccurate	5. Encourage leaders to commit to regular follow-up and support for data management tasks at all levels 6. Negotiating with the administrative wing on how to internalize and reduce the workload of healthcare workers to improve data quality 7. Provide pre- and in-service training on HIS for HMIS officers and healthcare workers prior to assignment to a facility to familiarize with the practical environment, as well as yearly refresher training	• Perform post-training tasks to improve ✓ the maximum level of data compilation ✓ data accuracy across the data sources by avoiding missed outliers and incorrect data values	• PHC-MD, CPH, and CTH	• The percentage of compiled data across the HMIS data sources ranges from 90% to 100% at healthcare centres, core processes and case teams	Monthly

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Table 6.14B2: Strategies to strengthen data management

Meta-inferences from combined data sets	Proposed strategies	Action points	Responsible body	Indicator of success	Time
A. Data presentation was significantly inadequate at all levels	8. Data visualization training integrated with advocacy to improve skills in how to present data in tables, graphs and different charts at all the levels 9. Data visualization incentives: Employees will be more motivated to exercise and improve their skills if performance evaluations and other benefits are based on data 10. Provide pin boards and/or data display technology for data presentation	• Providing training on data presentation and how to • Analyze presentation audience • Organize data for presentation • Develop and improve data presentation skills easily • Interact with the audience • Transmit the messages with clarity • Engage the audience in the presentation • Interpret and understand the mindsets of the listeners	• FMOH-PPMED, RHB-PMED, SCHOH	• Data are accurately presented according to the standards	Monthly
		• Perform post-training data presentation tasks	• PHC-MD, CPH, and CTH		
		• Assess post-training implementation	• FMOH-PPMED, RHB-PMED, SCHOH		
B. The absence of written HMIS plans to improve • Data quality • Healthcare performance	11. Preparing separate and written HMIS plan to support data management tasks at all levels	• Prepare a national HIS strategic plan	FMOH-PPD	• HMIS data management Plans are in place, implemented,	Quarterly
		• Customize the regional-level HIS plans	RHB-PMED		
		• Customize sub-city level HIS plans	SCHOH		

• Resource management		• Prepare and implement a customized HIS plan at PHC, CP, CT and individual levels to improve data quality, performance and resource management. • Monitor and evaluate the implementation of the HMIS plan • Lead HMIS activities by professionals who have good knowledge of data management and information use	• PHC-MD, CPH, and CTH	and accessible to all users	
C. There is no data management strategy to guide, facilitate and support HIS implementation.	12. Develop and customize data management strategy to guide, facilitate and encourage HIS implementation at all levels 13. Establish and implement HIS governance structure with legal framework	Developing national data management strategies • Determine data requirements (What data is required to achieve the HIS goals, and where will collect it?) • Create sustainable data processes for collecting, preparing, storing, and distributing data • Establish a data governance team at each level of the health institution to manage /govern data effectively • Build a knowledgeable team to use data effectively	• FMOH-PPMED, RHB-PMED, SCHOH	• A data management strategy is developed to guide, facilitate and encourage HIS implementation at all levels • HIS governance with a legal framework is developed and implemented	Quarterly
		• Implement data management strategies at all levels	• PHC-MD, CPH, and CTH		
		• Support, monitor, and evaluate the strategy • Provide written feedback and update on the strategies	FMOH-PPMED, RHB-PMED, SCHOH		

Note: FMOH-PPMED (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres).

Table 6.15C1: Strategies to strengthen information use

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**
A. Lack of culture for information repackaging **B.** The importance of information needs has not been recognized, particularly in case teams	**1.** Advanced training and practical exercise on: • information repackaging • information dissemination **2.** Creating and recognizing individual and team role models to encourage information repackaging and dissemination at all levels	Providing training on information repackaging and how to: • Identify and access important official reports • Identify the target audience • Select and organize key performance indicators • Prepare a first brief • Analyze the brief based on (the target audience, the content of the information and the required budget) • Select message carriers (brochures/newsletters) to attract readers	• FMOH-PPMED , RHB-PMED, SCHOH	• There is consistency and continuity in information repackaging across all levels	Quarterly
		• Repackage information on the message carrier • Design a feedback system to guide repackaging information • Document challenges, lessons learned and best practices	• PHC-MD, CPH, and CTH		
		Providing training on information dissemination and how to: • Define objectives • Define the target audience (who exactly is expected to be reached) • Define key messages (align messages with audience expectations) • Identify dissemination strategy (social media, workshops, seminars, mass media, and web sites)	• FMOH-PPMED • RHB-PMED, • SCHOH	• There is consistency and continuity in information dissemination across all levels	
		• Disseminate information to users • Design a feedback system to review the success of the information dissemination • Document challenges, lessons learned and best practices	• PHC-MD, CPH, and CTH		

	3. Establishing terms of reference to guide information repackaging and disseminating	• Set the purpose, objectives and scope of the term of reference • Put main activities, expected outcome and deliverables • Specify duties and responsibilities • Specify meeting frequency and time • Indicate approval and effective date of the terms of reference • Monitor progress, evaluate the functionality and share feedback on implementation	• FMOH-PPMED, • RHB-PMED, • SCHOH	• Terms and references are used as core guidance	
C. Decisions in healthcare facilities were made without sufficient evidence	**4.** Develop a cross cutting incentives system to: • Encourage information use • Create opportunity for learning and sharing best practices • Build data ownership • Promote evidence-based decision-making as a means of providing opportunities for staff development • Promote leadership contribution to data management and information use	• Develop incentive/motivation strategies at the national level, including: ✓ Create a positive working environment ✓ Recognize good performance and celebrate results or reward excellence in information use ✓ Monitor progress, share lessons and provide feedback regularly ✓ Regular panel discussions with leaders on HIS	• FMOH-PPMED, RHB-PMED, SCHOH	• High-level motivation	Quarterly

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Table 6.16C2: Strategies to strengthen information use

Meta-inferences from combined data sets	Proposed strategies	Action plans	Responsible body	Indicator of success	Time
D. There is limited information use and a lack of a culture that promotes information use	**5.** Establishing information use audits, followed by institutional accountability at all levels	• Use standard information; use the audit manual • Ensure technical, leadership and financial support • Set up base rules or set up auditing criteria • Perform information use audit • Prepare and share written feedback	• FMOH-PPMED, RHB-PMED, SCHOH	• The culture of information use is well established, and there is documented evidence of data-driven decision making	Quarterly
		• Document post-audit feedback • Prepare and implement a post-audit action plan	• PHC-MD, CPH, and CTH		
	6. Creating data learning and sharing forums at inter- and intra-healthcare facilities	• Provide financial and technical support to ensure forums at inter- and intra-healthcare facilities	• FMOH-PPMED, RHB-PMED	• Learning forums are established and performed at inter and intra-healthcare facilities to improve evidence-based decisions at all levels	Quarterly
		• Prepare forum guidance/manual	• FMOH-PPMED, RHB-PMED		
		• Prepare forum terms of reference at all levels	• SCHOH		
		• Take assignments through a post-forum action plan	PHC-MD, CPH, and CTH		
	7. Publishing brochures or newsletters linked to key performance at healthcare facilities	• Provide facility-based financial support to ensure the publication	• FMOH-PPMED, RHB-PMED, SCHOH	• Key performance indicators are published and shared quarterly as brochures or newsletters in healthcare facilities	Quarterly
		• Conduct a need assessment for HMIS implementation • Identify the type of information needs • Set the objective of the brochure/newsletters • Select an appropriate design template • Publish quality brochures/newsletters • Set strategies for how to distribute the brochure to users	• PHC-MD, CPH, and CTH		

		- Set feedback receiving and sending mechanism			
E. Insufficient budget for implementation of HMIS	**8.** Allocating a minimum of 2 to 5 per cent of the annual budget to strengthening and implementing HIS	- Identify HIS implementation gaps - Prioritize key HIS gaps - Conduct root cause analysis - Assign adequate budget from healthcare centre's internal revenue to strengthen HMIS by the governing board of healthcare centres - Use the budget to improve the HIS - Monitor and evaluate the budget contribution	- Governing board of healthcare centre	- 90%-100% sufficient budget is allocated to implement and strengthen HMIS at healthcare centres	Yearly
F. HIS written feedback is not provided, particularly at the level of the case teams	**9.** Establishing feedback delivery, control and tracking logbook/electronic system after the performance review meeting	- The log book should include at least ✓ Feedback type (performance review meeting, HIS supportive supervision, HMIS mentorship and HMIS assessment) ✓ Feedback mode of delivery (soft copy, hard copy or both)	- FMOH-PPMED - RHB-PMED, SCHOH	- Feedback delivery, control and tracking log books/electronic systems are 90%-100% in place and functional at all levels	Monthly, Quarterly, Biannual, Annually
		✓ Post-feedback implementation status (fully implemented/partially implemented/not implemented) - Prepare post-feedback action plans at all levels - Track, evaluate and communicate with staff the entire content of the feedback on a monthly basis	- PHC-MD, CPH, and CTH		

Note: FMOH-PPMED (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres)

6.4 DISCUSSION OF THE STRATEGIES

The purpose of this study was to develop strategies to strengthen health management information systems in Ethiopia.

6.4.1 Rationale for the HIS strategies

The interventions were derived and developed using the combined evidence from two data sets to address identified key gaps at all healthcare system levels. The study examined the gaps in HIS implementation from three perspectives: quality, management, and use. Key findings confirmed that there are poor data quality dimensions (accuracy, completeness and timeliness), a lack of effective practices on data management components (collection, compilation, analysis and presentation) and information use in healthcare facilities, all of which must be addressed with the proposed interventions to meet the HIS expectations on data quality, data management and information use.

6.4.2 Aim of the HIS strategies

The current reviewed and validated HIS strategies have a primary goal of improving HMIS implementation, performance, and functionality so that data quality, data management, and information use standards/expectations are met at health care facilities to support various decisions at all levels of the healthcare system since these decisions ultimately influence healthcare service quality, utilization, and overall performance.

6.4.3 Scope of the HIS strategies

This study was conducted in Addis Ababa's public healthcare facilities. As a result, the scope of these proposed HIS strategies can be applied at healthcare centres, hospitals, and clinics in Addis Ababa city. Also, the researcher believes that these strategies could be applied in other regions with a similar context.

6.4.4 Strategies to strengthen the quality of data

Data quality is the foundation for planning, performance measurement, policy formulation, and clinical decision-making in healthcare facilities (EFMOH 2016:9). In this study, the first research question was concerned with determining the quality of data generated in public healthcare facilities. The key findings revealed that the overall quality of maternal data produced in public healthcare facilities was significantly too poor to support various decision-making processes across all levels. This fact was underscored by additional key data quality gaps, such as a lack of well-established data quality and performance monitoring mechanisms and low levels of satisfaction with HMIS tools, which contribute to data variations across HMIS data sources.

Data from maternal health records were inconsistent; for example, in DHIS2.3, the number of repeat contraceptive users was 25% (n=1854) higher than in the family health register. Similarly, 30% (n=1462) of the ANC fourth visit users were not documented in the tally sheets compared to registers. Also, the number of safe abortion users in the reporting forms was 30% (n=131) lesser than the registers. The data values for antenatal care first-user mothers found in the counselling and testing column of the ANC registers, as well as the data values for skilled birth attendance user mothers found in the immediate postpartum family planning column, were found to be incomplete at a rate of 26% (n=2007) and 95% (n=3254), respectively.

In summary, the average level of data accuracy between registers and tallies for the five indicators, which included contraceptive acceptance rate (CAR), ANC, syphilis testing, Hepatitis testing, and abortion care, was found to be inaccurate/inconsistent for 43% (n= 2007) of the recording mothers. At the same time, the reproductive health records of the ten public healthcare facilities were not completely filled in for approximately 45% (n=18,814) of the recorded mothers with a minimum of one data element. This implies that maternal health data is significantly incomplete and inaccurate.

These findings reflected that data was gathered and documented simply without proper and regular validation processes for data quality, which has a negative impact on tracking the level of actual healthcare performance and quality of healthcare services. This is supported by Nicol et al. (2017:8), who identified data discrepancies (under or over-reporting) across data sources as a result of poor data validation processes in the healthcare system.

In response to the gaps mentioned above, this HIS strategy proposes actions for the development of a data quality assurance plan and the formation of new data review teams at core processes and case teams tasked with improving data quality. These strategies could be effective and successful if the action plans, responsible bodies, timeframes, and success measures outlined in Annexure 3 are consistently considered and applied during the planning, implementation, and measurement processes. Regular data reviews, data quality audits, and data quality control mechanisms, for example, have been shown to improve overall data quality, ultimately leading to improved healthcare performance and service delivery in healthcare facilities (Xiao et al. 2017:3; Measure Evaluation 2018:9). The data quality assurance plan has the potential to manage service effectiveness by prioritizing and ensuring the most efficient use of resources. Also, this plan helps to ensure that data management practices such as collection, compilation, analysis, and presentation are carried out.

Evidence of a lack of well-defined job descriptions for data management tasks was identified in healthcare facilities, appearing to affect key data management components. This also suggests that quality expectations were not met at all levels because healthcare providers did not understand the importance of timely managing, documenting, and reporting. These gaps were exacerbated by a lack of institutional support for HIS, which may have contributed to a significant drop in confidence and motivation in using the core functions of HMIS tools. In addition, these HIS gaps could have impacted monitoring overall data quality and measuring maternal healthcare performance and service quality. Andermann, Pang, Newton, Davis & Panisset (2016:3) also found that due to a lack of data management job descriptions and a lack of understanding of the importance of data quality, healthcare facilities have had difficulty tracking their level of healthcare performance. The confidence in the value of data may be lost, influencing future demand for data in decision-making processes (Homer et al. 2016:8).

The key strategies outlined in Table 6.10A1-Table 6.10A3 assume that if job descriptions on data management tasks are well-defined at all levels, a high level of HIS awareness will be developed, and adequate confidence and competence in managing data quality tasks among healthcare providers will result. In addition, if overall institutional support for HIS tasks is properly and consistently applied, challenges to data quality will be addressed. A recent study in Tanzania found that a lack of defined data management job descriptions, knowledge, and confidence in HMIS tools contributed to data inconsistencies between registers and reporting formats, as well as between the tally sheet and the registers (Anasel et al. 2019:18). A comparable study by the University of Iran showed that, on average, 62% of data elements and indicators were not properly recorded and collected in various data sources in healthcare facilities due to a lack of defined data management job descriptions, and a lack of knowledge and confidence (Asghari et al. 2016:2).

Furthermore, institutional ownership and adequate practice on HIS tasks will be established to facilitate and coordinate data management and clinical tasks if official case team leaders are appointed, which will, in turn, strengthen the capacity of these case team leaders and healthcare providers. In addition, if a paper and computer-based data quality monitoring logbook is updated and used regularly, as well as technical support such as HMIS mentorship and HIS supportive supervision are adequately provided, the data quality will improve. Further, if policymakers assign highly qualified professionals to manage data systems at the healthcare centre and to provide technical support and guidance at all levels, particularly case team levels, this will improve HMIS implementation. Another study found that training on data quality for health workers and program managers, followed by post-training feedback, as well as monthly data reviews and audits by performance review teams, resulted in improvements in data completeness and accuracy from 26% to 64% and 37% to 65%, respectively (Mphatswe, Mate, Bennett, Ngidi, Reddy, Barkerb & Rollinsc 2012:10). A related study also found that regular data quality audits and data review meetings improved routine data quality in healthcare facilities (Shimp, Mohammed, Oot, Kiyemba, Ssekitto & Alminana 2017:3).

6.4.5 Strategies to strengthen data management processes

Data-informed decision-making processes, HIS strategies, and client satisfaction are all strongly linked to the quality of data management practice in healthcare facilities (Dagnew et al. 2018:4). The key findings of this study confirmed that technical, behavioural and organizational determinants have a measurable and significant impact on the components of maternal data management processes. More specifically, the combined findings from the two data sets confirmed that the routine practice on the components of data management is poor in facilities, demonstrated by low commitments to data managing and reporting requirements, a large amount of shelved unprocessed data, poor data quality monitoring practice compared to the standard across levels; and data from key data sources being inaccurate, incomplete, and untimely reported.

