EFFECT OF CAPACITY BUILDING, STAFFING LEVELS AND TECHNOLOGY ON QUALITY OF HEALTH MANAGEMENT INFORMATION SYSTEM DATA ON MATERNAL DELIVERIES AT ARUA REFERRAL HOSPITAL, UGANDA

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DECLARATION

I, **Ahimbisibwe Julius** declare that this dissertation is my original work and has not been presented for any award in any other University.

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APPROVAL

We, the undersigned, certify that we have guided, read and here by recommend the dissertation for acceptance to be examined by the Directorate of Research and Graduate Training of Kyambogo University.

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DEDICATION

This dissertation is dedicated to my family for the tireless efforts they put in to support me. I also dedicate this piece of work to my supervisors, Head of Department (HOD) and friends.

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LIST OF ABBREVIATIONS

ANC	:	Antenatal Care
ARRH	:	Arua Regional Referral Hospital
CVI	:	Content Validity Index
DHIS 2	:	District Health Information System
DHO	:	District Health Officer
DQA	:	Data Quality Assessment
HIS	:	Health Information System
HMIS	:	Health Management Information System
HSSP	:	Health Sector Strategic Plan
HTML5	:	Hyper Text Mark-up Language version 5
ICT	:	Information and Communications Technology
MoH	:	Ministry of Health
RRH	:	Regional Referral Hospital
SDGs	:	Sustainable Development Goals
SOPs	:	Standard Operating Procedure
SPSS	:	Statistical Package for Social Scientist
UN	:	United Nations
USAID	:	United States Agency for International Development
WHO	:	World Health Organization

ABSTRACT

This study aimed to investigate the impact of capacity building, staffing levels, and technology on the Quality of Health Management Information System (HMIS) Data concerning maternal deliveries at Arua Referral Hospital (ARRH) in Uganda. The research focused on three specific objectives: evaluating how capacity building influences the completeness of HMIS data for deliveries, assessing the effect of staffing levels on the timeliness of HMIS data related to deliveries, and examining the impact of technology on the accuracy of HMIS data concerning deliveries. Using a descriptive cross-sectional design incorporating quantitative and qualitative methodologies, the study involved a population of 120 hospital staff members (6 administrators, 6 records officers, 58 midwives, and 50 nurses). Respondents were selected through a combination of random and purposive sampling methods. Quantitative data was analyzed using SPSS and R software, while qualitative data utilized Nvivo V14 for thematic analysis. Findings revealed a predominantly female workforce in departments critical to maternal health, aligning with national nursing demographics. Notably, capacity building initiatives showed a strong positive correlation (r=0.6) with the completeness of HMIS data for maternal deliveries. Staffing levels also correlated positively (r=0.5) with timeliness, particularly influenced by the presence of Records Officers. Technology showed a weaker positive correlation (r=0.4) with data accuracy, access to DHIS2 and computers contributing mildly, while internet connectivity showed limited impact. Recommendations from the study emphasize clear responsibilities in data management to address issues like incorrect register filling. It advocates for inclusive training sessions involving junior staff and promotes enhanced data sharing and dissemination practices to bolster data quality assurance processes. In conclusion, this study highlights the pivotal roles of capacity building, staffing adequacy, and appropriate technology utilization in enhancing quality of HMIS data for maternal deliveries.

CHAPTER ONE: INTRODUCTION

1.0 Introduction:

The study investigates how capacity building, staffing levels, and technological factors impact the quality of Health Management Information System (HMIS) data concerning maternal deliveries at Arua Referral Hospital (ARRH) in Uganda's West Nile sub-region. In this study, capacity building, staffing levels and technology are the independent variables while quality of HMIS deliveries data serves as dependent variable in this study. The chapter outlines study's background, problem statement, conceptual framework, study purpose, objectives, hypotheses, scope, significance, justification, and definitions of key terms.

1.1 Background to the study

Globally, the adoption of Health Management Information Systems (HMIS) has grown substantially over time, highlighting its role as a crucial tool for managing health information. By collecting, analyzing, and presenting data on various health indicators, HMIS enhances healthcare delivery, tracks health trends, and assesses the effectiveness of interventions. Government health departments have embraced the HMIS as a vital tool for collecting, managing, and analyzing health-related data at a national level. By leveraging this system, the ministry of health can effectively monitor and evaluate various aspects of healthcare, including disease surveillance, resource allocation, service utilization, and health outcomes (AbouZahr, 2021).

The data management process with HMIS begins with filling of primary registers by respective unit staff. Additionally, records officers fill out monthly HMIS report forms. Finally, the District Health Information System (DHIS 2) is completed by records officers or the HMIS focal person. To ensure this occurs, the hospital must possess competent staff members who are equipped with essential tools such as computers and internet access. Furthermore, they should have a comprehensive understanding of the variables being tracked in order to guarantee the desired outcome (Kimaro, 2020).

Once data has been entered into the online system (DHIS 2), the same staff members meticulously review the data to identify any errors or discrepancies, ensuring its accuracy, completeness, and timeliness (Mucee et al., 2019). The HMIS is specifically designed to support managers in making evidence-based decisions at every level of healthcare delivery. At the health centre level, HMIS is utilized by the health centre in-charge and the Health Unit Management Committee (HUMC) to plan and coordinate healthcare services within their designated area (HSSP, 2020/21)

The use of HMIS has resulted in significant advancements in health data management, decision-making processes, and healthcare delivery. Studies have shown that HMIS implementation has led to a substantial reduction in data entry errors, ensuring the availability of reliable information for decision-making. This has helped in identifying gaps in healthcare services, monitoring disease trends, and evaluating the effectiveness of health interventions (Mucee et al., 2019).

Considering a study by Mutale et al., (2020), HMIS has improved access to healthcare services, especially for marginalized and underserved communities. For example, accurate and current information on healthcare needs and service utilization through HMIS enables more effective resource allocation.

Elsewhere, HMIS has facilitated improved monitoring of critical health indicators, including immunization coverage, maternal and child health metrics, and disease prevalence rates. The ministry of health can track progress, identify areas of concern, and implement targeted interventions to address health challenges effectively. This has led to improved health outcomes, such as lower rates of infant and maternal mortality, increased immunization coverage, and better control of communicable diseases (Hiwot et al., 2019).

While HMIS has been recognized globally as a vital tool for health reform, the quality of data it generates has become a significant challenge for researchers and practitioners due to implementation failures. A study conducted in India revealed that the quality of maternal delivery data is affected by various factors, including staffing shortages, lack of computer and data entry skills, and non-user-friendly software design features (Mishra et al., 2017). Similarly, a study in Indonesia found that departments with a standard set of indicators, skilled personnel, well-designed reporting formats, and staff trained to complete these formats accurately were more likely to achieve high-quality data on deliveries. In contrast, departments without these elements were less successful in obtaining quality data (Teklegiorgis et al., 2021).

In Indonesia, many hospitals in the country have utilized HMIS to provide better healthcare services to the people. However, despite implementing HMIS with the intention of improving data quality, several hospitals are not experiencing the advantages of having accurate, timely, and comprehensive healthcare data on deliveries. According to the literature, this can be attributed to various underlying factors, including technological issues and slow documentation processes. (Renner, 2020).

Despite HMIS being a critical foundation for robust health systems, studies in Africa persistently highlight challenges with the quality of data on hospital deliveries collected with this kind of system, notably completeness and timeliness, accuracy, consistence and poor utilization of HMIS data (AbouZahr and Boerma, 2019). According to Xiao, et al. (2021), the issues regarding quality of HMIS among maternal deliveries data has affected data utilization for decision-making in the health sector.

A study in Ethiopia by Ouedraogo et al,. (2019) revealed that the capacity of the health workforce (Biostatisticians, records officers and HMIS focal persons) was influential in determining quality of deliveries data (completeness and timeliness) at health facility level. Thus, completeness and timeliness of HMIS reports was between 32% to 75% of the over-all hospital reporting rates. The same study alluded that integration of technology (internet and DHIS 2 access) in routine HMIS data management could expand the scope of analyses, thereby reducing the volume of reported data and facilitating quicker delivery of information to users. This in turn facilitates detection of errors and also facilitates the transmission of

disaggregated data to the national level, making the data validation process more straightforward.

Another study conducted by Bhattacharya et al. (2019) in Nigeria found that facility-reported deliveries data were incomplete 40% of the time. Additionally, there was significant under-reporting, ranging from 10% to 60%, at the facility level. This under-reporting was primarily attributed to low staffing levels, with few or no dedicated record-keeping personnel. In several Sub-Saharan African countries, internal data inconsistency is prevalent. Both under-reporting and over-reporting are frequently observed, and the extent of inconsistency varies across indicators, facilities, and districts (Karengera, et al 2022). In a related study by Teklegiorgis et al. (2021), it was found that the quality of HMIS data across all health facilities fell short of the national standard of 80%. Hospitals and health centers performed better than clinics. Factors impacting data quality included insufficient training, lack of supervisory decisions, and inadequate feedback. The study recommended that authorities should implement timely supervision and feedback, along with ongoing training for healthcare providers.

A study conducted in Rwanda observed that ante-natal care-related data was often over-reported compared to other indicators (Nshimyiryo and Sanyinzoga, 2020). The same study identified issues such as missing values, measurement errors, inaccuracies, and false reports from unidentified sources in certain cases. Despite these challenges, the study noted that the quality of Rwanda's HMIS data is generally high, particularly in terms of completeness and internal consistency for the indicators examined. This aligns with the original goal of the Rwanda HMIS,

established in 1998, to improve the quality of health data collected from community health workers (CHWs) and healthcare facilities nationwide. The upgrade to a web-based system, the District Health Information System version 2 (DHIS2), implemented by the Rwanda Ministry of Health in 2012, has facilitated these improvements (Karengera et al., 2022).

In Tanzania, there is evidence indicating a lack of quality in HMIS data, and recent assessments have not robustly evaluated the factors influencing this quality at primary health care and district levels. A study by Suzan et al. (2020) focused on evaluating the quality of routine HMIS data at primary health care facilities and district levels. This study examined the use of data capture tools and the consistency of records from the original source (health facility registers) to the final reporting point (national level). It aimed to identify differences in data quality and propose improvement strategies. The findings revealed that health facility reports were significantly over-represented compared to the records in the registers, with substantial discrepancies observed at the Health Facility stage of the reporting system.

Similarly in Kenya, Health workers support with compiling and submitting the monthly reports to the Health Information Assistants and Records Officers who then enter HMIS data directly into the DHIS 2. As a result, health workers prioritize the collection and transmission of data with minimal analysis and interpretation, which limits its utility for informing decisions and actions during the data collection process. Conversely, the limited amount of data collected from health facilities is often used by HMIS stakeholders including the District Health

office, implementing partners, Government Ministries, Departments and Agencies to inform programing. (Cheburet and Odhiambo, 2022)

The situation in Uganda is no different from most developing countries. For instance in a cross-sectional study to document Uganda's experience in strengthening quality of HMIS data through the roll-out of the District Health Management Information Software System version 2 (DHIS2) by Kiberu et al. (2019), it was found out that a number of factors including access to internet, limited number of staff and skills, capacity building interventions, low motivation, combined with lack of incentives and tools are responsible for the poor quality of Health facility/Hospital data compiled and reported through Health Management Information System (HMIS). The study concludes that the implementation of DHIS2 led to improvements in the timeliness and completeness of reporting routine outpatient, inpatient, and health service usage data from the district level to the national level. However, to further enhance the performance of DHIS2, continued onsite support, supervision, mentorship, and additional system and infrastructure improvements, including better internet connectivity, are necessary.

The assessment regarding quality of HMIS data among deliveries and utilization of information showed that completeness, reporting timeliness, and accuracy of HMIS data on maternal deliveries were 39%, 73%, and 76% respectively (Hiwot et al.,2019). In Ethiopia, there is evidence of a low level of data quality, which falls below the national standard. The data accuracy level for health centers was reported to be 36.2%, significantly lower than the national target 85%. This can

be attributed to various factors such as a lack of training and inadequate resources. Hiwot et al., (2019).

According to Jhpiego (2020), Arua Regional Referral Hospital has made significant progress in implementing the Health Management Information System (HMIS). They have transitioned from a completely paper-based system to incorporating electronic or computer-based systems.

In collaboration with partners, the hospital has implemented interventions to improve the quality of HMIS data. These interventions include the roll-out of revised HMIS tools/forms as guided by the Ministry of Health, targeted training activities, supportive supervision and mentorships and infrastructure development (MoH 2020). According to an Integrated Data Quality Assessment conducted by UNICEF (2019), there are discrepancies between physical counts and reported figures on 91% of indicators. This compromise in data quality is a concern. For instance, it was found that there was underreporting on maternity indicators such as fresh still births, macerated still births, low birth weight, and newborn deaths. On the other hand, there was over-reporting of severely acute malnourished children. UNICEF (2019) attributed these discrepancies to several factors including a lack of proper work schedule for implementing HMIS, issues related to understanding indicator definitions and reporting guidelines, among others.

There is concern that several hospitals don't evaluate their HMIS to document crucial factors that affect quality of deliveries data gathered. Study aims to investigate the effect of factors such as technology, staff capacity issues, and

workforce dynamics on quality of data for improvement of deliveries in the hospital.

1.2 Statement of the problem:

Since its integration in 1985, HMIS has been a cornerstone for processing deliveries data and all other healthcare data, guided by relevant policies (Ministry of Health 2021). With dedicated resources, including the establishment of an HMIS department within the ministry, efforts have been made to ensure quality deliveries data, through HMIS. Since then, staff have been recruited, their capacities improved, and necessary technological infrastructures put in place. Critical human resources, trainings, supervision visits, internet access, computers, and DHIS 2 are necessary for capturing, analyzing, and maintaining accurate, timely, and complete healthcare delivery data. This enables them to collect, analyze, and report high-quality data.

Despite this significant investment by government and partners in regional referral hospitals like Arua Regional Referral Hospital, challenges persist regarding quality of HMIS data for deliveries, particularly in terms of completeness, timeliness, and accuracy. Maternal deliveries data from Referral Hospitals is inaccurate, not reported in time, incomplete and results in report delays. This poor-quality deliveries data has led to inaccurate diagnoses resulting in increasing maternal deaths. As a result, several factors continue to impact quality of HMIS data on deliveries, including the collection, analysis, and reporting processes at Arua Regional Referral Hospital in West Nile Sub-region of Uganda. This formed basis for investigating the nature of the relationship

between capacity building, staffing levels, and technology on quality of deliveries data at Arua Regional Referral Hospital.

1.3 Conceptual framework

Figure 1.1 illustrates conceptual framework adopted for the study. This framework outlines the scheme of concepts operationalized to achieve the study's objectives. It represents the hypothesized model identifying the study's concepts and their interrelationships.