According to the Measure Evaluation (2018:17), the consistent practice of data management components is significantly limited and challenging in LMICs, including Ethiopia, due to a lack of expert validated and reviewed HIS strategies such as a written HIS plan, a data management strategy, overall leadership support, and commitment on improving the HIS. As a result, policymakers, managers, and leaders are constantly challenged to find high-quality and well-managed data to make evidence-based decisions regularly. The size, depth and scope of such challenges significantly vary by country, but they are unquestionably larger, deeper, and more complex in developing countries such as Ethiopia (Ndabarora et al. 2014:14-16).

Several pieces of evidence that are consistent with the findings of this study indicate that discussions on the components of data management were not conducted in LMICs in accordance with international standards due to a lack of leadership commitment and overall organizational support at all levels (Akhlaq et al. 2016:6; Measure Evaluation 2018:9). Also, a large number of health workers did not receive adequate technical support and guidance regularly to improve data management tasks, and did not understand the definitions of HMIS indicators and data elements. In Tanzania, data management practices are frequently rushed and ignored, resulting in data backlogs in healthcare facilities (Bhatia et al. 2016:5).

These gaps are wider, deeper and more complex at the lower levels of the healthcare facilities because health workers may not have the competence to recognize or internalize the importance of data management in improving healthcare quality across the levels. In response to these identified gaps, this study proposes HIS strategies, including HIS advocacy and standard operating procedure on data management (SOP) to guide data quality and use. Training and regular post-training follow-up are required to improve continuous improvement practices on data management components.

These strategies will be more effective and productive if performance evaluations, other data-driven benefits and incentives are implemented and established at all levels. In addition to that, if a written data management strategy; HMIS plan; pinboards and/or data display technology, and HIS governance structure with the legal framework are provided to guide and facilitate HIS implementation, it is assumed with reasonable certainty that the practice on the data management processes will be significantly improved to support various decisions at all levels. Several consistent pieces of evidence have documented the effectiveness of the proposed and validated data management strategies in significantly improving the components of data management processes such as collection, compilation, analysis, and presentation. In Cote d'Ivoire, for example, a national supervision guideline, a data management procedure manual, and a national data quality assurance protocol were developed as interventions to improve the components of data management processes (Nutley, Gnassou,Traore, Bosso & Mullen 2014:18). A Botswana study found that effective practice on data management components such as data collection, compilation, presentation, and reporting had all improved in Botswana as a result of regular on-the-job training, mentoring, and advocacy for healthcare personnel (Mpofu, Semo, Grignon, Lebelonyane, Ludick, Matshediso et al 2014:5). If data management training is combined with HIS advocacy to improve skills on how to present data in tables, graphs, and various charts at all levels, followed by data visualization incentives, employees will be more motivated and competitive to exercise and improve their skills in investing in improving data management. Uneke et al. (2017:5) confirmed that overall organizational and leadership support were among the most important interventions for ensuring smooth operation and communication on the components data management processes at all healthcare system levels.

6.4.6 Strategies to strengthen data-driven decision making

The evidence-based decision-making process is a fundamental requirement for a high-performing healthcare system. Public healthcare decision-making is dependent on well-managed, timely reported and high-quality data (Nutley & Reynolds 2013:5-7). This implies that information is essential for managing healthcare delivery and determining whether or not healthcare services are meeting their goals. Current findings confirmed that information use is insufficient, as evidenced by a lack of institutional HIS accountability to support information auditing and information use forums. This means there is a lack of understanding and internalization of the importance of evidence-based decision-making practice. Decisions in healthcare facilities are made without sufficient evidence, particularly in case teams. Healthcare facilities have not developed a culture of repackaging and promoting information. Ugwuogu (2015:6) also argued that healthcare facilities did not repackage, disseminate and use the information to support various decision-making processes. Generally, these findings suggest that a lack of information culture and understanding of the value of information use harms all healthcare decisions at all levels.

In response, the following key HIS strategies are suggested. Advanced training on formation use, in particular, is required to improve understanding of how, when, and why to use healthcare information. This should be aimed at helping healthcare providers and leaders improve their fundamental HIS skills. The training should provide everyone with a thorough understanding of their responsibilities and the knowledge and skills required to carry out their duties with more motivation to improve their overall performance. If advanced training and practical exercises on information repackaging and dissemination are given regularly to a targeted audience, information use practice will significantly improve at all levels. Additionally, there is a chance that individual and team role models in information use will emerge continuously and adequately. A comparable study confirmed that healthcare providers who received information use component training improved their knowledge, skills, confidence, and motivation in using the information to support various decision-making processes at all levels (Sadoughi et al. 2013:6).

Established terms of reference must further support the practice of information use to guide and facilitate information repackaging, dissemination and utilization. A concise and clear term of reference will help the information use processes run smoothly. This term of reference is intended to help keep irrelevant issues from being raised while also adding a level of professional objectivity. Simultaneously, an incentive system should be developed as part of the overall healthcare system strategy. Suppose this strategy is properly implemented, supported and measured. In that case, it will most likely and effectively encourage information use, provide opportunities for learning and sharing best practices, build data ownership, promote evidence-based decision-making to provide opportunities for staff development and encourage leadership contribution to data management and information use. Bhatia et al. (2016:17) stated that the concept and practice of linking data to the individual, team, and institutional performance measures, followed by implementing a comprehensive incentive and motivation system, will promote data use culture at the level of healthcare facilities. Additionally, the commitment of decision-makers, political leaders, and facility leaders to consistently support a data-use culture through the development of individual, team, and institutional models is regarded as an effective intervention in healthcare facilities (Homer & Abdel-Fattah 2014:16).

In Ethiopia, valuable and substantial health data remain unused for various decision-making processes across the levels (Dagnew et al. 2018: 5-8; Yarinbab & Assefa 2018:7; Abera et al. 2016:10). It is, therefore, important to establish and implement information use audits, followed by institutional accountability at all levels. The primary goals of information auditing are to identify and track information use challenges and to spread the best information use practices throughout the healthcare system, especially in healthcare facilities. This could be effective and productive if the following steps are taken: using a standard information use audit manual; ensuring technical, leadership, and financial support; establishing base rules or auditing criteria; preparing and sharing written feedback; documenting post-audit feedback; implementing a post-audit action plan. This will help and encourage establishing data learning and sharing forums at inter- and intra-healthcare facilities.

Quarterly data use workshops, systematic peer reviews, and information use audits with healthcare facilities are effective interventions for providing direct feedback and lessons learned, resulting in regular information use practice and providing an opportunity for healthy competition among healthcare facilities (Lee, Lynch, Hashiguchi, Snow, Herz, Webster, Parkhurst & Erondu 2020:7). At the same time, feedback delivery, control, and tracking a logbook or electronic system after performance review meetings should be established as an important strategy at all levels. The entire content of the strategy should include at least feedback type, feedback mode of delivery, post feedback action points, implementation status, and leadership support at all levels. These strategies will be successful if they are tracked, evaluated, and communicated at all levels on time. The Measure Evaluation (2018:22) indicated that on-site coaching for teams of health professionals who are data users and data producers, as well as regular data reviews across levels, followed by official recognition for change agents or models in scaling up data use practices within the healthcare system, are essential interventions to improve individual commitment, motivation and practice. Mucee et al. (2016:41-44) claimed that in Kenya, adequate budget allocation and written feedback had been found to be effective interventions for information use in healthcare facilities.

CHAPTER SEVEN

SUMMARY, CONTRIBUTIONS, RECOMMENDATIONS, LIMITATIONS AND CONCLUSIONS

7.1 INTRODUCTION

This chapter summarises combined findings, highlighting the study's contributions. It also acknowledges the limitation of the study and draws conclusions. There are key recommendations on how to improve data quality, data management, and information use. The researcher employed a quantitative study design to investigate the effect of technical, organizational and behavioural determinants on the components of data management and information use practices in order to develop HIS strategies to strengthen the HMIS in healthcare facilities.

The study was guided by the following four research questions: What is the quality of maternal data produced in public healthcare centres in Addis Ababa? How do technical, behavioural and organizational factors influence data management processes? What is the extent of health information use in healthcare centres? Which strategies could be used for effective data management and information use in public healthcare centres? Key findings were combined and interpreted to arrive at meta-inferences. Expert-validated strategies were developed to improve data quality, management, and information use.

7.2 SUMMARY OF KEY FINDINGS

7.2.1 Data quality

The key findings from the two phases of the investigation revealed that no consistent or sustainable mechanisms were in place to improve data quality at all levels of healthcare facilities. As a result, data quality accuracy, completeness, and timeliness were found to be poor in all healthcare facilities. These gaps could be linked to healthcare facilities lacking well-established HMIS performance and data quality review teams. Healthcare providers were dissatisfied with HMIS tools, resulting in significant variations in data across HMIS data sources such as registries, tallies, reporting forms, and DHIS2.

The combined findings of this study further showed that healthcare providers at all levels lacked defined job descriptions for managing, improving, and using data and understanding the importance of timely documentation and reporting. The quality of key data management components did not meet expectations. This disparity appeared to have been exacerbated by healthcare providers' lack of confidence in using HMIS tools. As a result, healthcare facilities did not fully implement HMIS-core functions to address data inconsistencies.

7.2.2 Data management

Data management processes were not practised in accordance with the standards at healthcare facilities. In addition, routine quality monitoring activities were not carried out per the standards to improve data management practice; similar findings show that significant indicators were compiled at a lower level than expected across multiple data sources, resulting in inaccurate and incomplete data. Furthermore, there was no data management strategy to guide, facilitate, and support the HIS's implementation in healthcare facilities. Similarly, healthcare facilities lacked written HMIS annual plans that would have assisted them in improving data management, performance, and healthcare resource management. The availability and effective implementation of HMIS annual plans and data management strategies should positively impact overall data management practices. However, in this study, data quality standards were lacking at all levels for data management components such as data collection, compilation, analysis, and presentation practices.

7.2.3 Information use

The key findings revealed that healthcare information was not being used as expected for various decision-making processes to improve maternal healthcare service quality and utilization. This low level of information use was compounded by the lack of a culture of repackaging information and realizing the importance of information, particularly at case team levels. It became evident that these healthcare facilities made decisions without adequate evidence. In general, information use was constrained in scope and quality due to a lack of guiding information-use strategies, insufficient annual budget allocation for HMIS implementation, and a lack of HIS regular supervision and little or no written feedback being given across levels, particularly at the case team level.

7.3 CONTRIBUTIONS OF THE STUDY

A research “contribution” is defined by Creswell & Creswell (2018:281) as the relevance of the research or the significance of the study findings for various audiences who may benefit from reading or implementing the findings and recommendations. The main driving and motivating factors to conduct this study was the fact that data quality, data management, and information use practices in the healthcare sector of Ethiopia were perceived to be poor, limited in scope, and overall unsatisfactory, with a lack of validated interventions, particularly at the level of public healthcare centres and below (Trant 2015:7-9).

This study was therefore designed with the assumption that technical, organizational and behavioural factors would have a measurable impact on maternal health data at the facility and below. Hence, the PRISM theoretical framework was selected, conceptualized and adapted to guide and frame the literature review, synthesis, data collection, integration and interpretation of results from phase one and two data sets, and conclusions were drawn. The focus was on the relationship between determinant and outcome variables, calculating the outcome for data quality, data management, and information use practices, and using study objectives to frame the processes further. This means that the impact of technical, organizational, and behavioural factors related to the HIS implementations and HMIS data sources, including maternal healthcare data, was not sufficiently identified and adequately known by merely combining data sets like a retrospective document review and a quantitative survey. Key challenges were not widely assessed or adequately addressed using expert-validated strategies. For those reasons, most decisions and guiding interventions were made without concrete evidence, resulting in the failure of many healthcare service programs at all levels, including maternal healthcare programs and activities (Chen et al. 12014:15-17).

Naturally, the healthcare system is a data and information-intensive industry that generates massive amounts of data from various health service units daily, including maternal healthcare data. This implied that healthcare data needed to be managed optimally to improve the quality of care at the point of delivery of healthcare services, including maternal health services. It implies that access to accurate, consistent, timely, and complete data is required for safe healthcare services. More importantly, data quality, data management and information use are among the top priorities and transformation agendas of the Ethiopian government and its development partners to strengthen and improve the HIS to achieve the health sector's strategic objectives. Among those objectives is maternal healthcare, even though the HIS implementation has lagged behind expectations.

In response to these identified and combined key challenges, the HMIS has been assumed and considered to be a highly essential component and an effective vehicle for the successful implementation of the HIS via validated and comprehensive strategies to make health data and information available, accessible, and usable for decision-making processes. This ultimately affects the quality and equity of healthcare delivery at all levels of care, including maternal healthcare services (EFMOH 2016:16).

When maternal health data are of sufficient quality, they can be used at the facility level for effective clinical management, at the sub-city level to assess how well healthcare facilities are performing in comparison to the standard, and at the regional and national levels to review and update policies and resource allocation. High-quality maternal data can help produce reliable estimates of service delivery coverage and effective utilization at all healthcare system levels, allowing communities to determine whether they are accessing and receiving maternal healthcare services. Chen et al. (2014:6) support the significance of data quality in providing credible evidence of the performance of the healthcare program. This, in turn, can assist policy makers in monitoring, evaluating, planning, and improving health services.

In general, this study made significant contributions to three critical areas of HIS: determining maternal health data based on the three dimensions of completeness, accuracy, and timeliness; determining the effectiveness of the components of data management processes currently used in healthcare facilities; and whether a use is made of this information for evidence-based decisions in managing maternal healthcare activities. The investigation found that the dimensions of data quality, the components of data management processes, and information use practices were limited and unsatisfactory due to a complex combination of technical, organizational and behavioural factors.

Data quality: The value of the data relating to the majority of maternal healthcare indicators which were investigated (such as new and repeat family planning users, antenatal care first and fourth visits, total syphilis and hepatitis testing, safe and post-abortion care users, and early postnatal care visits), proved to be inconsistent and incomplete across all HMIS data sources throughout all healthcare facilities in the different levels. This was largely due to a lack of regular mechanisms for data quality monitoring tasks and a lack of well-established HMIS performance and data quality monitoring systems. These findings resonate with those reported by Nutley & Reynolds (2013:7), who confirmed that in Africa, healthcare data are frequently of poor quality and not adequately used in strategic and annual planning, healthcare advocacy and program implementation. The study found that organizational factors, behavioural factors, and technical factors such as poor HMIS design contribute to low satisfaction in healthcare providers, hampering their active involvement.

The current study may contribute to and improve the level of understanding of data quality in the following areas: First, the extent of data quality across a specific period; the level of data quality based on facility location; and the level of data variations across various HMIS data sources.

Data accuracy: The document review provided additional knowledge on the extent of variations and similarities in the level of accuracy either from one of the single data sources or across the four HMIS tools on average (registers, tallies, reporting forms, and DHIS2.3). As a result, this study can add to the existing body of knowledge about data quality in the following ways: specific data accuracy information at the data element or indicator level, helping to understand the minimum and maximum levels of data variations across the four data sources, and the average magnitude of data variations between and across data sources.

In summary, this study confirmed that the three dimensions of data quality, accuracy, completeness, and timeliness, were lower than expected in all facilities. The data value in the maternal health registers did not match the tally sheets in 43% (n=2007) of the documented cases. The data values in the skilled birth attendance, live birth, and early postnatal care visit indicators did not match the DHIS2 data values in 48% (n=1559) of the recorded cases. Similarly, the reproductive health records were not fully completed in all registers, lacking at least one data element in about 45% (n=18, 814) of the recorded cases. Finally, 60% (n=6) of the healthcare centres did not submit service reports to the next level timeously through the DHIS2 database. A similar finding was made by Anasel et al. (2019:18), who found that data was not reported completely, timeously and consistently in Tanzanian healthcare facilities. Adejumo (2017:38) provided evidence consistent with the current study that the data values of the reporting forms from Nigerian healthcare facilities reflected untimely, incomplete and inconsistent data across all sources.

Data management: In this study, eight indicators/items were used to calculate a single mean score of data management practice across the different levels (Table 3.10). As a result, in general, the routine practice on the components of data management (including data collection, compilation, analysis and presentation) was found to be poor at all levels. The identified level-based gaps could be attributed to organizational factors such as low leadership commitment and overall support, resulting in a large amount of unprocessed data and inadequate data presentation practices, as well as a lack of a written HMIS plan and a data management strategy to guide, facilitate, and support HIS implementation at all levels. Most healthcare providers did not receive technical assistance, resulting in a lack of understanding of the details of the data management tasks, particularly at case team levels. These findings are supported by Akhlaq et al. (2016:6) and the Measure Evaluation (2018:9), who argued that regular discussions on data management components were not conducted in low- and middle-income countries in accordance with standards due to a lack of leadership commitment, overall and technical support. Bhatia et al. (2016:5) and Nicol et al. (2017:10) argued that data management practices are frequently rushed in Tanzania and South Africa, respectively, resulting in data backlogs in healthcare facilities due to a lack of confidence, dissatisfaction, and poor understanding of HMIS tools.

Information use: In this study, twelve study variables were used to calculate the single mean score of information use across the levels, as it was indicated in Table 3.14. The current study confirmed that health information from health facilities was not being used adequately and consistently in various decision-making processes. Moreover, these facts are exacerbated by a lack of institutional accountability of support for a culture of information repackaging, information dissemination, and information auditing and a lack of understanding and internalizing the importance of evidence-based decision-making practice, leading to decisions in healthcare facilities being made without adequate evidence. Similar to these findings, it was established that in Kenya, poor leadership, weak accountability, and complex HIS processes all contributed to a low priority for data quality and limited use of health information in decision-making (Barasa, Cleary, English & Molyneux 2016:11). Wickremasinghe, Hashmi, Schellenberg and Avan (2016:5) also found that information is not always the driving force behind policy and program decisions in low- and middle-income countries and that data can be overshadowed by personal interests, political pressure, and competing agendas in healthcare facilities. This suggests that healthcare providers collect a large amount of data daily without effectively using the information to guide local actions, decisions, and interventions in the locations where the data were collected (Cai & Zhu 2015:4-6).

This study contributed by providing multiple shreds of evidence, such as the magnitude and influencing factors of data management and information use practices at three distinct levels, namely healthcare centres, core processes, and case teams, which had not previously been studied or explored in such depth by levels as well as meta-inference combined findings from two separate and linked phases. This can potentially increase in-depth understanding for a wide range of users.

Furthermore, this study provided facts supported by advanced statistical procedures. These analyses aided in determining the combined effects of multiple factors on the outcome variables. It included the strength of an independent variable's influence on the outcome variable, the direction of the effect, and the statistical level of significance in light of socio-demographic, technical, organizational, and behavioural factors. Those findings can aid in understanding the impact of a single factor or a combination of factors to prioritize and design evidence-based interventions. The practice of data management and information use has been statistically linked to a combination of multiple behavioural factors such as knowledge, confidence, competency and motivation.

Key findings of this study show the degree of correlation between the technical design of HMIS tools and the likelihood of effective engagement with data management processes to ensure a high level of data quality and appropriate information use. This may benefit the field by providing new knowledge about how poor HMIS system design is likely to harm the data management components at all levels due to low satisfaction among healthcare providers with the current design. This study also contributed by investigating the strength of the relationship between optimal data management and information use practices and behavioural determinants such as adequate knowledge, a high level of confidence, motivation, and competence at all levels. Additionally, the degree of effects of organizational determinants on the achievement of HMIS tasks was highlighted. This brings to light the extent to which healthcare providers' involvement determines the quality and continuity of data management and information use practices.

This study confirmed that healthcare providers did not participate actively in HIS tasks to improve data quality dimensions, data management, and information use due to a lack of knowledge, skills, confidence, and motivation. This may add to the body of knowledge about the extent to which healthcare providers participate in HIS tasks and why the identified challenges persisted at all levels, particularly at the lower levels. More specifically, the main findings of the current study have the potential to significantly encourage and motivate healthcare providers to take responsibility for improving the implementation of the HIS at all levels.

The current findings will assist administrative leaders at sub-city, regional and national levels in better understanding the practical and theoretical challenges of HIS implementation, allowing them to apply these evidence-based facts to address these challenges using currently developed HIS strategies.

Taking everything into account the HIS strategies along with the documented action plans that involve all responsible bodies across levels and success indicators with specific timeframes for HIS evaluation may contribute significantly to improving the HMIS at all healthcare system levels. Levels of data quality and optimal information use can be significantly improved if these validated interventions are accepted, properly implemented, and rigorously measured. Additionally, high data quality may significantly impact the quality of healthcare services, including maternal healthcare, to optimise service utilization and maximise client satisfaction.

The findings are likely to inspire the health sector to reconsider and question why, despite a large number of resources allocated from various sources with high priority given at the local, national, and international levels to meet data quality expectations, high-quality maternal healthcare data have not been achieved and continue to be poor.

Overall, if the proposed data quality interventions are aligned with the available interventions and applied, healthcare facilities will most likely be able to generate quality data and build strong healthcare systems, particularly maternal healthcare data/information.

7.4 RECOMMENDATIONS

Recommendations are the most important aspect of research, as they propose specific interventions or strategies to address the issues and constraints identified in the study.

7.4.1 Data quality

Core and combined findings of the current study indicate that the dimensions of data quality, including accuracy, completeness and timelines are poor at all levels. Therefore, the following expert-validated strategies are recommended to address all the identified key and combined data quality gaps.

Healthcare facilities (healthcare centres, core processes and case teams):

- The data quality assurance plan developed and validated by experts in this study should be implemented and measured quarterly in order to achieve an indicator score data accuracy verification factor of 90% to 100% in healthcare facilities.
- The existing performance and data quality review teams at the health centre should be strengthened, and new performance and data quality review teams at the core process and case team levels should be established and empowered to quarterly measure evidence of review team roles and performed tasks across the levels.
- Quarterly, the level of success in the understanding and regular practice of healthcare providers on the components of data management, such as data collection, compilation, analysis, problem identification, and action plan development, should be measured and monitored to see if it has reached 90% to 100% at all levels. At the same time, this HIS

strategy should be followed by post-training follow-up and HIS experience sharing to meet expectations.

- Internal HMIS mentorship should occur monthly in healthcare facilities and at lower levels to improve data quality based on expectations. Evidence of success should be tracked in light of the availability of the HMIS mentorship plan, as well as evidence of standard mentorship implementation that results in high data quality and information use at all levels.
- It is recommended that health facilities conduct HIS internal supportive supervision, with a particular emphasis on lower levels such as case teams. The implementation of HIS supervision should be documented and communicated as evidence at health centres, core processes, case teams, and individual levels.

Administrative levels (Federal Ministry of Health, Regional Health Bureau, and Sub-city Health Office):

- The implementation of HIS should be monitored and measured quarterly to determine its establishment and functionality within the framework of data governance at all levels.
- To address data quality gaps, job descriptions that clearly distinguish the roles and responsibilities of leaders and healthcare workers are highly recommended.
- Developing the capacity of HMIS officers to regularly provide technical support and guidance to case teams at the facility level is highly valued for improving HIS implementation.

7.4.2 Data management

Healthcare facilities (healthcare centres, core processes and case teams):

- The effectiveness of these strategies should be monitored and measured quarterly to ensure that all professionals understand the significance of improving data quality and are putting it into practice. In addition, the percentage of analysed data that meets the standard should be measured and should be within the range of 90% to 100%.
- The use of pin boards and or data display technology for data presentation will promote healthy competition and data use culture at all levels. The successful practice of data

presentation should be monitored, measured and documented monthly, with an emphasis on evaluating accurate and consistent data presentation in accordance with standards at all levels.

Administrative levels (Federal Ministry of Health, Regional Health Bureau, and Sub-city Health Office):

- Basic training combined with advocacy to improve data management practices, particularly skills in presenting data using tables and various charts at all levels.
- A data management strategy is suggested to be developed and implemented to guide, facilitate, and encourage HIS implementation at all levels.

7.4.3 Information use

Healthcare facilities (healthcare centres, core processes and case teams):

- Advanced training and practical exercises on information repackaging and dissemination are strongly recommended. Simultaneously, the success of such strategies/interventions should be tracked, measured and documented quarterly to ensure consistency and continuity of information repackaging and dissemination across all levels.
- Establishing individual and team role models in data management and information use tasks at healthcare facilities is preferable, as this will encourage healthy competition both within and between healthcare facilities, resulting in an improved information use culture.
- The components of information use, such as information repackaging and dissemination, should be guided by terms of reference at all levels.
- Creating data learning and sharing forums at inter- and intra-healthcare facilities, followed by the publication of a brochure or newsletter linked to performance at healthcare facilities.

Administrative levels (Federal Ministry of Health, Regional Health Bureau, and Sub-city Health Office):

- Key findings of this study indicate that decisions in healthcare facilities are made without sufficient evidence. To address this gap, it is more important to develop a cross-cutting incentive system that will undoubtedly encourage data use, provide opportunities for learning and sharing best practices, increase data ownership, and promote evidence-based decision-making.

- Information use audits and institutional accountability will improve information use and accountability at all levels.

Further research on the following aspects is recommended

- Considering that the current study's document review phase focused solely on maternal healthcare records, other HIS documents from public healthcare facilities should be further studied to produce a comprehensive view of non-maternal health records, aiming to strengthen the current study.
- Finally, the proposed expert-evaluated HIS interventions should be piloted and evaluated as an interventional study for their effects on improving data quality, data management, and information use in healthcare facilities.

7.5 LIMITATIONS OF THE STUDY

The following limitations of the study are noted and acknowledged: the document review in the study was limited to maternal health documents such as registers, tallies, and reporting formats. Maternal health documents were used because they are more relevant and receive more attention and support on all levels, from the national to the healthcare facilities. This study was also limited to public healthcare facilities in Addis Ababa. Private health facilities' HIS records were not included.

To overcome the constraints mentioned above and to ensure external and internal validity, a representative and adequate sample size (n=590) was used to ensure and support generalization.

Finally, a multidimensional phase-to-phase study approach was used to improve the authenticity of findings.

7.6 CONCLUSIONS

The PRISM theoretical framework guided the overall research processes in this study. The first research question was: What is the quality of maternal data produced in public health centres? The study identified several factors that impede the quality and use of routine healthcare data in decision-making. Three dimensions of data quality, accuracy, completeness, and timeliness, were found to be poor at all levels of healthcare facilities. This means that data values were found to be inconsistent or inaccurate across the HMIS data sources, such as registers, tallies, reporting forms and DHIS2. The reproductive health records of the public health system were found to be incomplete, with at least one data element missing in about 45% (n=18, 814) of the recorded mothers. Moreover, 60% (n=6) of health facilities failed to document expected and actually reported data elements in the data quality monitoring logbook. The magnitude of health problems was not prioritized in 60% (n=6) of public health centres. In 90% (n=9) of the public healthcare centres, action plans were not prepared. 70% of the reports sent from case teams did not document the date of submission by healthcare centres in the data quality monitoring logbook, and these public health centres did not provide written feedback to their respective case teams on the timeliness of the report every month. Also, 60% (n=6) of the healthcare centres did not submit service reports to the next level on a timely basis through the DHIS2 database.

The identified practical gaps were found to be more pronounced at the lowest level of Ethiopia's healthcare system, failing to maintain and meet the country's HIS expectations effectively. Technical, organizational, and behavioural determinants were responsible for poor data quality, ineffective data management practices, and insignificant use of information across healthcare facilities.

Low data quality can be attributed to a variety of root causes and is aggravated when healthcare workers are not incentivized or motivated to collect data accurately. Data quality practices are also negatively influenced by leaders who do not value and incentivize quality data for decision-making. Poor data result from a lack of organizational support to define roles and responsibilities, promote procedures for data quality improvement, and design a health information system that makes data management components simple, effective and useful. In general, the quality of data produced in public healthcare facilities, including in maternal healthcare services, is extremely poor. Data management and information use practices are inadequate and deeply unsatisfactory at all levels. This resulted in key data sources, including those for maternal healthcare, generating a large amount of low-quality data left unprocessed or shelved, thus not adding any measurable value to the healthcare system at any level. This negatively impacts monitoring and measuring service quality in healthcare facilities, making decisions about the performance and service quality of healthcare facilities, particularly maternal healthcare services, almost impossible.

The combined findings from the two data sets revealed that data management practices were poor at all levels, linked to a low commitment to reporting requirements and low data analysis skills, resulting in unprocessed data being shelved. Routine data management activities such as data collection did not appear to be performed according to the standard, and substantial indicators were compiled or collated below average. Data presentations were inadequate in terms of coverage and quality at all levels. The absence of a data management strategy and written HMIS plans has contributed to poor data management components, low healthcare performance and utilization, and mismanagement of healthcare resources at all levels. These gaps are even broader, deeper, and more complex at the lower levels, such as case teams.

Discussions on data management components were not conducted adequately and regularly according to set standards due to a lack of leadership commitment, the absence of established HIS-related accountability, a lack of overall technical and organizational support, or insufficient understanding of the detailed definitions of HMIS indicators and data elements, as well as poor management of various HMIS data sources.

Well-managed, timely-reported, and high-quality data are essential for decision-making at all levels of public healthcare. However, the investigation found that health information from healthcare centres was not being used adequately in decision-making processes at all levels of healthcare facilities. There is a lack of culture for information repackaging and significant and measurable variations in different data sources. This negatively impacts information use and causes a lack of understanding of the importance of information use at the leadership and healthcare worker levels, particularly at the level of case teams. Overall, the findings show that healthcare facilities may have made routine decisions without considering the impact of data on various healthcare programs, policies, healthcare service quality and utilization, and effective resource management at all levels. Healthcare data were not used routinely to revise various implementation strategies, adapt annual or strategic plans, monitor day-to-day operations, or respond to high-priority healthcare needs at all levels.

These gaps also suggested that a lack of control over the healthcare system and accountability in decision-making may discourage future data demand. Healthcare workers would simply collect data daily without using it to guide local actions, prioritize healthcare decisions, and implement effective interventions in the areas where the data was collected.

The detected gaps also imply that healthcare facilities do not establish and implement information use audits and institutional accountability at all levels. There are no data learning and sharing forums at inter- and intra-healthcare facilities and no practice of publishing brochures or newsletters linked to healthcare facilities' performance. In addition, this study found that there was no incentive system in place to encourage information use, create opportunities for learning and sharing best practices, build data ownership, or promote evidence-based decision-making to provide opportunities for staff development.

These facts imply that data was not institutionally incentivized and internalized by linking individual and team performance measures to improve information use through healthy competition at all levels. This is a strong indication that the commitment of decision-makers, political leaders, and individual healthcare workers to support data use in healthcare facilities regularly was ineffective or ignored, a matter which was exacerbated by a lack of institutional accountability; insufficient budget; and a poor culture in written feedback provision at all levels.

In conclusion, combined key findings indicated that a large amount of data was not managed adequately across data management processes, lacked data quality, and was rarely used at all levels. As a whole, the importance of data quality, data management and information needs was not recognized at all levels, particularly at case teams, leading to poor data processing practices. The proposed strategies may be beneficial in strengthening data management processes.