INDEPENDENT VARIABLES **DEPENDENT VARIABLE**

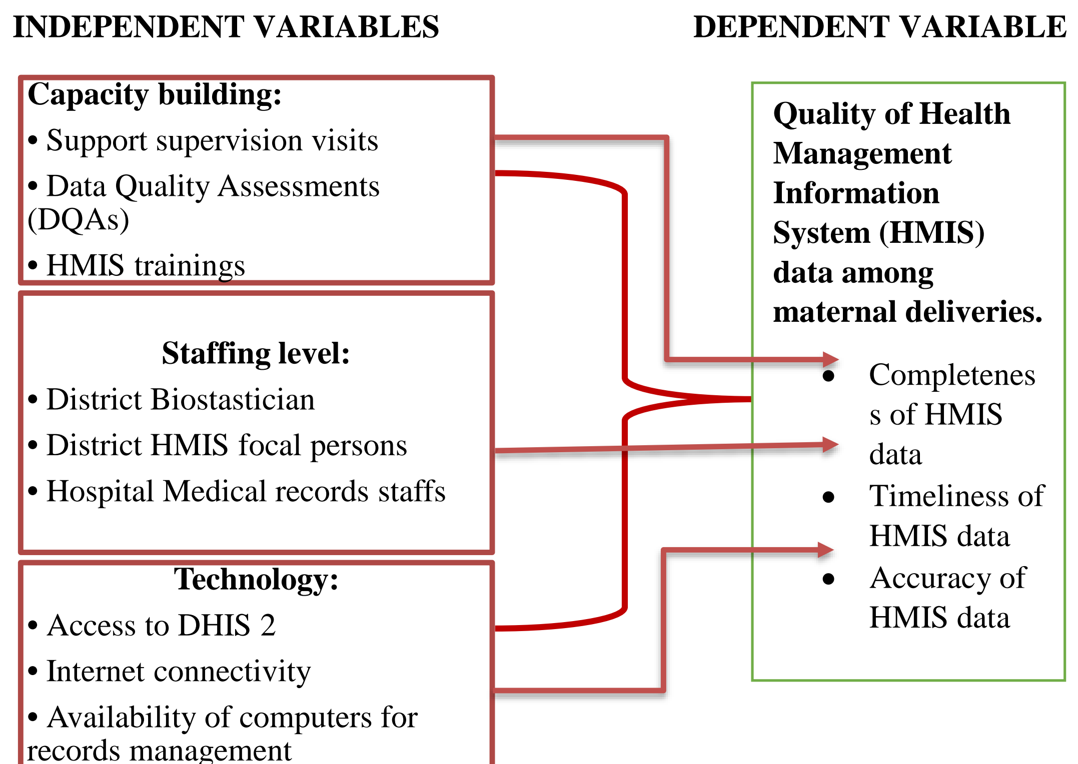


Figure 1. 1: A conceptual framework illustrating the relationship between study variables

The conceptual framework in figure 1 above explains the relationship between independent variables (capacity building, staffing levels and technology,) and dependent variable (quality of HMIS data among maternal deliveries). Capacity building attributes included support supervision visits, data quality assessments

and HMIS trainings. Staffing levels referred to Human resource base for example Hospital Biostatistician, HMIS focal person, medical records staff. Technology included attributes like DHIS 2 access, internet access and availability of computers. The dependent variable was measured in terms of three data quality parameters of; Accuracy, Timeliness and Completeness. Each of the data quality parameter was linked to a single independent study variable as indicated in the figure above.

1.4 General objective of the study:

The general objective of the study was to assess the effect of capacity building, staffing levels and technology on quality of HMIS deliveries data at Arua Regional Referral Hospital.

1.5 Specific objectives of the study

The study was guided by the following specific objectives. For purposes of this study, quality of HMIS data was measured using-completeness, timeliness and accuracy:

- To determine the effect of capacity building on completeness of HMIS data for improved maternal deliveries.
- To examine the effect of staffing levels on timeliness of HMIS data for improved maternal deliveries
- To investigate the effect of technology on accuracy of HMIS data for improved maternal deliveries.

1.6 Research hypotheses

- There is no significant effect of capacity building on completeness of HMIS data for improved maternal deliveries.
- There is no significant effect of staffing levels on timeliness of HMIS data for improved maternal deliveries.
- There is no significant effect of technology on accuracy of HMIS data for improved maternal deliveries.

1.7 Scope of the study

1.7.1 Time scope:

Study was commenced during 2020/21 academic year and reviewed Monthly HMIS data on deliveries for Arua Regional Hospital for the period January to December 2020.

1.7.2 Geographical scope:

The study was conducted at Arua Regional Referral Hospital, situated in the city of Arua within the Arua District of the West Nile sub-region in Northern Uganda. The hospital is located approximately 251 kilometers (156 miles) northwest of Gulu Regional Referral Hospital and about 480 kilometers (308 miles) from the capital city, Kampala. The referral serves 12 districts in the entire West Nile sub-region including refugee communities. For purposes of this study, the researcher will assess HMIS Maternal data on deliveries at Arua Regional referral hospital. This hospital was selected as part of the study because it's bigger catchment population that poses a big risk on the quality of health data. It's important to note that it's the only RRH in the whole of west-Nile region and some parts of Acholi

sub-region; the hospital also serves people from the neighbouring South Sudan, DRC and the refugee community.

1.7.3 Content scope

This study focused on how capacity building, staffing levels and technology, influence quality of Health Management Information System (HMIS) data among deliveries at Arua Regional Referral Hospital in Westnile Sub-region of Uganda.

1.8 Justification of the study

This study is justified by the urgent need to improve the quality of Health Management Information System (HMIS) data for maternal deliveries at Arua Referral Hospital. It aims to mitigate risks associated with data inaccuracies and delays in healthcare decision-making by identifying factors contributing to poor data quality and proposing strategies for improvement. By enhancing capacity building initiatives and leveraging technology such as DHIS 2, the study seeks to optimize resource allocation, reduce data inconsistencies, and expedite reporting processes. Opportunities lie in unlocking the potential of HMIS data to inform evidence-based decisions, empowering healthcare personnel through effective training, and integrating technology to streamline data management. Ultimately, these efforts aim to strengthen Uganda's health system by ensuring reliable health data governance, enhancing service delivery, and improving maternal health outcomes.

1.9 Significance of study

This study holds significant importance for several stakeholders involved in healthcare management and policy development, particularly within the context of Arua Referral Hospital and similar healthcare settings in the following ways;

Capacity building initiatives aimed at training healthcare personnel on data management practices and utilizing technology such as DHIS 2 can enhance their ability to accurately record and report maternal delivery data. This can reduce errors and discrepancies in reporting, thereby improving the reliability of health statistics used for decision-making.

Adequate staffing levels and efficient use of technology, including internet access and computerized data entry systems, can expedite the reporting process. This ensures that maternal delivery data is reported promptly to relevant authorities, facilitating timely interventions and resource allocation.

High-quality HMIS data enables healthcare administrators and policymakers to make informed decisions. Accurate and timely data on maternal deliveries can highlight trends, identify areas needing improvement, and evaluate the impact of healthcare interventions. This facilitates evidence-based policymaking aimed at improving maternal health outcomes.

By improving quality of HMIS data, healthcare facilities like Arua Referral Hospital can optimize resource allocation. This includes ensuring adequate staffing, procuring necessary equipment and supplies, and targeting interventions

to areas with the greatest healthcare needs, ultimately enhancing overall healthcare service delivery.

Research findings from this study contribute to the broader discourse on improving health data quality, aligning with global efforts to standardize HMIS practices and enhance data interoperability. This aligns with Sustainable Development Goals (SDGs) and other international health agendas focused on maternal and child health.

1.10 Definition of terms

Health Management Information System (HMIS): HMIS is an integrated system utilized by the Ministry of Health, development partners, and stakeholders to routinely collect and manage relevant information. This data supports monitoring of Health Sector Strategic and Development Plan (HSSDP) indicators, facilitating planning, decision-making, monitoring, and evaluation within healthcare delivery system. The system is designed to help managers make evidence-based decisions at all levels of healthcare service delivery.