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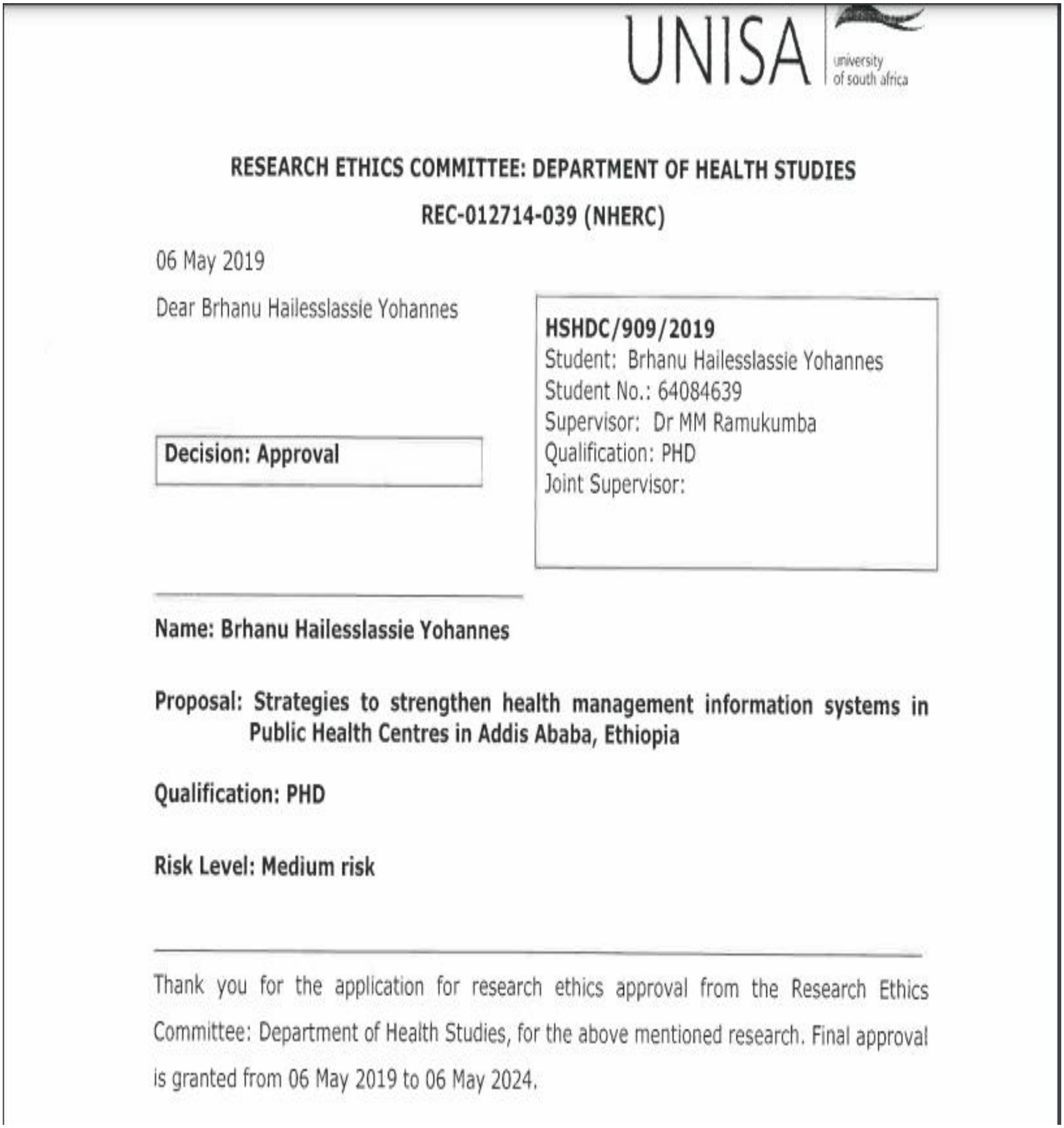
Annex-1: Research ethical certificate from department of health studies



UNISA university of south africa

RESEARCH ETHICS COMMITTEE: DEPARTMENT OF HEALTH STUDIES

REC-012714-039 (NHERC)

06 May 2019

Dear Brhanu Hailesslassie Yohannes

HSHDC/909/2019
Student: Brhanu Hailesslassie Yohannes
Student No.: 64084639
Supervisor: Dr MM Ramukumba
Qualification: PHD
Joint Supervisor:

Decision: Approval

Name: Brhanu Hailesslassie Yohannes

Proposal: Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia

Qualification: PHD

Risk Level: Medium risk

Thank you for the application for research ethics approval from the Research Ethics Committee: Department of Health Studies, for the above mentioned research. Final approval is granted from 06 May 2019 to 06 May 2024.

Annex-2: Research Ethical letter from UNISA Ethiopian learning center

UNISA
university of south africa

08 OCTOBER, 2019

UNISA-ET/KA/ST/29/08-10-19

Addis Ababa Health Bureau
Public Health Research and Emergency Management Directorate
Addis Ababa

Dear Madam/Sir,

The University of South Africa (UNISA) extends warm greetings. By this letter, we want to confirm that Mr. Brhanu HaileSilassie Yohannes (student number 64084639) is a PhD student in the Department of Health Studies at UNISA. Currently, he is at the stage of data collection on his doctoral research entitled "***Strategies to strengthen health management information systems in Public Health centers in Addis Ababa, Ethiopia***".

This is therefore to kindly request you to assist the student in any way that you can. Attached, please find the ethical clearance that he has secured from the Department of Health Studies.We would like to thank you in advance for all the assistance that you will provide to the student.

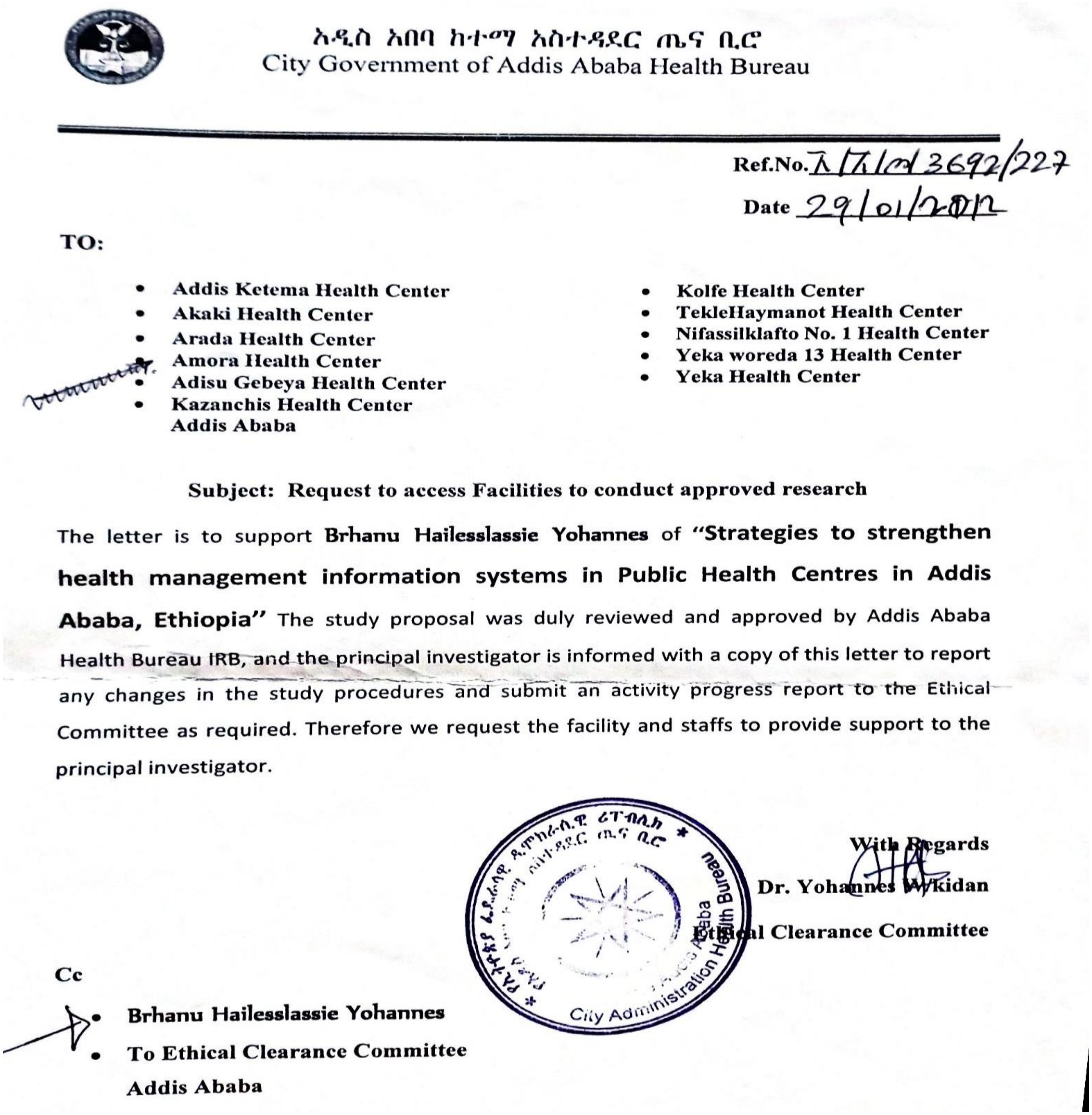
Sincerely,

Dr. Tsige GebreMeskel Aberra
Director

UNISA REGIONAL LEARNING CENTRE
PO BOX 13836 ADDIS ABABA ETHIOPIA
TEL +251-114-350141
+251-114-350078
FAX +251-114-351243
MOBILE +251-912-191483

University of South Africa
Regional Learning Center
P.O. Box: 13836, Addis Ababa, Ethiopia
Telephone: +251 11 435 2244 / +251 11 435 0078
Facsimile: +251 11 435 1242/ 43/ 44
Mobile: +251 912 19 1483

Annex-3: Ethical clearnace from health bureau to conduct approved research



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City Government of Addis Ababa Health Bureau

Ref.No. ኢ/ሊ/ጠ/3692/227
Date 29/01/2012

TO:

- **Addis Ketema Health Center**
- **Akaki Health Center**
- **Arada Health Center**
- **Amora Health Center**
- **Adisu Gebeya Health Center**
- **Kazanchis Health Center**
- **Kolfe Health Center**
- **TekleHaymanot Health Center**
- **Nifassilklafto No. 1 Health Center**
- **Yeka woreda 13 Health Center**
- **Yeka Health Center**

Addis Ababa

Subject: Request to access Facilities to conduct approved research

The letter is to support **Brhanu Hailesslassie Yohannes** of **"Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia"** The study proposal was duly reviewed and approved by Addis Ababa Health Bureau IRB, and the principal investigator is informed with a copy of this letter to report any changes in the study procedures and submit an activity progress report to the Ethical Committee as required. Therefore we request the facility and staffs to provide support to the principal investigator.

With Regards
Dr. Yohannes W/kidan
Ethical Clearance Committee

Cc

- **Brhanu Hailesslassie Yohannes**
- **To Ethical Clearance Committee**

Addis Ababa

Annex-4: Checklist to review maternal health documents in health centres in Addis Ababa, Ethiopia

Section-0: General Information

I. Health centre code: ___________________ II. Date of document review (dd/mm/yyyy): _____/_____/________

1.Accuracy is defined as if all the value of data elements and indicators at registers, tally sheets, reporting forms and data base are found uniform and identical in all the six consecutive reporting months (from April 2019 to September 2019)

Section-A: Standard checklists to review data accuracy

Health center code: ……… Date of review………… **Review start.........................Review end...................**			**Consistency of reported data with original records/registers**																											
SN	***Maternal Health Indicators and data elements***		**Registers**							**Tally sheets**							**Reporting forms**							**DHIS2**						
			Apr 2019	**May 2019**	**Jun 2019**	**Jul 2019**	**Aug 2019**	**Sep 2019**	**Total reported**	**Apr 2019**	**May 2019**	**Jun 2019**	**Jul 2019**	**Aug 2019**	**Sep 2019**	**Total reported**	**Apr 2019**	**May 2019**	**Jun 2019**	**Jul 2019**	**Aug 2019**	**Sep 2019**	**Total reported**	**Apr 2019**	**May 2019**	**Jun 2019**	**Jul 2019**	**Aug 2019**	**Sep 2019**	**Total reported**
QDA1	**Family planning visit**																													
	QDA11	**New contraceptive users by age**																												
	QDA12	**Repeat contraceptive users by age**																												
QDA2	**ANC 1st visit**																													
QDA3	**ANC 4th visit**																													
QDA4	**syphilis test**																													
	QDA41	Total tested																												
	QDA42	Test result-Reactive																												
	QDA43	Test Result- Non-Reactive																												
QDA5	**Hepatitis test**																													
	QDA51	Total tested																												
	QDA52	Test result-Reactive																												
	QDA53	Test Result- Non-Reactive																												
QDA6	**Skilled Birth Attendance (SBA)**																													
QDA7	live birth																													
QDA8	Early postnatal Care (EPNC) visit																													
QDA9	Abortion care services																													
	QDA91	safe abortion care performed																												
	QDA92	Post abortion care performed																												
QDA10	Maternal deaths																													

2. **Content (data elements & indicators) completeness,** in this study, is defined as the maternal health data elements and indicators are filled completely in the maternal health registers during the last consecutive six months from April 2019 to September 2019.

Section-B-1: Standard checklists to review content completeness of register

SN	Indicators and data elements			Responses						
				April 2019	May 2019	June 2019	July 2019	August 2019	September 2019	Total reported
QCC1	**Family planning visit**									
	QCC11	Are the **two** data elements completely filled under counseling? Namely: 1. HIV Test performed 2. Target population code filled	Total cases documented in FP-registers							
			Total cases completely filled							
			Total cases not completely filled at least with one data element							
QCC2	**ANC 1st visit**									
	QCC21	Are the six data elements completely filled under personal information? Namely: 1. Serial number 2. Name of the client 3. Medical record number 4. Age 5. Last Menstruation Period (DD/MM/YY) 6. Expected data of delivery (DD/MM/YY)	Total cases documented in ANC registers							
			Total cases completely filled							
			Total cases not completely filled at least with one data element							
	QCC22	Are the two data elements completely filled under HIV Assessment? Namely: HIV Test accepted Target population code filled	Total cases documented in ANC registers							
			Number of data elements completely filled							
			Number of data elements not filled completely							
	QCC23	Are the four data elements completely filled under partner Test? Namely: Infant feeding Identified and counselled on danger signs Family planning methods Maternal Nutrition	Total cases documented in ANC registers							
			Total cases completely filled							
			Total cases not completely filled at least with one data element							

2.Content (data elements & indicators) completeness, in this study, is defined as the maternal health data elements and indicators are filled completely in the maternal health registers during the last consecutive six months from April 2019 to September 2019.

Section-B-1: Standard checklists to review content completeness of registers

				Responses						
				April 2019	May 2019	June 2019	July 2019	August 2019	September 2019	Total reported
QCC3	**Skilled Birth Attendance**									
	QCC31	Is the **one** data element completely filled under immediate postpartum family planning (IPPFP)? Namely: 1. Type of contraceptive acceptance filled (New or repeat)	Total cases documented in delivery registers							
			Total cases completely filled							
			Total cases not completely filled at least with one data element							
QCC4	**Early postnatal Care visit**									
	QCC41	Are the **two** data elements completely filled in under HIV Assessment? 1. HIV Test performed 2. Target population code filled	Total cases documented in postnatal care register							
			Total cases completely filled							
			Total cases not completely filled at least with one data element							

3. **Recording and reporting tool completeness,** in this study, is defined as all the expected recording and reporting tools including registers, tally sheets, and reporting forms of the maternal health services are completed during the six months from April 2019 to September 2019.
4. **Timeliness** is defined as if all the expected report types from case teams and public health centres are checking and reporting to their next levels during the six months (from April 2019 to September 2019) consecutively within a due date.

Annex-C: Documentation of data elements, implementation of data quality improving activities, and timeliness from April to September 2019

Health center code: …………..Date of review……………… Review start: ....Review end.......................			Responses						
			April 2019 Y=1; N=0	May 2019 Y=1; N=0	June 2019 Y=1; N=0	July 2019 Y=1; N=0	August 2019 Y=1; N=0	September 2019 Y=1; N=0	Total Y=1; N=0
Code	Documentation of data elements at the data quality monitoring logbook								
QC1	Are number of expected reportable data element from case team documented in the data quality monitoring logbook (check logbook)?								
QC2	Are number of completed reportable data element from case team documented in the data quality monitoring logbook (check logbook)?								
QC3	The status of intra-data element inconsistency								
	QC31	Are the data elements with inconsistency documented at the intra-data element inconsistency check sheet?							
	QC32	Are possible causes of intra-data element inconsistency documented in the performance monitoring logbook?							
	QC33	Are actions taken for intra-data element inconsistency documented in the performance monitoring logbook?							
Code	Implementation status of different data quality improving activities								
QC4	Is Lot Quality Assurance Sampling (LQAS) performed for service report (check logbook)?								
QC5	Is Lot Quality Assurance Sampling (LQAS) performed for outpatient department (OPD) report (check logbook)?								
QC6	Is Lot Quality Assurance Sampling (LQAS) performed for inpatient department (IPD) report (check logbook)?								
QC7	Is discussion on data quality performed (check logbook)?								
QC8	Are health problems prioritized by the performance monitoring team (PMT) based on the following criteria								
	QC81	Magnitude of the problem							
	QC82	Community concern of the problem							
	QC83	Seriousness of the problem							
	QC84	feasibility of interventions							
QC9	Is action plan prepared to solve prioritized problems? (check logbook)								
QC10	Was Routine Data Quality Assessment (RDQA) implemented by the health center to monitor data quality (check document)?								
Code	Timeliness (expected report types are checked and reported to next levels within a due date)								
QT1	Is report received date from case teams documented in the data quality monitoring logbook (check logbook)?								
QT2	Is written feedback about the report timeliness provided from the HMIS unit for case teams? (check written feedback)								
QT3	Has the Health Center been reporting its service reports to the next level on a timely basis? (Check timeliness on DHIS2)								

Annex-5: Questionnaire/survey on strategies to strengthen HMIS in public health centres in Addis Ababa, Ethiopia, English version

Section-0: General Information

II. Respondent code: ______**Health centre code: _______: Date of data collection (dd/mm/yyyy): __/__/___**

Section-A: BACKGROUND INFORMATION

Please complete the following items by filling or circling the appropriate response. Please give your most honest response to each question.

Section-A-1: BACKGROUND INFORMATION

Code	Socio-demographic Determinants (SD)	Choice/options	Reponses
SD1	Age	Add years	__________
SD2	Sex	Female	1
		Male	0
SD3	Years of experience in present position	Add year	__________
SD4	Position/ responsibility	Health worker	1
		Case team head	2
		Core process head	3
		Medical director/head	4
		HMIS/HIT officer	5
SD5	Education	Diploma	1
		Degree	2
		Master	3
		PhD	4

SECTION B: Technical, organizational and behavioural determinants

Please indicate your opinion whether you agree or disagree with the following statements. There is no right or wrong answer. Use Likert scale: **Strongly Disagree=1, Disagree=2, neither agree nor disagree=3, Agree=4, strongly agree=5**

Section B-1: Technical determinants

Please indicate your level of agreement or disagreement using the Likert scale: Strongly Disagree=1, Disagree=2, neither agree nor disagree=3, Agree=4, strongly agree=5

Code	**Technical Determinants (TD)**	**Reponses**				
		1	**2**	**3**	**4**	**5**
QTD1	**Computer literacy**					
	1.1. I have basic computer skill to manage data					
QTD2	**The following HMIS tools are always available**					
	2.1. Registers					
	2.2. Tally sheets					
	2.3. Report formats					
	2.4. HMIS manuals					
QTD3	**Knowledge of HMIS tools**					
	3.1. I have adequate knowledge on how to manage HMIS manuals					
	3.2. I understand the definitions of HMIS indicators					
	3.3. I have adequate knowledge on how to collect data in HMIS registers					
	3.4. I have adequate knowledge on how to compile data in tallies					
	3.5. I know how to manage data in reporting formats					
QTD4	**Perceived user-friendliness of HMIS tools**					
	4.1. It takes long time to complete data from HMIS registers					
	4.2. HMIS tools are easy to use					
	4.3. Organization of the HMIS tools is practical					
	4.4. I feel comfortable using these HMIS tools					
	4.5. Generally, I am satisfied with HMIS tools					

Section B-2: Organizational Determinants

Please indicate your level of agreement or disagreement using the Likert scale: Strongly Disagree=1, Disagree=2, neither agree nor disagree=3, Agree=4, strongly agree=5

Code	Organizational Determinants	Reponses				
		1	2	3	4	5
QOD1	**A written data management strategy is available at**					
	1.1. health centre level					
	1.2. core process level					
	1.3. case team level					
QOD2	**A written information use strategy is available at**					
	2.1. health centre level					
	2.2. core process level					
	2.3. case team level					
QOD3	**Culture of information use is well promoted at**					
	3.1. health centre level					
	3.2. core process level					
	3.3. case team level					
QOD4	**Separate HMIS plan is available at**					
	3.1. health centre level					
	3.2. core process level					
	3.3. case team level					
QOD5	**Internal supervision is provided monthly to strengthen HMIS at**					
	5.1. health centre level					
	5.2. core process level					
	5.3. case team level					
QOD6	**Motivation to strengthen HMIS is always encouraged at**					
	6.1. health centre level					
	6.2. core process level					
	6.3. case team level					
	6.4. individual level					
QOD7	**Staff empowerment, onsite training, and accountability**					
	7.1. Staff is encouraged to make evidence based decisions					
	7.2. Onsite training is conducted regularly to strengthen HMIS					
	7.3. Accountability is promoted to strengthen HMIS					
QOD8	**Budget**					
	8.1. Adequate budget is allocated yearly to strengthen HMIS					
Code	**Section B-3: Behavioural Determinants (BD)**	**Reponses**				
		1	2	3	4	5
QBD1	I have adequate **knowledge** to optimize information use					
QBD2	I am **confident** in information use					
QBD3	I am **competent** in information use					
QBD4	I am **motivated** to optimize information use					
QBD5	I am **involved** in data management tasks to optimize information use					
QBD6	I have adequate **knowledge** to manage data process activities					
QBD7	I am **confident** to manage data process					
QBD8	I am **competent** in data process					

Section-C: Data management

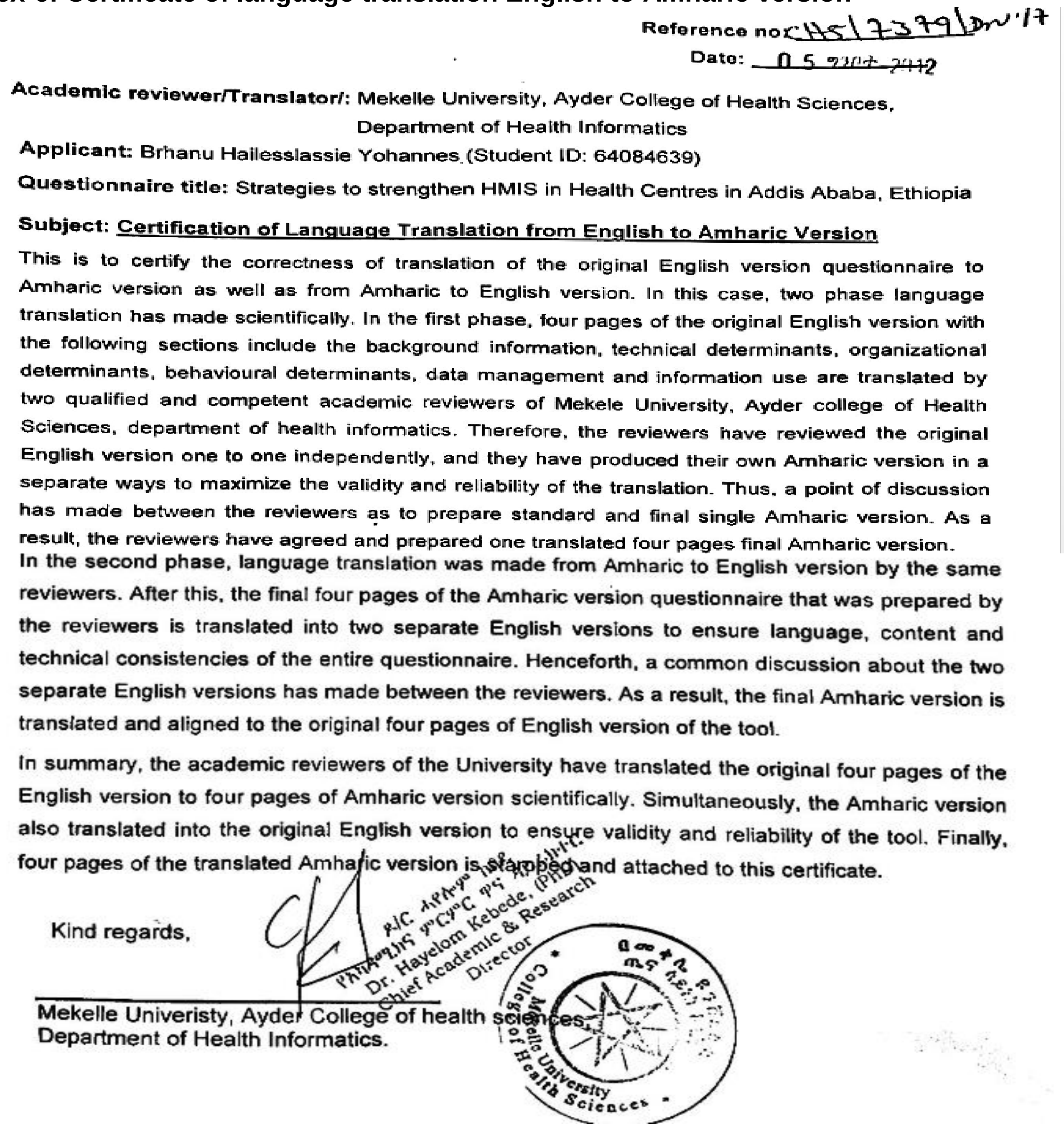
Indicate your response on the following statements. Please express your response using (Yes=1, No=2; Not sure=3) in the given empty space		
Code	**Data Management (DM)**	**Response** **Y=1; N=2; NS=3**
	Data collection	
QDM1	The value of quality data collection is well established at	
	1.1. health centre level	
	1.2. core process level	
	1.3. case team level	
QDM2	**Data collation/compilation**	
	2.1.Data compilation processes are often rushed at health Centre level	
	2.2. Do you have adequate knowledge to compile data scientifically?	
	Data analysis	
QDM3	3.1. Do you have skill to analyze data scientifically?	
QDM4	There is adequate support for data analysis processes at	
	4.1. health centre level	
	4.2. core process level	
	4.3. case team level	
	Data presentation	
QDM5	5.1. Do you have skills to display data using different charts?	
QDM6	The data presentation is visible at	
	6.1. health centre level	
	6.2. core process level	
	6.3. case team level	
QDM7	Weekly case presentations are held to manage data problems at	
	7.1. health centre level	
	7.2. core process level	
	7.3. case team level	
	Data Quality, Data documentation, RDQA and LQAS	
QDM8	**Data accuracy:** The value of data accuracy is not adequately established at	
	8.1. health centre level	
	8.2. core process level	
	8.3. case team level	
QDM9	**Data completeness:** The value of data completeness is not adequately established at	
	9.1. health centre level	
	9.2. core process level	
	9.3. case team level	
QDM10	**Report timeliness:** The value of report timeliness is not adequately established at	
	10.1. health centre level	
	10.2. core process level	
	10.3. case team level	
QDM11	**Data documentation:** The value of data documentation is not adequately established at	
	11.1. health centre level	
	11.2. core process level	
	11.3. case team level	
QDM12	Routine data quality assurance **(RDQA)** is an important data management practice at	
	12.1. health centre level	
	12.2. core process level	
	12.3. case team level	
QDM13	Lot quality assurance sampling **(LQAS)** implementation is done to improve data quality at	
	13.1. health centre level	
	13.2. core process level	
	13.3. case team level	

Section-D: Information use

Indicate your response on the following statements. There is no right or wrong answer. Therefore, please express your response using (Yes=1, No=2; Not sure=3) in the given empty space

Code	Information Use	Response
		Y=1; N=2, NS=3
	Information re-packaging and dissemination	
QIU1	Information repackaging processes are practiced at	
	1.1. health centre level	
	1.2. core process level	
	1.3. case team level	
QIU2	Information disseminating processes are practiced at	
	2.1. health centre level	
	2.2. core process level	
	2.3. case team level	
	Analytical reports production, action plan preparation and monitoring	
QIU3	Are analytical reports of key indicators displayed monthly using graphs at	
	3.1. health centre level?	
	3.2. core process level?	
	3.3. case team level?	
QIU4	Evidence based action plan is prepared at	
	4.1. health centre level	
	4.2. core process level	
	4.3. case team level	
	4.4. individual level	
QIU5	Evidence based action plan is monitored continuously at	
	5.1. health centre level	
	5.2. core process level	
	5.3. case team level	
	5.4. individual level	
	Culture of feedback, information utilization and new knowledge development	
QIU6	Is monthly written feedback given from	
	6.1. board to Health centre?	
	6.2. health centre to core processes?	
	6.3. core process to case teams?	
	6.4. case team to individuals?	
QIU7	**Is information used at health centre level to**	
	7.1. revise implementation strategies?	
	7.2. implement new strategies?	
	7.3. revise annual plans?	
	7.4. monitor day to day activities?	
	7.5. respond priority health service needs	
	7.6. link decisions with evidence	

Annex-6: Certificate of language translation English to Amharic version



Reference no: HS\7379\ዐሥ'17

Date: 05 ግንቦት 2012

Academic reviewer/Translator/: Mekelle University, Ayder College of Health Sciences,
Department of Health Informatics

Applicant: Brhanu Hailesslassie Yohannes (Student ID: 64084639)

Questionnaire title: Strategies to strengthen HMIS in Health Centres in Addis Ababa, Ethiopia

Subject: **Certification of Language Translation from English to Amharic Version**

This is to certify the correctness of translation of the original English version questionnaire to Amharic version as well as from Amharic to English version. In this case, two phase language translation has made scientifically. In the first phase, four pages of the original English version with the following sections include the background information, technical determinants, organizational determinants, behavioural determinants, data management and information use are translated by two qualified and competent academic reviewers of Mekele University, Ayder college of Health Sciences, department of health informatics. Therefore, the reviewers have reviewed the original English version one to one independently, and they have produced their own Amharic version in a separate ways to maximize the validity and reliability of the translation. Thus, a point of discussion has made between the reviewers as to prepare standard and final single Amharic version. As a result, the reviewers have agreed and prepared one translated four pages final Amharic version.
In the second phase, language translation was made from Amharic to English version by the same reviewers. After this, the final four pages of the Amharic version questionnaire that was prepared by the reviewers is translated into two separate English versions to ensure language, content and technical consistencies of the entire questionnaire. Henceforth, a common discussion about the two separate English versions has made between the reviewers. As a result, the final Amharic version is translated and aligned to the original four pages of English version of the tool.

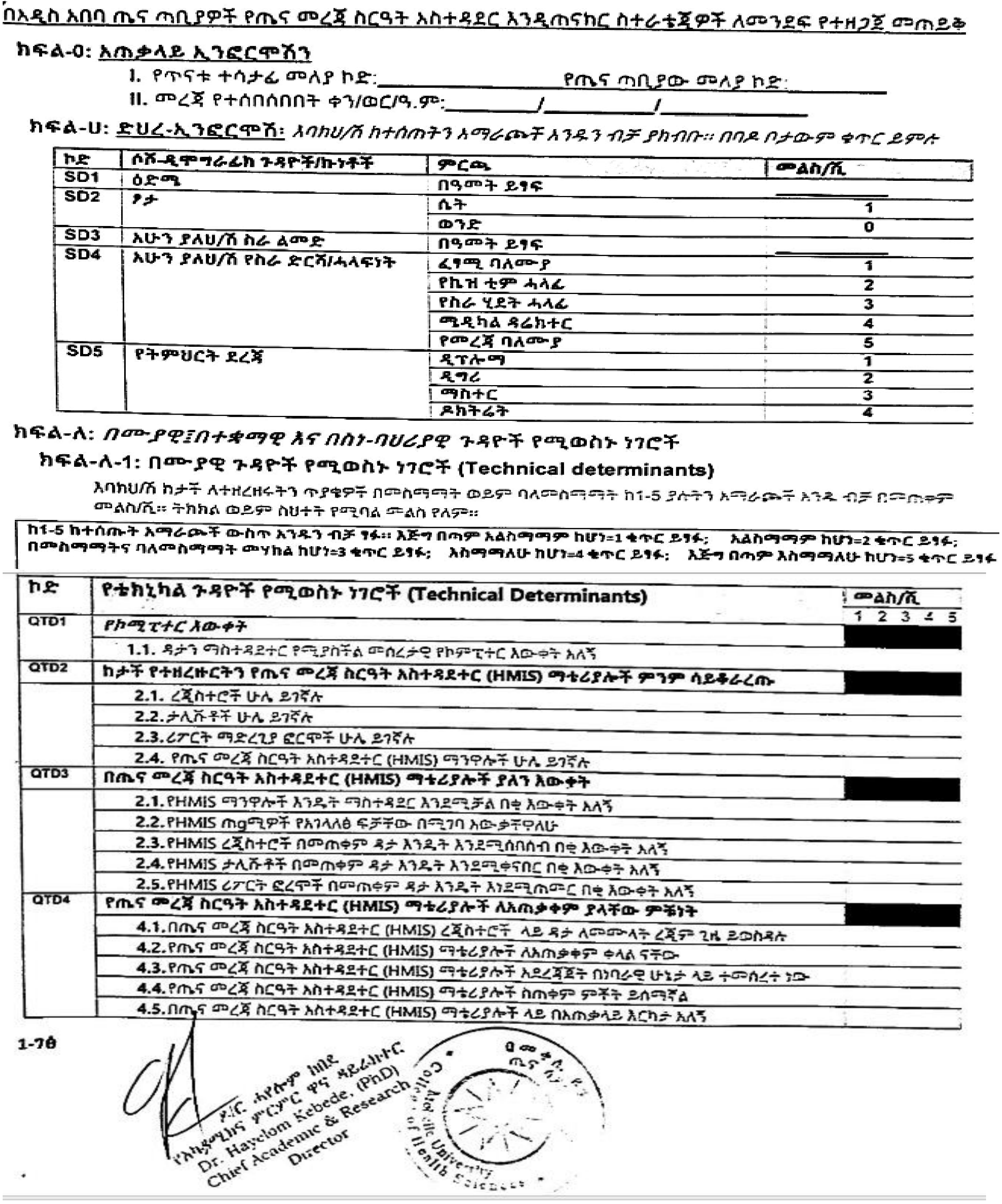
In summary, the academic reviewers of the University have translated the original four pages of the English version to four pages of Amharic version scientifically. Simultaneously, the Amharic version also translated into the original English version to ensure validity and reliability of the tool. Finally, four pages of the translated Amharic version is stamped and attached to this certificate.