Data: Refers to raw observations, acts, or statistics collected for the purpose of reference or analysis.

Data Quality: This refers to Accuracy, Timeliness and Completeness of data reported by health facilities through the Ministry of Health's Health Management Information System.

DHIS 2: A web-based application designed for the collection, validation, analysis, and presentation of aggregate statistical data related to integrated health

information management activities. DHIS 2, introduced in 2004, is an upgrade of DHIS version 1.

Timeliness: Implies that HMIS data is available at proper frequency to enable timely decision making

Completeness: Completeness is the extent to which all required data elements are recorded/filled ensuring that no essential information is missing. For this study, data was considered incomplete if some data columns were found blank with no entries.

Accuracy: Accuracy is the degree to which reported data reflects reality i.e number of deliveries in maternity register should be equal to deliveries in report forms (HMIS 105) and should be the same as deliveries reported in DHIS 2.

Technology: This refers to Health information technology that include computerized health information databases (electronic Medical Records), internet access for sharing information and DHIS 2.

CHAPTER TWO: LITERATURE REVIEW

2.0. Introduction

The chapter examines existing literature about effect of capacity building, technology and staffing levels on Quality of Health Information System (HMIS) data for deliveries and shows literature gaps.

2.1 Theoretical review

The study employed the evidence-based health information system theory by Carbone (2008) and reviewed various scholarly works that utilized this theory in their own research.

In a study conducted by Lorenzi (2018) in Melbourne, Australia, the author applied the evidence-based health information system theory to address the disconnect between information systems theory and health service delivery. Lorenzi argued that both information systems literature and the health sector have yet to establish an effective approach for adopting information systems in healthcare settings. Despite this, he highlighted the value of the evidence-based health information system theory, noting that evidence-based information is crucial for effective functioning of any information system. Lorenzi reviewed established methods for developing information systems theory and the foundational knowledge involved, emphasizing that only existing evidence and collected health information can enhance the availability of relevant data, which is essential for the effective utilization of technology in routine practice.

Little (2019) emphasized that for health information to be valuable for decision-making, it must be collected and processed with rigorous attention to quality to meet its intended purpose. He referenced the evidence-based health information system theory, asserting that credible evidence is essential for ensuring that information is both available to health workers and deemed reliable for health-related functions. Additionally, Little highlighted the importance of training health workers in data management, so that the information they collect is well-regarded and supported by sufficient evidence, making it suitable for use by decision-making bodies.

In a study by Shaw (2019), it was argued that high-quality data is essential to reduce delays in decision-making. Shaw applied the evidence-based health information system theory, asserting that such systems are fundamental to extending healthcare services to patients. He noted that while information technology can help reduce medication errors in hospitals, it is crucial to obtain reliable health information from health workers and other personnel responsible for data collection in healthcare facilities.

In East Africa, the evidence-based health information system theory has been applied to enhance health information management and service delivery. A study by Muriithi et al. (2020) in Kenya investigated the integration of evidence-based health information systems in local health facilities. They found that the theory significantly improved data accuracy and decision-making processes by providing a structured framework for data collection and analysis. The study highlighted

evidence-based practices led to better health outcomes by ensuring that health information used in decision-making was reliable and actionable

2.2 Factors known to affect data quality on maternal deliveries.

In Uganda, several factors impact the quality of data on maternal deliveries, including systemic issues and data management practices. A study by Opendi et al. (2021) highlighted that inconsistencies in data collection practices and insufficient training for healthcare workers were major contributors to data quality issues. The research identified that gaps in the training programs for health professionals often led to errors in recording maternal delivery data and inadequate use of standardized data collection tools. Additionally, the study emphasized that limited resources and poor infrastructure exacerbated these problems, affecting the reliability and completeness of maternal health data

Another critical factor affecting the quality of maternal delivery data in Uganda is the state of healthcare infrastructure and technology. Research by Namazzi et al. (2020) investigated how inadequate technological support and infrastructure hinder the accuracy and timeliness of maternal health data. The study found that many health facilities lacked proper electronic health record systems, leading to reliance on paper-based records that were often incomplete or prone to human error. Furthermore, the study highlighted that frequent power outages and limited access to reliable internet services significantly impacted the ability to maintain accurate and up-to-date records. The researchers recommended improving technological resources and infrastructure to enhance data quality and support better maternal health outcomes.

Based on the Ministry of Health's assessment, technology, human resource base, and capacity development are necessary in health facilities to address issues with maternal deliveries data. This include accurate records, incomplete data, double counting, and aggregation (MoH, 2016).

According to Measure Evaluation (2010), there was a gap between the self-perceived capacity and actual competencies of HMIS staff at health facility level. This gap specifically relates to tasks such as data quality checking, analysis, and utilization of information within the HMIS.

The factors influencing data quality on maternal deliveries in routine health management information systems have been categorized into behavioral, infrastructural, and systems-based factors (Glele Ahanhanzo et al., 2014). The researchers found out that behavioural factors encompass staff motivation and the presence of incentives or disincentives. Infrastructural factors include availability of appropriate data collection tools and equipment, the quantity and quality of human resources dedicated to health information systems, and the use of technology. Systems-based factors involve the level of data demand and usage, feedback mechanisms within health administration, routine data quality checks, and the existence of comprehensive health information system policies (Glele Ahanhanzo et al., 2014).

According to Odhiambo-Otieno (2005), the data on maternal deliveries in the HMIS was primarily collected by records personnel in health facilities. However, there was a lack of feedback provided on the reported data, or the feedback provided was minimal. It was observed that the routine collection of delivery data

was insufficiently clean for the purpose of planning and evaluating service delivery.

The most common challenges include a lack of feedback to local districts, inadequate knowledge of HMIS concepts and personnel, limited understanding of DHIS2, insufficient ICT infrastructure, challenges in conducting Data Quality Assessments (DQAs), insufficient support supervision, difficulties in data cleaning, staff competence issues, and high workload (Hotchkiss et al.,2010). Although health facilities received several supervisory visits which were not scheduled, less than 45% had received feedback (Hotchkiss et al.,2010).

2.3 Capacity building and quality of HMIS data for maternal deliveries

According to Simba and Mwangu (2006), support supervision had no relationship with completeness of HMIS data for maternal deliveries generated and compiled by a health facility. According to them, there was need to revisit the techniques employed in support supervisory visits including its composition to target the specific needs of health professionals. The study recommends that for support supervision to be impactful on data quality, it should be integrated to include all key stakeholders in the health sector. Research study adopted a cross-sectional design, incorporating structured questionnaire, targeting health facility in-charges across sixty-nine health facilities in Kinondoni Municipality, Tanzania. An observation checklist was also used to supplement the questionnaire. The study however missed out important information through qualitative approaches that would have additionally provided the level of influence of trainings and support supervision of the quality of HMIS data among deliveries.

Nass et al. (2019) emphasized that the completeness of HMIS data on deliveries is significantly influenced by the frequency of supervision visits to hospitals. Through these visits, relationships are strengthened, performance is evaluated, and enhance problem-solving skills among the supervision team. Research conducted in various contexts has shown that such supervision can lead to improvements in different aspects of health service delivery, including the quality of HMIS data on deliveries. For instance, a study conducted in Tanzania using an electronic checklist observed a statistically significant rise of 3–7 percent in the average performance scores for hospital deliveries, attributed to more frequent supervisory visits by oversight authorities (Nass et al., 2019).