Kind regards,

Dr. Hayelom Kebede, (PhD)
Chief Academic & Research
Director

Mekelle Univeristy, Ayder College of health sciences,
Department of Health Informatics.

Annex-7: Questionnaire/Survey on Strategies to Strengthen HMIS in Public Health Centres in Addis Ababa, Ethiopia, Amharic Version



በአዲስ አበባ ጤና ጣቢያዎች የጤና መረጃ ስርዓት አስተዳደር እንዲጠናከር ስተራቴጂዎች ለመንደፍ የተዘጋጀ መጠይቅ

ክፍል-0: አጠቃላይ ኢንፎርሞሽን

I. የጥናቱ ተሳታፊ መለያ ኮድ:__________ የጤና ጣቢያው መለያ ኮድ:__________

II. መረጃ የተሰበሰበት ቀን/ወር/ዓ.ም:______/______/______

ክፍል-ሀ: ድሀረ-ኢንፎርሞሽ: *እባክህ/ሽ ከተሰጡትን አማራጮች አንዱን ብቻ ያክብቡ። በባዶ ቦታውም ቁጥር ይሙሉ*

ኮድ	ሶሾ-ዲሞግራፊክ ጉዳዮች/ኩነቶች	ምርጫ	መልስ/ሺ
SD1	ዕድሜ	በዓመት ይፃፍ	______
SD2	ፆታ	ሴት	1
		ወንድ	0
SD3	አሁን ያለሀ/ሽ ስራ ልመድ	በዓመት ይፃፍ	______
SD4	አሁን ያለሀ/ሽ የስራ ድርሻ/ሓላፍነት	ፈፃሚ ባለሙያ	1
		የኬዝ ቲም ሓላፊ	2
		የስራ ሂደት ሓላፊ	3
		ሜዲካል ዳሬክተር	4
		የመረጃ ባለሙያ	5
SD5	የትምህርት ደረጃ	ዲፕሎማ	1
		ዲግሪ	2
		ማስተር	3
		ዶክትሬት	4

ክፍል-ለ: *በሙያዊ፤በተቋማዊ እና በስነ-ባህሪያዊ ጉዳዮች የሚወስኑ ነገሮች*

ክፍል-ለ-1: በሙያዊ ጉዳዮች የሚወስኑ ነገሮች (Technical determinants)

እባክህ/ሽ ከታች ለተዘረዘሩትን ጥያቄዎች በመስማማት ወይም ባለመስማማት ከ1-5 ያሉትን አማራጮች አንዱ ብቻ በመጠቀም መልስ/ሺ። ትክክል ወይም ስህተት የሚባል መልስ የለም።

ከ1-5 ከተሰጡት አማራጮች ውስጥ አንዱን ብቻ ፃፉ። እጅግ በጣም አልስማማም ከሆነ=1 ቁጥር ይፃፉ; አልስማማም ከሆነ=2 ቁጥር ይፃፉ; በመስማማትና ባለመስማማት መሃከል ከሆነ=3 ቁጥር ይፃፉ; እስማማለሁ ከሆነ=4 ቁጥር ይፃፉ; እጅግ በጣም እስማማለሁ ከሆነ=5 ቁጥር ይፃፉ

ኮድ	የቴክኒካል ጉዳዮች የሚወስኑ ነገሮች (Technical Determinants)	መልስ/ሺ				
		1	2	3	4	5
QTD1	*የኮምፒተር እውቀት*	■	■	■	■	■
	1.1. ዳታን ማስተዳደተር የሚያስችል መሰረታዊ የኮምፒተር እውቀት አለኝ					
QTD2	**ከታች የተዘረዙርትን የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ምንም ሳይቆራረጡ**	■	■	■	■	■
	2.1. ሪጂስተሮች ሁሌ ይገኛሉ					
	2.2. ታሊሹቶች ሁሌ ይገኛሉ					
	2.3. ሪፖርት ማድረጊያ ፎርሞች ሁሌ ይገኛሉ					
	2.4. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማንዋሎች ሁሌ ይገኛሉ					
QTD3	**በጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ያለን እውቀት**	■	■	■	■	■
	2.1. የHMIS ማንዋሎች እንዴት ማስተዳደር እንደሚቻል በቂ እውቀት አለኝ					
	2.2. የHMIS ጠgሚዎች የአገላለፅ ፍቻቸው በሚገባ አውቃቸዋለሁ					
	2.3. የHMIS ሪጂስተሮች በመጠቀም ዳታ እንዴት እንደሚሰበሰብ በቂ እውቀት አለኝ					
	2.4. የHMIS ታሊሹቶች በመጠቀም ዳታ እንዴት እንደሚቆናበር በቂ እውቀት አለኝ					
	2.5. የHMIS ሪፖርት ፎረሞች በመጠቀም ዳታ እንዴት እነደሚጠመር በቂ እውቀት አለኝ					
QTD4	**የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ለአጠቃቀም ያላቸው ምቹነት**	■	■	■	■	■
	4.1. በጤና መረጃ ስርዓት አስተዳደተር (HMIS) ሪጂስተሮች ላይ ዳታ ለመሙላት ረጂም ጊዜ ይወስዳሉ					
	4.2. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ለአጠቃቀም ቀላል ናቸው					
	4.3. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች አደረጃጀት በነባራዊ ሁኔታ ላይ ተመስረተ ነው					
	4.4. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ስጠቀም ምቾት ይሰማኛል					
	4.5. በጤና መረጃ ስርዓት አስተዳደተር (HMIS) ማቴሪያሎች ላይ በአጠቃላይ እርካታ አለኝ					

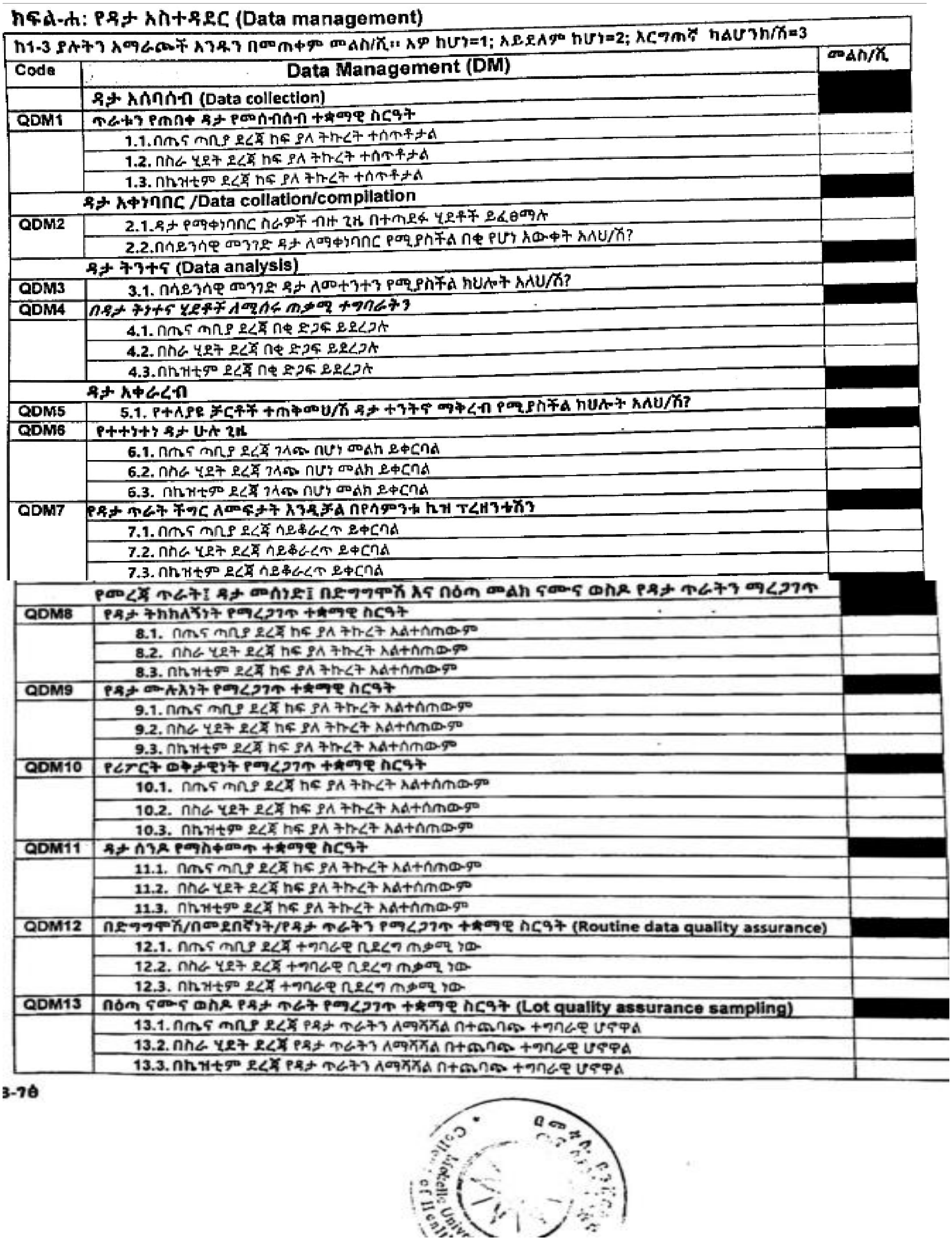
1-7θ

ዶ/ር. ሓየሎም ከበደ
የአካዳሚክና ምርምር ዋና ዳይሬክተር
Dr. Hayelom Kebede, (PhD)
Chief Academic & Research
Director

ክፍል-ለ-2: የተቋማዊ ጉዳዮች የሚወስኑ ነገሮች (Organizational Determinants)

ከ1-5 ከተሰጡት አማራጮች ውስጥ አንዱን ብቻ የፋ። እጅግ በጣም አልስማማም ከሆነ=1 ቁጥር ይፃፉ; አልስማማም ከሆነ=2 ቁጥር ይፃፉ; በመስማማትና ባለመስማማት መሃከል ከሆነ=3 ቁጥር ይፃፉ; እስማማለሁ ከሆነ=4 ቁጥር ይፃፉ; እጅግ በጣም እስማማለሁ ከሆነ=5 ቁጥር ይፃፉ

		መልስ/ሺ				
Code	በተቋማዊ ጉዳዮች የሚወስኑ ነገሮች (Organizational Determinants)	1	2	3	4	5
QOD1	*የዳታ አስተዳደር የተፃፈ ስትራቴጂ*					
	1.1. በጤና ጣቢያ ደረጃ አለ					
	1.2. በስራ ሂደት ደረጃ አለ					
	1.3. በኬዝ ቲም ደረጃ አለ					
QOD2	*የመረጃ አጠቃቀም የተፃፈ ስትራቴጂ*					
	2.1. በጤና ጣቢያ ደረጃ አለ					
	2.2. በስራ ሂደት ደረጃ አለ					
	2.3. በኬዝ ቲም ደረጃ አለ					
QOD3	*የመረጃ አጠቃቀም ባህል*					
	3.1. በጤና ጣቢያ ደረጃ በሚገባ አድጓል					
	3.2. በስራ ሂደት ደረጃ በሚገባ አድጓል					
	3.3. በኬዝ ቲም ደረጃ በሚገባ አድጓል					
QOD4	*የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ራሱን የቻለ የተለየ እቅድ*					
	4.1. በጤና ጣቢያ ደረጃ አለ					
	4.2. በስራ ሂደት ደረጃ አለ					
	4.3. በኬዝ ቲም ደረጃ አለ					
QOD5	**የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ለማጠናከር በየወሩ የውስጠ-ድጋፋዊ ክትትል**					
	5.1. በጤና ጣቢያ ደረጃ ይካሄዳል					
	5.2. በስራ ሂደት ደረጃ ይካሄዳል					
	5.3. በኬዝ ቲም ደረጃ ይካሄዳል					
	5.4. በፈፃሚዎች ደረጃ ይካሄዳል					
QOD6	**የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ለማጠናከር የማነቃቂያ ተግባራት**					
	6.1. በጤና ጣቢያ ደረጃ በተጨባጭ ይሰራሉ					
	6.2. በስራ ሂደት ደረጃ በተጨባጭ ይሰራሉ					
	6.3. በኬዝ ቲም ደረጃ በተጨባጭ ይሰራሉ					
	6.4. በፈፃሚዎች ደረጃ በተጨባጭ ይሰራሉ					
QOD7	*የሰራተኞች ውሳኔ ሰጪነት፤ የስራ ቦታ ስልጠና እና የመረጃ ተጠያቂነት ስርዓት*					
	7.1. የተቋሙ ሰራተኞች መረጃን መሰረት ያደረገ ውሳኔ እንዲወስኑ ይበረታታሉ					
	7.2. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ለማጠናከር በጤና ጣቢያ ውስጥ ስራ ቦታ ስልጠና ይሰጣል					
	7.3. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ለማጠናከር የተጠያቅነት ስርዓት በሁሉም ደረጃዎች አለ					
	በጀት					
QOD8	8.1. የጤና መረጃ ስርዓት አስተዳደተር (HMIS) ለማጠናከር በየዓመቱ ራሱን የቻለ በጀት ይመደብለታል					
	ባህሪያዊ ጉዳዮች የሚወስኑ ነገሮች (Behavioural Determinants)					
QBD1	የተተነተነ የጤና መረጃ አጠቃቀም ከፍ ለማድረግ በቂ እውቀት አለኝ					
QBD2	የተተነተነ የጤና መረጃ ለመጠቀም ከፍ ያለ በራስ መተማመን አለኝ					
QBD3	የተተነተነ የጤና መረጃ ለመጠቀም ከፍ ያለ ብቃት አለኝ					
QBD4	የተተነተነ የጤና መረጃ ለመጠቀም ከፍ ያለ መነቃቃት አለኝ					
QBD5	የተተነተነ የጤና የመረጃ አጠቃቀም ከፍ ለማድረግ በዳታ አስተዳደር ስራዎች በንቃት እሳተፋለሁ					
QBD6	የዳታ አስተዳደር የተግባር ሂደቶች ለመተግበር የሚያስችል በቂ እውቀት አለኝ					
QBD7	የዳታ ሂደቶችን ለማስተዳደር በቂ በራስ መተማመን አለኝ					
QBD8	የዳታ ሂደቶችን ለማስተዳደር በቂ ብቃት አለኝ					



ክፍል-ሐ: የዳታ አስተዳደር (Data management)

ከ1-3 ያሉትን አማራጮች አንዱን በመጠቀም መልስ/ሺ። አዎ ከሆነ=1; አይደለም ከሆነ=2; እርግጠኛ ካልሆንክ/ሽ=3

Code	Data Management (DM)	መልስ/ሺ
	ዳታ አሰባሰብ (Data collection)	■
QDM1	ጥራቱን የጠበቀ ዳታ የመሰብሰብ ተቋማዊ ስርዓት	
	1.1. በጤና ጣቢያ ደረጃ ከፍ ያለ ትኩረት ተሰጥቶታል	
	1.2. በስራ ሂደት ደረጃ ከፍ ያለ ትኩረት ተሰጥቶታል	
	1.3. በኬዝቲም ደረጃ ከፍ ያለ ትኩረት ተሰጥቶታል	
	ዳታ አቀነባበር /Data collation/compilation	■
QDM2	2.1. ዳታ የማቀነባበር ስራዎች ብዙ ጊዜ በተጣደፉ ሂደቶች ይፈፀማሉ	
	2.2. በሳይንሳዊ መንገድ ዳታ ለማቀነባበር የሚያስችል በቂ የሆነ እውቀት አለህ/ሽ?	
	ዳታ ትንተና (Data analysis)	■
QDM3	3.1. በሳይንሳዊ መንገድ ዳታ ለመተንተን የሚያስችል ክህሎት አለህ/ሽ?	
QDM4	*በዳታ ትንተና ሂደቶች ለሚሰሩ ጠቃሚ ተግባራትን*	■
	4.1. በጤና ጣቢያ ደረጃ በቂ ድጋፍ ይደረጋሉ	
	4.2. በስራ ሂደት ደረጃ በቂ ድጋፍ ይደረጋሉ	
	4.3. በኬዝቲም ደረጃ በቂ ድጋፍ ይደረጋሉ	
	ዳታ አቀራረብ	■
QDM5	5.1. የተለያዩ ቻርቶች ተጠቅመህ/ሽ ዳታ ተንትኖ ማቅረብ የሚያስችል ክህሎት አለህ/ሽ?	
QDM6	የተተነተነ ዳታ ሁሉ ጊዜ	■
	6.1. በጤና ጣቢያ ደረጃ ገላጭ በሆነ መልክ ይቀርባል	
	6.2. በስራ ሂደት ደረጃ ገላጭ በሆነ መልክ ይቀርባል	
	6.3. በኬዝቲም ደረጃ ገላጭ በሆነ መልክ ይቀርባል	
QDM7	የዳታ ጥራት ችግር ለመፍታት እንዲቻል በየሳምንቱ ኬዝ ፕረዘንቴሽን	■
	7.1. በጤና ጣቢያ ደረጃ ሳይቆራረጥ ይቀርባል	
	7.2. በስራ ሂደት ደረጃ ሳይቆራረጥ ይቀርባል	
	7.3. በኬዝቲም ደረጃ ሳይቆራረጥ ይቀርባል	
	የመረጃ ጥራት፤ ዳታ መሰነድ፤ በድግግሞሽ እና በዕጣ መልክ ናሙና ወስዶ የዳታ ጥራትን ማረጋገጥ	■
QDM8	የዳታ ትክክለኛነት የማረጋገጥ ተቋማዊ ስርዓት	■
	8.1. በጤና ጣቢያ ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	8.2. በስራ ሂደት ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	8.3. በኬዝቲም ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
QDM9	የዳታ ሙሉእነት የማረጋገጥ ተቋማዊ ስርዓት	■
	9.1. በጤና ጣቢያ ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	9.2. በስራ ሂደት ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	9.3. በኬዝቲም ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
QDM10	የሪፖርት ወቅታዊነት የማረጋገጥ ተቋማዊ ስርዓት	■
	10.1. በጤና ጣቢያ ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	10.2. በስራ ሂደት ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	10.3. በኬዝቲም ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
QDM11	ዳታ ሰነዶ የማስቀመጥ ተቋማዊ ስርዓት	■
	11.1. በጤና ጣቢያ ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	11.2. በስራ ሂደት ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
	11.3. በኬዝቲም ደረጃ ከፍ ያለ ትኩረት አልተሰጠውም	
QDM12	በድግግሞሽ/በመደበኛነት/የዳታ ጥራትን የማረጋገጥ ተቋማዊ ስርዓት (Routine data quality assurance)	■
	12.1. በጤና ጣቢያ ደረጃ ተግባራዊ ቢደረግ ጠቃሚ ነው	
	12.2. በስራ ሂደት ደረጃ ተግባራዊ ቢደረግ ጠቃሚ ነው	
	12.3. በኬዝቲም ደረጃ ተግባራዊ ቢደረግ ጠቃሚ ነው	
QDM13	በዕጣ ናሙና ወስዶ የዳታ ጥራት የማረጋገጥ ተቋማዊ ስርዓት (Lot quality assurance sampling)	■
	13.1. በጤና ጣቢያ ደረጃ የዳታ ጥራትን ለማሻሻል በተጨባጭ ተግባራዊ ሆኖዋል	
	13.2. በስራ ሂደት ደረጃ የዳታ ጥራትን ለማሻሻል በተጨባጭ ተግባራዊ ሆኖዋል	
	13.3. በኬዝቲም ደረጃ የዳታ ጥራትን ለማሻሻል በተጨባጭ ተግባራዊ ሆኖዋል	

3-7ፀ

ክፍል-መ: የተተነተነ መረጃ አጠቃቀም (Information use)

ከ1-3 ያሉትን አማራጮች አንዱን በመጠቀም መልስ/ሺ። አዎ ከሆነ=1; አይደለም ከሆነ=2; እርግጠኛ ካልሆንክ/ሽ=3		
Code	የተተነተነ መረጃ መጠቀም (Information use)	መልስ/ሺ
	የተነተነ መረጃ መልሰ-ማተምና ማሰራጨት	
QIU1	*የተተነተኑ መረጃዎች መልሶ-የማሳተም ሂደቶች*	
	1.1. በጤና ጣቢያ ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
	1.2. በስራ ሂደት ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
	1.3. በበኬዝቲም ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
QIU2	*የተተነተኑ መረጃዎች የማሰራጨት ሂደቶች*	
	2.1.በጤና ጣቢያ ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
	2.2.በስራ ሂደት ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
	2.3.በበኬዝቲም ደረጃ ሳይቆራረጡ ተግባራዊ ሆኖዋል	
	የተተነተኑ ሪፖርቶች ማቀናበር፤ የድርጊት መርሃ-ግብር ማዘጋጀትና መከታተል	
QIU3	*የቁልፍ ጠቋሚዎች/ኢንዲከተሮች/ ወርሓዊ ሪፖርቶች*	
	3.1.በጤና ጣቢያ ደረጃ ተተንትነው በግራፍ ይቀርባሉን?	
	3.2. በስራ ሂደት ደረጃ ተተንትነው በግራፍ ይቀርባሉን?	
	3.3. በኬዝቲም ደረጃ ተተንትነው በግራፍ ይቀርባሉን?	
QIU4	ማስረጃ መሰረት ያረደገ የድርጊት መርሃ-ግብር	
	4.1. ጣቢያ ደረጃ ሁሉ ይዘጋጃል	
	4.2.በስራ ሂደት ደረጃ ሁሉ ይዘጋጃል	
	4.3.በኬዝቲም ደረጃ ሁሉ ይዘጋጃል	
	4.4.በግል-ፈፃሚዎች ደረጃ ሁሉ ይዘጋጃል	
QIU5	ማስረጃ መሰረት ያረደገ የድርጊት መርሃ-ግብር	
	5.1.በጤና ጣቢያ ደረጃ በቀጣይነት ክትትል ይደረግለታል	
	5.2.በስራ ሂደት ደረጃ በቀጣይነት ክትትል ይደረግለታል	
	5.3. በኬዝቲም ደረጃ በቀጣይነት ክትትል ይደረግለታል	
	5.4. በግል-ፈፃሚዎች ደረጃ በቀጣይነት ክትትል ይደረግለታል	
	ግብረ-መልስ የመስጠት ባህል፤ የመረጃ ጥቅም እና አዲስ እውቀትን ማግኘት	
QIU6	**የተፃፈ ግብረ-መልስ**	
	6.1. ከቦርድ ለጤና ጣቢያ በየወሩ ይሰጣልን?	
	6.2. ከጤና ጣቢያ ለስራ ሂደት በየወሩ ይሰጣልን?	
	6.3. ከስራ ሂደት ለኬዝቲም በየወሩ ይሰጣልን?	
	6.4. ከኬዝቲም ለፈፃሚዎች በየወሩ ይሰጣልን?	
QIU7	**የተተነተነ የጤና መረጃ በጤና ጣቢያ ደረጃ**	
	7.1.የአፈፃፀም ስትራቴጂዎች ለመከለስ ጥቅም ላይ ይውላልን?	
	7.2. አዳዲስ ስትራቴጂዎች ለመተግበር ጥቅም ላይ ይውላልን?	
	7.3. ዓመታዊ ዕቅድ ለመከለስ ጥቅም ላይ ይውላልን?	
	7.4. የየቀኑ ስራዎች ለመተግበር ጥቅም ላይ ይውላልን?	
	7.5.የሕብረተሰቡ የጤና አገልግሎት ቀዳሚ ፍላጎቶች ለመመለስ ጥቅም ላይ ይውላልን?	
	7.6.ውሳኔዎች በማስረጃ አስተሳስሮ አቅጣጫ ለመስጠት ጥቅም ላይ ይውላልን?	

Annex-8: Information sheet and consent form

Annex 8. A: Information sheet

Ethics clearance reference number: **REC-012714-039**

May 2020

Title: "Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia."

Dear Prospective Participant: My name is Brhanu Hailesslassie Yohannes and I am doing research with Professor MM RAMUKUMBA (PhD), a Senior Lecturer in the department of Health Studies towards Ph.D. in the University of South Africa. We are inviting you to participate in a study entitled Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia.

WHAT IS THE PURPOSE OF THE STUDY? I am conducting this research to evaluate technical, organizational and behavioral determinants in data management and information use practices in order to develop a model as strategy to strengthen health management information systems in Ethiopia.

WHY AM I INVITED TO PARTICIPATE? To complete this study, your participation is important because you are 18 years and above; and had working for the last one year in this health centre. Your contact list is obtained from the electronic human resource information system of your health centre.

WHAT IS THE NATURE OF MY PARTICIPATION IN THIS STUDY? This survey will take 30 minutes of your time. The survey will focus on the technical, organizational & behavioural factors of data management and information use practices in your health centre.

CAN I WITHDRAW FROM THIS STUDY EVEN AFTER HAVING AGREED TO PARTICIPATE? Participating in this study is voluntary and you are under no obligation to consent to participation. If you do decide to take part, you will be given this information sheet to keep and be asked to sign a written consent form. You are free to withdraw at any time and without giving a reason.

WHAT ARE THE POTENTIAL BENEFITS OF TAKING PART IN THIS STUDY? There is no direct medical benefit to you. However, by participating, you will have the opportunity to share your practice on data management and information us. Moreover, your practice will be used to develop strategies to strengthen the data management and information use for public health centres which can benefit your and other health facilities directly.

ARE THEIR ANY NEGATIVE CONSEQUENCES FOR ME IF I PARTICIPATE IN THE RESEARCH PROJECT? There will be no known risks of participating in this study. This study will involve direct human participants and have low risk. The only predictable risk of harm is the potential for minor psychological discomfort or inconvenience, thus research would not pose a risk above the everyday norm.

WILL THE INFORMATION THAT I CONVEY TO THE RESEARCHER AND MY IDENTITY BE KEPT CONFIDENTIAL? You have the right to insist that your name will not be recorded anywhere and no one will be able to connect you to the answers you give. No one, apart from the researcher and supervisor, will know about your involvement in this research. You will be given a code number or a pseudonym and you will be referred to in this way in the entire data. The findings of this study will be processed into a research report, journal publications and/or conference proceedings that will bear no direct link to you. The researcher and supervisor can only access the data unless you give permission for other people to see the records.

HOW WILL THE RESEARCHER(S) PROTECT THE SECURITY OF DATA? All paper-based records like demographic, technical, organizational, behavioral factors and signed consent form will be kept in a locked filing cabinet for future research or academic purposes. Computer-based records and backup drive will be saved in the password-protected computer and folder. Future use of the stored data will be subject to further Research Ethics Review and approval. The research data will be retained in accordance with the Unisa policy that is a minimum of 5 years and then will be destroyed. Paper-based records will be shredded and electronic copies will be permanently deleted from the hard drive of the computer with a relevant software program.

WILL I RECEIVE PAYMENT OR ANY INCENTIVES FOR PARTICIPATING IN THIS STUDY? There will be no incentives for participating in this study and you will not be incurred to any financial obligation for taking part.

HAS THE STUDY RECEIVED ETHICS APPROVAL? This study has obtained written approval from the Research Ethics Review Committee of the Unisa.

HOW WILL I BE INFORMED OF THE FINDINGS/RESULTS OF THE RESEARCH? If you would like to be informed of the final research findings, please contact Brhanu Hailesslassie

Yohannes on +251-914750970. A summary of the research findings will be made available to the health centre too. If you require any further information or want to contact the researcher about any aspect of this study, please contact Brhanu Hailesslassie at email: brhanuhailesslasse@gmail.com.

If you have concerns about the way in which the research has been conducted, you may contact Dr. MM RAMUKUMBA (Ph.D). Email : ramukmm@unisa.ac.za; Tel : **Tel:** 012 429 6719 **|** **Cell:** 072 6302504

If you have any ethical concerns, please contact the research ethics chairperson Professor EL Kempen, kempeel@unisa.ac.za

Thank you for taking the time to read this information sheet and for participating in this study.

Brhanu Hailesslassie Yohannes.

Annex 8. B: **Consent form for research participants**

Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia

Title: Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia.”

I, __________________ (participant name), confirm that the person asking my consent to take part in this research has told me about the nature, procedure, potential benefits and anticipated inconvenience of participation.

I am agreeing to validate the proposed **Strategies to strengthen health management information systems in Public Health Centres in Addis Ababa, Ethiopia**. I understand that I will be asked to answer a number of questions related to this topic, and that answering the survey questions will take approximately 20-30 minutes.

I accept the invitation from the Principal Investigator, **Brhanu Hailesslassie Yohannes**, to validate the proposed strategies about data quality, data management and information use as expert of HIS..

I am participating in this research because I want to and not because anybody forced me. I understand that this study poses no physical risk

Benefits: I understand that my participation in the validation of the proposed strategies as expert of HIS may add to an understanding of data quality management and information use in public health centres. If I request and provide my contact information, a summary of the results of this research will be sent to me upon completion of the work. The summary will contain information about the whole group of participants, and my individual results will not be contained in the summary nor available to me or to anyone other than the researchers.

I understand that all information gathered in this study will be held confidential. Special steps will be taken by the researchers to protect my confidentiality. “Confidentiality” means here that only the researchers directly involved with the project will have access to information that can link, via a code number, my identifying information to my answers. I understand that my validation will be shredded five years after the completion of the project or publication (whichever comes later), unless I give my consent to the researchers to retain my validation for further follow-up studies.

I understand that the researcher Brhanu Hailesslassie Yohannes will be available to me by telephone +251914750970 or e-mail: 64084639@mylife.unisa.ac.za to answer any questions or to address any comments or concerns that I have about the study before or after validation the proposed strategies.

I certify that I am 18years and above; I understand the purposes and procedures of this study. By signing below, I am giving my full consent to validate the proposed strategies.

Participant Name & Sur-name :____________________________(Please print)

Participant Signature :______________________________Date-________________

Researcher’s Name & Surname **Brhanu Hailesslassie Yohaness** (Please print)

Researcher’s signature _.Date: May 2020

Annex-9: Proposed HIS strategies submitted to experts for review

The strategy has two sections. **Section-I** covers the socio-demographic information of the experts. **Section II** focuses on meta-inference facts derived from two data sets; proposed strategies to strengthen data management and information use; action plans to implement proposed strategies; responsible body; indicator of success for proposed strategies; and time frame for evaluating strategy implementation. Section two is further subdivided into three key areas:

Area-1 (Section-II-A) contains ten proposed strategies to improve the level of data quality (n=10)

Area-2 (Section-II-B) contains seven proposed strategies to improve data management (n=7), and

Area-3 (Section-II-C) contains eight proposed strategies to improve information use (n=8).

Instructions: Please use the three point Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column of section-II: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the **comment section**.

NB: The above instruction is also written at the top of each page of the proposed strategies, which serves as a guide how to assign a code to each proposed strategy in the response column of section-II.