Supportive supervision has been demonstrated to enhance the completeness of health facility delivery data, improve competency, ensure adherence to protocols, and reduce patient complications (Snowdon et al., 2017). Engaging health workers in identifying and addressing issues not only boosts workplace morale and motivation but also improves job retention and satisfaction. This involvement has contributed to advancements in infrastructure, staff management, service delivery, record-keeping, and technical competencies, thereby facilitating the provision of high-quality, standards-driven healthcare (Suh et al., 2007).

Mboya (2017) highlights the importance of ongoing training for frontline healthcare workers in HMIS data management, particularly for delivery data. This continuous training is crucial for raising awareness and ensuring that staff possess the necessary skills and confidence to implement HMIS effectively, thereby improving data quality. Similarly, Bailey et al. (2016) stress that all health

workers involved in data collection across different healthcare sections should receive regular capacity building and training. Such training helps them gain a deeper understanding of the stages where data quality can be impacted. Moreover, Bailey et al. argue that training should not be limited to focal persons and department heads but should also include all service providers to ensure the overall quality of HMIS data on maternal deliveries.

HMIS training needs of available human resource has also been identified by Mphatswe et al., (2012) as one of the capacity needs parameters affecting quality of HMIS data on maternal deliveries and hospital specific data elements. They reasoned that training of health staff in HMIS data elements has potential to enable them understand and appreciate the importance of HMIS and contribute to effectively implementing the system for routine quality data. He attributes increased accuracy of health data, timely submission of reports, completion of reports to the various trainings provided in HMIS targeting health facility staff. Their argument however lacks concrete evidence to be able to tell the level of influence on each of the data quality parameters.

2.4 Staffing levels and quality of HMIS data for maternal deliveries

Maintaining data quality in routine health information systems heavily relies on the effective management of human resources. Effective health information systems rely on robust core components, which are supported by a dynamic workforce in the health sector (Health Metrics Network, 2005).

In Kinondoni Municipality, Dar es Salaam, Tanzania, a cross-sectional study was performed and found that having an HMIS focal person enhances data processing,

thereby improving the timeliness, relevance, and accuracy of maternal delivery data. However, the study did not explore the advantages and disadvantages of appointing an HMIS focal person. It highlighted the importance of a team-based approach within the Primary Health Care (PHC) strategy and noted that assigning HMIS responsibilities to a single individual could potentially hinder the system's integration with other programs. The study utilized a random sample of 41 private health facilities, representing 25% of all private facilities, and included all public facilities due to their smaller number. The analysis focused on assessing the impact of having an HMIS focal person on the quality of maternal delivery data. The results indicated that private facilities with an HMIS focal person achieved a higher data completion rate (69.9%) compared to those without one (44.7%). Only one public facility had an HMIS focal person, so comparisons in the public sector were not feasible (Isabalija et al., 2011)

In a descriptive cross-sectional study conducted by Nyamtema (2015) on quality assurance practices within 21 health centers (HCs) in Kayunga revealed that 43% of the participating health facilities had Human resource challenges including understaffing for the categories of medical records staff, Biostatisticians etc. Relating this human resource gap, it was found out that the same Health facilities had quality challenges including 49% report submissions in DHIS 2 by closing day of reporting. Data on maternal deliveries was gathered through detailed interviews with HMIS focal persons and by analyzing HMIS records and guidelines. The quality assurance practices for HMIS in Kayunga were found to be lacking. Recruitment of the District Biostatistician was required as the district

didn’t have one, 89% of the HCIIIs didn’t have a medical records Officer and hence needed one, the HMIS focal person was acting and thus the district didn’t have someone in full capacity.

In a study aimed at establishing the determinants of routine health information system performance, explored in a selection of health facilities in Kenya; found out The availability of resources and adequate staffing for HMIS tasks showed a significant positive relationship particularly the medical records officers and timelines of HMIS data elements on Babies born before arrival and maternal deliveries in unit. This was so because the same study found out Medical records officers or Assistants play a critical role of ensuring that basic HMIS orientations are rolled-out across departments of maternity, OPD and ART clinic and ensure availability of action plans for HMIS implementation, promotion of a culture of information among others (Silas, 2017).

A cross-sectional study examining data utilization and the factors affecting the performance of health management information systems in Uganda found that most HMIS focal persons across eleven districts in the eastern, West Nile, and western regions were not specialized in health information management. The study identified the lack of skilled HMIS staff in data management and analysis as a significant issue impacting the timeliness of medical record handling. It recommended that the Ministry of Health in Uganda establish a dedicated cadre for data analysis and clarify responsibilities at all levels. For the HMIS to function effectively, there must be consistency and integrity across human resources, supplies, and processes (Leonard et al., 2021)

Since human resources are vital for the effective operation of routine health information systems, broader issues affecting the effectiveness and efficiency of staff in health systems may also affect these information systems. A review of performance-based financing in health systems globally indicated that financial incentives improved the quality and efficiency of healthcare staff in different facilities (Witter et al., 2013).

2.5 Technology and quality of HMIS data for maternal deliveries

Green (2015) recognizes DHIS 2 access and user friendliness improves accuracy of Health Management Information System data among institutional deliveries in referral hospitals by averagely 90%. In his study, he employed a cross-sectional descriptive design along with a document analysis approach for a total of 42 facilities, both district and referral hospital in Uganda spread across all districts. Results indicated that most (57%) of the drivers for accurate data were technological in nature majorly involving access to the District Health Information System 2 (DHIS 2) and capacity to use it in managing health facility data which were available and operational. Respondents noted that the manual HMIS was challenging due to its labor-intensive nature, difficulties in managing and retrieving records, limited availability of necessary HMIS forms, and problems in delivering hard copies of reports to relevant stakeholders. These were identified as significant issues that have been addressed by DHS 2.

According to Uganda's Ministry of Health (2014), the introduction and use of DHIS2 technology has significantly enhanced the quality of HMIS data on reported deliveries. The nationwide implementation of DHIS2 starting in 2011

improved the timeliness and completeness of reporting for inpatient and outpatient services, as well as selected health service coverage data from districts to the national level. This improvement is attributed to the training provided to district-level health workers on data entry into DHIS2, which reduced errors and minimized bureaucratic delays compared to paper-based systems. Similar benefits have been observed in other countries such as Kenya, South Africa, and Malawi. For example, Kenya and South Africa reported better reporting rates and more effective tracking of health indicators after adopting DHIS2 (Makumbi et al., 2016). In Malawi, a mid-term review praised the district health information system as one of the best in Africa due to its adoption of DHIS2 (Chaulagai et al., 2015)

According to a study by Kiberu et al., (2020), data quality issues continue to occur, and these are largely attributed to poor access to the internet among others. In their study, they suggest that for the quality issues to be addressed, there is a need to scale-up DHIS2 to lower-level health facilities to improve accuracy of HMIS data among deliveries collected at that level before they are submitted to the district and national levels. The study concluded that internet access contributed on average 5% of the HMIS implementation challenges.

In a study done by Divya (2015) on the impact of technology on primary healthcare information management in India, it was discovered that access to DHIS 2 serves as an efficient enabler that reduces manual documentation practices by ably connecting to available computers and databases much more easily. It was also found that the technology-based systems (DHIS 2) have helped

in generation of districtwide data on the numbers of pregnancies, abortions, stillbirths, and institutional new-born deliveries, thus providing an e-health solution for improving maternal and child health. However, this study only utilized qualitative approach using key informant interviews and in-depth interviews which may have not provided sufficient data to tell the influence of technology on quality of data.

Simba (2005) suggests that the challenges in data quality are compounded by the complexities of managing technology, such as mobile health information exchange and the growing number of users and applications. A key informant in the study noted that the 'availability of computers' is a limiting factor for enhancing data processing effectiveness and efficiency. The computers available are often designated for specific purposes, and many donors impose restrictions on their use, preventing them from being utilized for routine HMIS tasks within health institutions. Measure Evaluation (2017) argues that enhancing user capacity with existing technologies is crucial for improving data quality. This approach will lead to a better understanding of data quality issues in a more effective and efficient manner. The report provides for access to computers, sharing of data and expansion of uses and users as the only parameters for technology hence ignoring things like internet bundles, DHIS2 among others.

A study by Mwebaza et al. (2020) examined the availability of computers in health facilities across Uganda and its impact on health information management. The research highlighted that many health facilities are facing significant challenges due to insufficient access to computers. The study revealed that a

considerable number of health centers still don’t have adequate computers, which hampers their ability to effectively manage and report health data. The researchers emphasized that this lack of adequate computing resources contributes to inefficiencies in data processing and delays in reporting, which can affect overall healthcare delivery. The study called for increased investment in modern computing infrastructure to enhance the capacity of health facilities to manage data effectively.

Simba (2005) explored the impact of computer availability on health information systems in Ugandan health facilities. The study highlighted that many health facilities experience challenges related to the availability and functionality of computers. Simba (2005) noted that inadequate access to reliable and modern computing equipment often results in inefficiencies and constraints in data management processes. The research identified that many facilities face issues such as limited numbers of functional computers, outdated hardware, and restrictions imposed by donor conditions on computer use. These challenges contribute to delays in data entry and reporting, affecting the overall effectiveness of health information systems. The study concluded that addressing the availability of quality computers is essential for improving data management and supporting effective healthcare delivery.

2.6 Quality of Health Management Information System (HMIS) data

Quality in Health Management Information Systems (HMIS) data is defined by how well the data reflects the intended measurements established during the system's design. Data quality is a multifaceted concept, with each phase—from

design through to decision-making—having the potential to influence overall quality (Shrestha and Bodart, 2012). In this study, the parameters used to assess HMIS data quality included accuracy, timeliness, completeness, relevance, and consistency.

The demand for high-quality data from Health Management Information Systems (HMIS) has grown over time, driven by the need for accurate country-level progress reports related to the United Nations Millennium Development Goals and global health initiatives (Karuri et al., 2014). This demand has intensified with the introduction of the Sustainable Development Goals (SDGs). According to Measure Evaluation (2012), global policymakers require timely and accurate data from routine health activities to guide policy formulation, allocate resources, and make day-to-day management decisions. HIS Hub (2013) highlights the increasing global recognition of the critical role of health information systems in strengthening health systems, shaping public health policies, and enhancing accountability and transparency. Consequently, it is crucial to reorient and motivate health workers at all levels to improve their approach to data management in order to align with organizational values (Anyangwe and Mtonga, 2012)

Measure Evaluation (2010) underscores that poor data quality hampers stakeholders' ability to utilize data for evidence-based decision-making and negatively affects facilities' strategic planning and resource advocacy efforts. The study identified poor data quality as the main technical barrier to effective decision-making by staff. Additionally, data entry backlogs contributed to delays

in reporting, impacting the use of information. Both information users and producers viewed inadequate HMIS skills as a major individual constraint, with data users expressing a need for training to enhance their data collection and analysis capabilities

2.7 Gaps in literature reviewed:

The reviewed literature indicates that data quality was typically assessed using measures of data completeness and timeliness. Consequently, definitions of data quality varied depending on these indicators. Additionally, few studies employed inferential statistics to examine the relationship between dependent variables, such as data quality, and independent variables, including capacity building, staffing levels, and technology. The impact of HMIS design, the complexity of reporting tools, and standard indicators on HMIS performance was explored in only a limited number of the studies reviewed. The literature reviewed also grouped common factors influencing quality of HMIS data as; Technical, Organizational and Behavioural factors not specific stand-alone factors. It was also observed that some findings of different studies reviewed were based on qualitative methodological approaches as compared to mixed methodological approaches. The researcher will therefore widen the scope and study in detail how specifically capacity Building, staffing levels and technology contribute to the quality of HMIS data among deliveries in Regional Referral Hospitals in Uganda.

CHAPTER THREE: MATERIALS AND METHODS

3.0. Introduction

This chapter outlines and details the methods and techniques employed by the researcher to collect data and address research questions. It covers research design, study population, sample size and selection, sampling techniques and procedures, data collection methods and instruments, as well as measures for ensuring data quality (validity and reliability). Additionally, it describes data collection process, data analysis methods, and measurement of variables.

3.1 Research design

The study utilized a descriptive cross-sectional design to enable generalization of findings from a sample to the entire population. This design was chosen because it focuses on providing a detailed contextual analysis of a specific set of events or conditions and their interrelationships. It involves gathering data from a sample of respondents at one point in time. This approach facilitated the examination of the status of study variables and their relationships (Mugenda & Mugenda, 2003). The Study design consisted of mixed methodologies of both qualitative and quantitative approaches to study and provide valid explanations regarding factors affecting quality of HMIS data with much focus on technology, capacity building and staffing levels of Arua Regional Referral Hospital, Uganda. Using both approaches in addition helped cover more areas while using only one approach could have been defective.

3.2 Study population

The target population for this study included 120 staff members from Arua Regional Referral Hospital (ARRH), encompassing personnel from the maternity ward, antenatal care (ANC), family planning clinic, as well as records and administration departments. ARRH was chosen due to its large catchment area, which presents potential challenges to the quality of HMIS data. As the sole Regional Referral Hospital (RRH) serving the entire West Nile region and parts of the Acholi sub-region, and also providing services to individuals from South Sudan, the DRC, and refugees, it represents a critical hub for health data. Given the study’s focus on 'deliveries' data, the researcher deemed it pertinent to concentrate on departments directly involved with maternal care, including maternity, family planning, and ANC.

3.3 Sample size and selection

The study utilized a sample size of 92, drawn from a population of 120, using a blend of probabilistic and non-probabilistic sampling methods. Personnel categories listed in Table 3.1 were selected based on the assumption that these individuals have been involved in HMIS implementation within the hospital and its extended network, making them well-positioned to provide accurate and reliable information for the study. Sample size was arrived at scientifically using the Krejcie and Morgan (1970) table.

Table 3. 1: Category of respondents

Department	population size	Sample Size	Sampling technique
Hospital Administration	6	2	Purposive
Medical Records	6	2	Purposive sampling
Maternity ward	58	46	Simple Random
Antenatal care	28	24	Simple Random
Family Planning	22	18	Simple Random
Total	**120**	**92**	

Source: Human Resource Records ARRH (2020)

3.4 Sampling techniques and procedure

3.4.1 Purposive sampling

In this method, the researcher targeted specific departments and categories of staff in Arua Regional Referral Hospital who were thought to be well-informed about HMIS, making them capable of providing reliable and comprehensive information to supplement other sources of data.

3.4.2 Simple random sampling

Simple random sampling was adopted in sampling Hospital Staff (from maternity, ANC and Family planning units) to take part in the study. Employing this approach, every ward in aforementioned categories had an equal and independent chance of being selected, thus reducing potential bias (Mugenda and Mugenda, 2003). The researcher obtained a list of the Hospital staff working in each of the mentioned wards above from the Human Resource Department. After obtaining

this list, sequential numbers were assigned to each staff (i.e 1,2,3,4,..n) to create a sampling frame from which a simple random sample was selected. The final sampling units were then obtained using a random number generator.

3.5 Data collection methods

Data for this study were obtained from both primary and secondary sources. To thoroughly investigate the study variables, the researcher employed a combination of data collection methods through methodological triangulation. This approach allowed the different methods to complement each other, addressing the weaknesses inherent in each individual method. Consequently, the researcher was able to gather a broader range of information, identify more discrepancies in the data, and reduce biases more effectively than if using a single method alone (Mugenda and Mugenda, 2003). Data collection involved primary data from a questionnaires and interviews, and secondary data from document reviews and analysis of reported HMIS data.