Section-I: Socio-demographic data

Code	Socio-demographic data	Choice/options	Reponses
SD1	Age	Add years	_____________
SD2	Gender	Female	1
		Male	0
SD3	Organization	Add organization	____________________
SD4	Position	Add Position	____________________
SD5	Years of experience in present position	Add years	
SD6	Level of Education	Master	1
		PhD	2

Section-II-A1: Strategies to strengthen the level of data quality

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ▸ **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
A. Absence of regular mechanisms for data quality monitoring **B.** Lack of a well-established HMIS performance and data quality review mechanisms **C.** Data are significantly varied across HMIS data sources	1. Develop and implement data quality assurance plan	• Provide financial support to monitor data quality	• FMOH-PPMED and RHB-PMED	• Assessed indicators score data accuracy verification factor of between 90% and 110%	Every quarter		
	2. Establish performance and data quality review teams with standard term of reference at all levels	• processes on a regular basis using a checklist • Compare data values across data sources • Identify and measure errors on data management • • Review performance and data quality based on the data quality plan and term of reference • Cross-check the data collection, recording, compilation, analysis, and documentation • Share written feedback and lesson learning routinely	SCHOH, PHC-MD, CPH, and CTH FMOH-PPMED, RHB-PMED and SCHOH	• There is evidence of review teams roles and performed tasks across the levels			
	3. Establish HIS accountability within the framework of data governance at all levels	• Set clear HIS performance and data quality expectations • set measurements or a HIS code of conduct • Implement accountability conversations on ✓ repeated commitment failures on data quality and use ✓ HMIS performance and data quality review ✓ Poor data management and data use culture • Monitor individual and team progress	• FMOH-PPMED, RHB-PMED • SCHOH • Governing board of the healthcare facilities	• HIS accountability is established and operated within the framework of data governance at all levels	Every quarter		
D. Less satisfaction with HMIS tools	4. Revise and improve the interface of HMIS system	• Review the existing system prior to revision • Define data needs of relevant healthcare units • Determine an appropriate and effective data flow • the data collection and reporting tools • Develop the procedures for data processing • Pre-test the new HMIS tools to incorporate feedback • Provide training for data providers and data users • Monitor and evaluate the system • Develop effective feedback mechanisms	• FMOH-PPMED, • RHB-PMED • SCHOH	• The satisfaction level of healthcare providers with HMIS tools ranges from 90% to 100% at healthcare centres, core processes and case teams	Every quarter		

Note: **FMOH-PPMED** (Federal Minister of Health Policy, Planning, Monitoring and Evaluation Director); **RHB-PMED** (Regional Health Bureau Planning, Monitoring & Evaluation Director); **SCHO**H (Sub-city Health Office Head); **PHCMD** (Public Healthcare Centres Medical director); **CPH** (Core Process Head in health centres); **CTH** (Case Team Heads in health centres)

Section-II-A2: Strategies to strengthen the level of data quality

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
E. Job descriptions of healthcare providers on data management are not defined	5. Develop job descriptions with roles and responsibilities clearly differentiated	**Define job descriptions to be applicable at all levels** - Perform a job analysis - Identify and include summary objective of the level - List job duties and responsibilities - Identify the skill-sets to perform the job task - Set reporting and supervision plan (who does this employee report to?) - Set performance measurement - Monitor and evaluate implementation regularly - Communicate implementation via written feedback	- FMOH-PPMED - RHB_PMED - SCHOH	- Every position has a clearly defined job description and reporting mechanism	Monthly		
F. Little understanding of the importance of timely documentation and reporting **G.** The quality of key data management components did not meet expectations	6. HIS training to improve - level of understanding on timely documentation and reporting - the quality of key data management components such as data collection, compilation, analysis, problem identification, and action plan development	- Set organizational training objectives - Identify and recruit certified trainers - Select training approach (video, semi and fully interactive) - Prepare a budget for training - Evaluate training output (pre and post training tests)	- FMOH-PPMED RHB-PMED - SCHOH	- The quality of each data management component ranges from 90% to100% at all levels	Quarterly		
		- Perform post training on ✓ the practice of timely documentation ✓ the implementation of data management components	- PHC-MD, CPH, & CTH	- Improved knowledge on the importance of quality data - Improved confidence in use of HMIS tools			
H. low level of knowledge on the importance of quality data **I.** low confidence in the use of HMIS tools	7. HIS training focusing on knowledge and skill to boost confidence in the use of HMIS tools	- Monitor and provide written feedback to improve timely reporting and data documentation as per the standard - Assess post training implementation	- FMOH-PPMED RHB-PMED - SCHOH				
		- Document implementation success, lesson learning and key challenges	- PHC-MD, CPH, & CTH				

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Section-II-A3: Strategies to strengthen the level of data quality

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ► **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
J. Healthcare facilities do not fully practice the core functions of HMIS to address causes of data inconsistencies	8. Keeping and using a data quality monitoring log book	• Prepare and use standard data quality monitoring logbook at PHC, CP and CT levels	• FMOH-PPMED, RHB_PMED, and SCHOH	• The rate of functionality of the data quality monitoring logbook to track reporting timeliness, completeness, and accuracy ranges from 90% to 100% at all levels	Monthly		
		• Monitor implementation using checklist • Provide written feedback for all levels					
		• Prepare action points on the status of data quality monitoring logbook to improve data consistency in accordance with the standard at all levels	• PHC-MD, CPH, & CTH				
	9. HMIS mentorship at • Healthcare centre • Core process • Case team • Individual	• Prepare mentorship guide • Prepare standard checklist for HMIS mentorship • Provide a budget support for mentoring	• FMOH-PPMED, RHB-PMED, and SCHOH	• There is mentorship plan and evidence of implementation according to the standard	Monthly		
		• Prepare and implement mentorship action points at levels	• SCHOH and RHB-PMED to health centres • PHCMD to core processes • CPH to case teams • CTH to individual				
K. Case teams received minimum HIS internal support	10. HIS internal supportive supervision with special focus to lower levels such as case teams	• Prepare checklist for healthcare facilities including the three levels • Conduct HIS supervision • Provide feedback • Prepare and implement action plan		• HIS supervision is provided and documented as evidence at health centres, core processes, case teams and individual levels	Quarterly Monthly Bimonthly Weekly		

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Section-II-B1: Strategies to strengthen data management

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ▶ **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
A. Low commitment to reporting requirements	1. Providing training for technical leaders to improve • the level of understanding of data quality as priority agenda • information use at all levels	**Providing training for technical leaders how to** • Increase data ownership at all levels • Prioritize data quality gaps with evidence • lead and decide routinely with evidence • Motivate health workers to use data • Share lessons and feedback on data quality	• FMOH-PPMED • RHB-PMED • SCHOH	• All professionals have advanced understanding of the importance of data quality • The percentage of analysed data according to the standard ranges from 90% to 100%	Monthly		
B. Shelved unprocessed data due to low data analysis skills	2. Data analysis training to improve percentage of processed data	**Providing training on data analysis how to** • Understand simple data analysis • Practice and improve data analysis • Organize analyze data routinely • Justify and interpret analyzed data • Report analyzed data to users					
C. Routine quality monitoring activities did not appear to be performed according to the standard		• Perform post training tasks including ✓ conversation on data quality ✓ compiling and analysing data on regular basis	• PHC-MD, CPH, and CTH		Monthly		
		• Assess post training implementation • Monitor and provide written feedback on the leadership roles, commitment and ownership of data to improve data quality as per standard at all levels	• FMOH-PPMED • RHB-PMED • SCHOH				
	3. Establish peer learning networks through WhatsApp/ telegram to monitor routine data	• Establish peer learning networks to monitor data regularly	• FMOH, RHB and SCHO		Monthly		
		• Capacitate peer learning network facilitators at all levels					
		• Monitor peer learning network on regular basis • Share lessons of peer learning networks • Provide feedback on peer learning networks	• FMOH, RHB and SCHO				
D. Substantial indicators compiled below average. E. Data from key data sources were significantly inaccurate	4. Skill based HIS training • to ensure the maximum level of data compilation • to improve data accuracy across the data sources by avoiding missed, outliers and incorrect data values	• Perform post training tasks to improve ✓ the maximum level of data compilation ✓ data accuracy across the data sources by avoiding missed, outliers and incorrect data values	• PHC-MD, CPH, and CTH	• The percentage of compiled data across the HMIS data sources ranges from 90% to 100% at healthcare centres, core processes and case teams	Monthly		

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Section-II-B2: Strategies to strengthen data management

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally,** if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action points**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ▶ **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
G. Data presentation were significantly inadequate at all levels	5. Data presentation training to improve skills how to present data all the levels	**Providing training on data presentation how to** • Analyze presentation audience • Organize data for presentation • Develop and improve data presentation skill easily • Interact with the audience • Transmit the messages with clarity • Engage the audience in the presentation • Interpret and understand the mindsets of the listeners	• FMOH-PPMED, RHB-PMED, SCHOH	• Data is accurately presented according to the standards	Monthly		
		• Perform post training data presentation tasks	• PHC-MD, CPH, and CTH				
		• Assess post training implementation	• FMOH-PPMED, RHB-PMED, SCHOH				
6. Absence of written HMIS plans to improve • Data quality • Healthcare performance • Resource management	6. Preparing separate and written HMIS plan to support data management tasks at all levels	• Prepare national HIS strategic plan	FMOH-PPD	• HMIS data management Plans are in place, implemented, and accessible to all users	Quarterly		
		• Customize regional level HIS plan	RHB-PMED				
		• Customize sub-city level HIS plan	SCHOH				
		• Prepare and implement a customized HIS plan at PHC, CP, CT and individual levels to improve data quality, performance and resource management. • Monitor and evaluate implementation of HMIS plan	• PHC-MD, CPH, and CTH				
7. There is no data management strategy to guide, facilitate and support HIS implementation.	7. Developing data management strategy to guide, facilitate and encourage HIS implementation at all levels	**Developing national data management strategies** • Determine data requirements (What data is required to achieve the HIS goals, and where will collect it?) • Create sustainable data processes for collecting, preparing, storing, and distributing data • Establish data governance to handle data effectively • Build a knowledgeable team to use data effectively	• FMOH-PPMED, RHB-PMED, SCHOH	• Data management strategy is developed to guide, facilitate and encourage HIS implementation at all levels	Quarterly		
		• Implement data management strategies at all levels	• PHC-MD, CPH, and CTH				
		• Support, monitor, and evaluate the strategy • Provide written feedback and update on the strategies	FMOH-PPMED, RHB-PMED, SCHOH				

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Section-II-C1: Strategies to strengthen information use

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ► **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
A. lack of culture for information repackaging B. The importance of information needs has not been recognized, particularly at case teams	1. Advanced training on ► information repackaging ► information dissemination	**Providing training on information repackage how to** • Identify and access important official report • Identify target audience • Select and organize key performance indicators • Prepare a first brief • Analyze the brief based on (the target audience, the content of the information and the required budget) • Select message carrier (brochure/newsletter) to attract readers	• FMOH-PPMED, RHB-PMED, SCHOH	• There is consistency and continuity in information repackaging across all levels	Quarterly		
		• Repackage information on the message carrier • Design a feedback system to guide repackaging information • Document challenges, lesson learned and best practices	• PHC-MD, CPH, and CTH				
		Providing training on information dissemination how to • Define objectives • Define target audience (who exactly expected to be reached) • Define key messages (align messages with audience expectations) • Identify dissemination strategy (social media, workshops, seminars, mass media, and web sites)	• FMOH-PPMED • RHB-PMED, • SCHOH	• There is consistency and continuity in information dissemination across all levels			
		• Disseminate information to users • Design a feedback system to review success of the information dissemination • Document challenges, lesson learned and best practices	• PHC-MD, CPH, and CTH				
	2.Establishing term of reference to guide • information repackaging • information disseminating	• Set purpose, objectives and scope of term of reference • Put main activities, expected outcome and deliverables • Specify duties and responsibilities • Specify meeting frequency and time • Indicate approval and effective date of the terms of reference	• FMOH-PPMED, • RHB-PMED, • SCHOH	• Terms and reference are used as core guidance			

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Section-II-C2: Strategies to strengthen information use

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** ▶ **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
C. Decisions in healthcare facilities were made without sufficient evidence	3.Develop incentives system to • encourage information use • create opportunity for learning and sharing best practices • build data ownership • promote evidence-based decision-making as a means of providing opportunities for staff development	• Develop incentive/motivation strategies at national level include: ✓ Create a positive working environment ✓ Recognize good performance and celebrate results or reward excellence in information use ✓ Monitor progress, share lesson and provide feedback regularly	• FMOH-PPMED, RHB-PMED, SCHOH	• High level motivation	Quarterly		
D. There is a limited of information use and a lack of a culture that promotes information use	4. Establishing information use audits at all levels	• Use standard information use audit manual • Ensure technical, leadership and financial support • Set up base rules or set-up auditing criteria • Perform information use audit • Prepare and share written feedback	• FMOH-PPMED , RHB-PMED, SCHOH	• The culture of information use is well established and there is documented evidence of data driven decision making	Quarterly		
		• Document post-audit feedback • Prepare and implement post-audit action plan	• PHC-MD, CPH, and CTH				
	5. Creating data learning and sharing forums at inter- and intra-healthcare facilities	• Provide financial and technical support to ensure forums at inter- and intra-healthcare facilities	• FMOH-PPMED, RHB-PMED	• Learning forums are established and performed at inter and intra-healthcare facilities to improve evidence based decisions at all levels	Quarterly		
		• Prepare forum guidance/manual	• FMOH-PPMED, RHB-PMED				
		• Prepare forum terms of reference at all levels	• SCHOH				
		• Take assignment through post-forum action plan	PHC-MD, CPH, and CTH				
	6. Publishing brochure or newsletter at healthcare facilities	• Provide technical and financial support regularly to ensure publication	• FMOH-PPMED, RHB-PMED, SCHOH	• Key performance indicators are published and shared quarterly as brochures or newsletters in healthcare facilities	Quarterly		
		• Identify the type of information needs • Set objective of the brochure/newsletters • Select an appropriate design template • Publish quality brochure/newsletters • Set strategies how to distribute brochure to users • Set feedback receiving and sending mechanism	• PHC-MD, CPH, and CTH				

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Section-II-C3: Strategies to strengthen information use

Please use the Likert scale to indicate your agreement or disagreement with each proposed strategy in the response column: Put=1 if you strongly disagree/disagree; put 2 if you are neutral; and put 3 if you agree/strongly agree. **Additionally**, if you strongly disagree/disagree with any of the proposed strategies, or if you are neutral, please write your suggestions for better strategies or modifications in the last column under the comment section.

Meta-inferences from combined data sets	**Proposed strategies**	**Action plans**	**Responsible body**	**Indicator of success**	**Time**	**Response**	**Comment section** **If you strongly disagree/disagree or neutral in each strategy Please add your optional strategy in this column**
F. Insufficient budget for implementation of HMIS	7. Assigning budget for strengthening and implementing HIS	• Identify HIS implementation gaps • Prioritize key HIS gaps • Conduct root cause analysis • Assign adequate budget from healthcare centres internal revenue to strengthen HMIS by the governing board of healthcare centres • Use budget to improve HIS • Monitor and evaluate budget contribution	• Governing board of healthcare centre	• 90%-100% sufficient budget is allocated to implement and strengthen HMIS at healthcare centres	Yearly		
G. HIS written feedback not provided particularly at the level of the case teams	8. Establishing feedback delivery, control and tracking log book/electronic system after performance review meeting	• The log book should include at least ✓ Feedback type (performance review meeting, HIS supportive supervision, HMIS mentorship and HMIS assessment) ✓ Feedback mode of delivery (soft copy, hard copy or both)	• FMOH-PPMED • RHB-PMED, SCHOH	• Feedback delivery, control and tracking log books/electronic systems are 90%-100% in place and functional at all levels	Monthly, Quarterly, Biannual, Annually		
		✓ Post feedback implementation status (fully implemented/partially implemented/not implemented) • Prepare post-feedback action plans at all levels • Track, evaluate and communicate with staff the entire content of the feedback on monthly basis	• PHC-MD, CPH, and CTH				

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Annex-10: Validation criteria for HIS strategy

Instruction-1: Please read the final reviewed and improved HIS strategies listed below in tables 6.10A1 to A3, in table 6.11B1&B2, and in Table 6.12 C1 & C2.

Instruction-2: This section has five criteria to validate the final and improved HIS strategies using the three-point Likert scale. As a result, please put 1 if you strongly disagree/disagree, 2 if you neutral, and 3 if you agree/strongly agree in the response column.

SN	HIS strategies validation criteria	Response column
1	**Scope and purpose**	
	The scope and purpose of the reviewed and improved HIS strategies are well defined	
2	**Clarity and simplicity**	
	The reviewed and improved HIS strategies are clear and simple	
3	**Feasibility**	
	The reviewed and improved HIS strategies are relatively cost-effective to implement	
4	**Importance**	
	The reviewed and improved HIS strategies are important to improve data management and information use	
5	**Quality content**	
	The reviewed and improved HIS strategies have sufficient content quality to improve data management and information use	