3.5.1 Questionnaire survey

A self-administered survey questionnaire was used to collect quantitative data from respondents, as detailed in Table 3.1. The preference for this method stemmed from the need to capture variables that could not be directly observed, requiring insights from respondents' views, opinions, and feelings.

3.5.2 Interviews

The researcher carried out Key Informant Interviews from carefully selected key informants to generate qualitative data to complement quantitative data generated from survey questionnaire. Key informants included; Hospital Administrator, IT

Officer, Biostatistician, and HMIS focal person. This approach facilitated acquisition of comprehensive, precise, and sensitive information that was not accessible through the questionnaire method alone (Mugenda and Mugenda, 2003).

3.5.3 Document review

Document analysis was employed to review existing literature and documents to identify gaps that the study could address or to find evidence that supports or contradicts the quantitative findings. To thoroughly investigate the study, the researcher used triangulation to gather diverse information and uncover discrepancies that might not be revealed by a single method (Mugenda and Mugenda, 2003). The researcher reviewed the HMIS implementation manual, the DHIS 2 reported data, physical HMIS reporting templates to ascertain availability of required HMIS tools at the hospital.

3.6 Data collection instruments

The study employed three research instruments to gather both primary and secondary data: a mobile questionnaire, a key informant interview guide, and a document review checklist. The choice of these instruments was determined by the type of data to be collected, the available time, and the study's objectives.

3.6.1 Mobile questionnaire

A self-administered mobile questionnaire with structured questions, uploaded on KOBO, was used for data collection. This method was chosen for its efficiency, as it facilitates data collection and entry to be done at once and also mitigates

possible errors. The questionnaire begun with a consent for the respondent to freely participate and for confidentiality purposes.

3.6.2 Interviews guide

Qualitative interviews were conducted with four people from the administration, records, district and ministry of health aimed at collecting qualitative data. An interview guide was drafted and used throughout the interview process to guarantee uniformity and consistency in the information provided. The interview guide permitted probing beyond the pre-determined questions, enabling the researcher to elicit detailed and precise information. This approach was instrumental in exploring the issues under investigation more thoroughly.

3.6.3 Document checklist

The document checklist was used to gather relevant information from secondary sources, aiming to collect related data and insights about the study's focus on capacity building, staffing and technology on quality of HMIS data. Data was collected about deliveries in unit from; Registers, Monthly HMIS reports and the DHIS 2.

3.7 Data analysis

3.7.1 Quantitative data analysis

Data collected from the questionnaires using KOBO Collect were exported to Statistical Package for Social Sciences (SPSS) and R software for analysis. The data were then analyzed to determine the association between study variables using correlation coefficients. These coefficients range from -1 to 1, where 1 or -1

represents a perfect correlation. A positive correlation indicates that as one variable increases, the other variable also increases, while a negative correlation shows that as one variable increases, the other decreases. A value close to zero suggests no significant association between the variables. The findings from the questionnaires were presented in the form of frequency tables, charts, and graphs.

3.7.2 Qualitative data analysis

For the qualitative data, responses from various participants were organized into common themes. This descriptive data was gathered from key informant interviews with selected staff members at Arua Regional Referral Hospital. The qualitative findings were presented in alignment with the study's objectives and were used to complement and support the quantitative results. Themes and relevant responses from the interviews were highlighted, with direct quotations from respondents included to reinforce the quantitative findings, as noted by Kothari (2004).

3.8 Procedure for data collection

After developing a research proposal under the supervision of his advisors, the researcher received an introductory letter from Kyambogo University. This letter facilitated his introduction to the relevant departments and respondents at Arua Regional Referral Hospital. The researcher prepared questionnaires for data collection and secured consent from participants to ensure that their responses would remain confidential and used solely for academic purposes. He personally

administered the electronic questionnaires and conducted face-to-face interviews with selected staff members

3.9 Quality control issues

The researcher led the entire process from proposal to thesis to ensure high quality outputs. The researcher worked closely with the office of the Hospital Medical Records in order to ensure sampled staff are accessed for interviews as planned. This also made it possible to access secondary data source documents. Data was collected using KOBO mobile application and the form had data validation checks like skip logic, single select, multiple select, cascades to minimize possible errors. The study instruments were first piloted/pre-tested on selected respondents in Kuluva Hospital Arua District and the results realized were utilized to determine the content reliability of the tools, which were found worth using for data collection.

3.9.1 Validity

Validity refers to the accuracy of findings and the extent to which the instrument measures what it is intended to measure (Earl-Babbie, 2013). The quantitative validity of the instrument was assessed using the Content Validity Index (CVI). This process involved experts evaluating the relevance of the questions in relation to the study variables. Instruments with a CVI score above 0.7 were considered to be within acceptable ranges. The CVI was calculated using the following formula;

$$CVI = \frac{\text{Number of items regarded relevant by reviewers}}{\text{Total number of items}}$$

3.9.2 Reliability:

To ensure the reliability of the instruments qualitatively, a pilot test of the questionnaire was conducted to verify its consistency, dependability, and effectiveness in addressing the study's objectives. The results of this pilot test were subjected to a reliability analysis (Creswell, 2003). Quantitatively, reliability was assessed using the Cronbach's Alpha Reliability Coefficient test. A Cronbach's Alpha value of 0.7 or higher indicates that the items in the instrument are considered reliable. The scales for the variables, based on the Cronbach's Alpha Coefficient, were found to be reliable. For psychometric tests, a Cronbach's Alpha value within the range of 0.7 or above is required for the test to be deemed reliable (Bill, 2011).

3.10 Plan for dissemination of study findings:

The researcher adhered to the University's schedule for routine presentations, at the department and faculty. After successful completion and submission of thesis, the researcher intends to organize a hybrid workshop (with both physical and virtual participants) for disseminating findings of the study to the target stakeholders who will include Arua Regional Referral Hospital Staff, DHO staff, Health sector partners, Kyambogo university staff particularly Graduate school and graduate Students.

3.11 Ethical considerations

Permission to undertake the study was sought from the office of the Head of department (HoD) Biological Sciences Kyambogo University. Later permission

from Arua Regional Referral Hospital Management was sought before seeking consent of the respondents to participate in the study. Strict confidentiality was observed. Names of study participants were not recorded on questionnaires and interview guides. Collected data was kept in a computer database with an access password that is known to the researcher.

3.12 Measurement of variables

Measurement refers to the formulas or scales used in the study to assess the variables (Kothari, 2004). The study utilized nominal and ordinal measurement types for the variables. Specifically, the questionnaires administered to respondents employed a four-point Likert Scale, where responses ranged from 'strongly agree' to 'strongly disagree,' reflecting varying degrees of agreement. For analytical purposes, the scale responses were simplified into two categories: 'Agree' and 'Disagree.

3.13 Limitations and delimitations

- Some target respondents asked for facilitation before or after sparing their time to participate in the interviews. This however was managed by carefully explaining to them about the purpose of the study and how it's purely for academic purposes.
- Part of the research activities happened at the time when the country and the rest of world were grappling with COVID19 pandemic. As guided by the Ministry of Health, the researcher endeavored to observe COVID19 Standard operating procedures (SoPs) in order not to put the lives of the

study participants and others at risk. In addition, this is why the researcher opted for Mobile Data Collection.

- There was a risk that some of the sampled health workers might not find time to participate in the study due to heavy work-loads/busy schedules. This was mitigated by closely working with the hospital Administration to help in mobilizing target respondents ahead of time.

CHAPTER FOUR: RESULTS

4.0: Introduction

This chapter presents analysis, interpretation and presentation of the findings of the study. The responses from different respondents in different Hospital departments were captured/collected using a KOBO mobile Data collection Application installed on an android device. Data was then imported into excel for cleaning and further analyzed using SPSS version 26 and R with both quantitative descriptive statistics computed for critical study variables.

4.1: Demographic characteristics of respondents.

Respondent's demographic characteristics were captured on Sex, Department/ward, Cadre, Education level and Duration of employment. This data was analyzed, disaggregated and presented inform of tables and charts as indicated below;

4.1.1: Population size and sex composition of respondents.

Table 4.1 below reveals that a total of 92 respondents participated in this study.

The percentage of males was 32% while females was 68%.

Table 4. 1: Sex composition of respondents

Sex	Number	Percentage
Male	29	32.0
Female	63	68.0
Total	**92**	**100**
Sex ratio	**-**	**47.1**

Source: Primary Data

4.1.2: Distribution of respondents by hospital department

In figure 4.1, of the 92 respondents that participated in the study, the majority who were 46 were from maternity department, 24 were from antenatal unit, 18 from family planning unit, 2 from administration and 2 from medical records department.

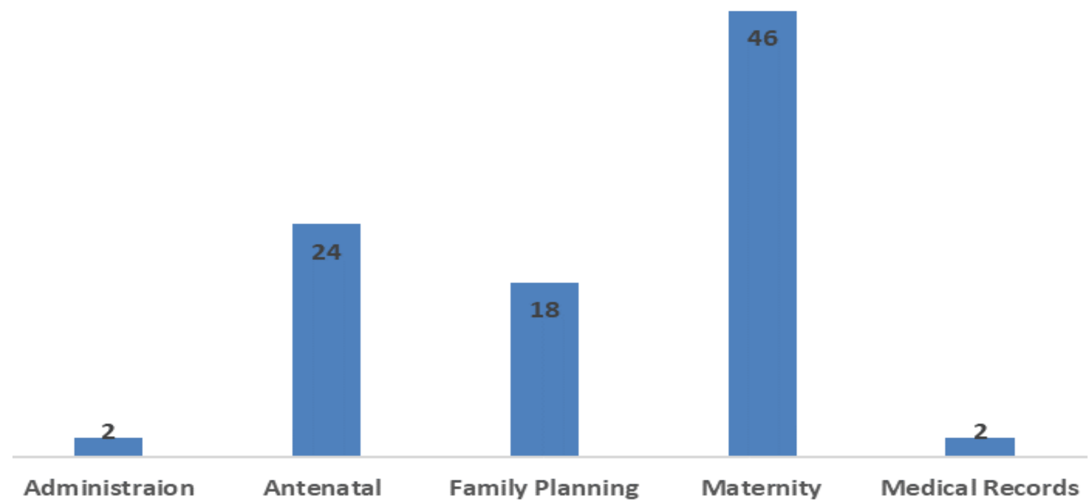
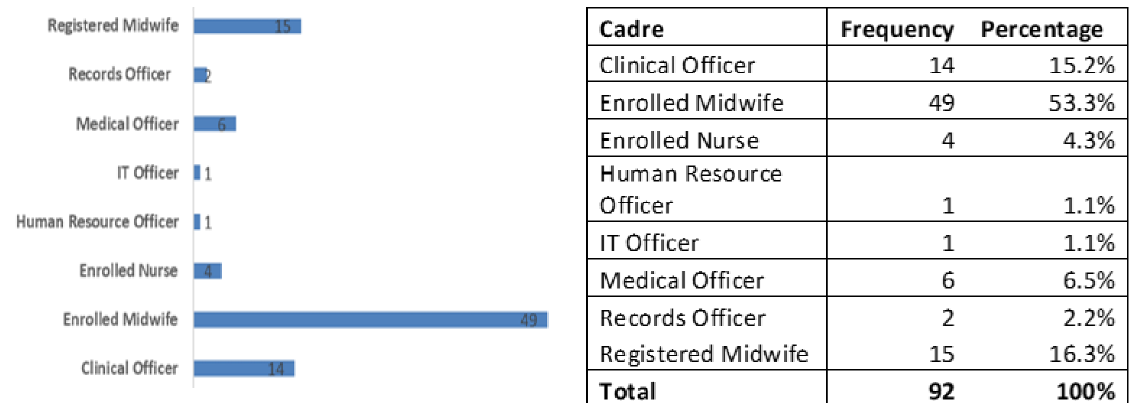


Figure 4. 1: Distribution of respondents by hospital department

4.1.2: Cadre of respondents

According to figure 4.2 below, staff interviewed in various hospital departments were found to be of the following cadre; 49 (53.3%) were Enrolled Midwives, 15 (16.3%) were Registered Midwives, 14 (15.2%) were Clinical Officers, 6 (6.5%) Medical Officers, 4 (4.3%) Enrolled Nurses, 2 (2.2%) Records Officers and 1 (1.1%) Human Resource Officer and Information Technology Officer.

The study assessed respondents by their cadre and the results are presented below;



Cadre	Frequency	Percentage
Clinical Officer	14	15.2%
Enrolled Midwife	49	53.3%
Enrolled Nurse	4	4.3%
Human Resource Officer	1	1.1%
IT Officer	1	1.1%
Medical Officer	6	6.5%
Records Officer	2	2.2%
Registered Midwife	15	16.3%
Total	**92**	**100%**

Figure 4. 2: Distribution of respondents by cadre

4.1.3: Distribution of respondents by education level

From table 4.2 below, majority of the study respondents (46.7%) had a diploma as their highest level of education, of whom 51.1% were males and 48.9% females. This was followed by certificate holders (44.6%), then degree holders at 5.4% and master's holders at 3.3%.

Table 4. 2: Respondents by education level

	Female		Male		Grand Total	
Education level	**Freq**	**Percentage**	**Freq**	**Percentage**	**Freq**	**Percentage**
Certificate	41	65.1%	0	0.0%	41	44.6%
Degree	1	1.6%	4	13.8%	5	5.4%
Diploma	21	33.3%	22	75.9%	43	46.7%
Masters	0	0.0%	3	10.3%	3	3.3%
Total	**63**	**68.5%**	**29**	**31.5%**	**92**	**100.0%**

Source: Primary Data

4.1.4: Distribution of respondents by period of employment in current department

The study established period of employment in current department by respondents. The results are summarized and presented in figure 4.3;

As seen in the figure 4.3, majority (55.4%) of the staff had stayed for between 5-9 years at the Hospital, 32.6% for less than 15 years, 9.8% for above 15 years and just 2.2% for between 10-15 years

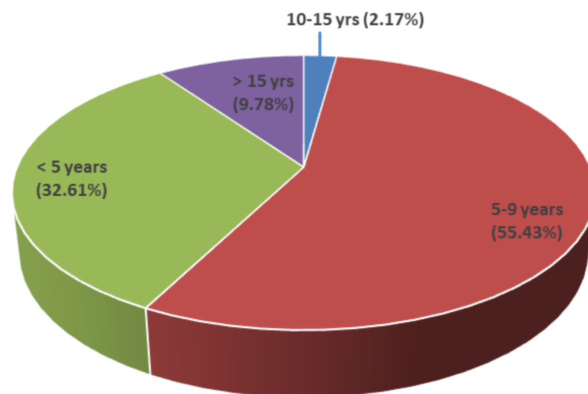


Figure 4. 3: Respondents by period of employment in current department

4.2: Effect of capacity building on completeness of HMIS data for maternal deliveries

Correlation coefficient test was used to measure the association between anticipated capacity building variables (supportive supervision visits, data quality assessments and HMIS trainings) and completeness of maternal deliveries data. Because the variables were ordinal, spearman's Rank correlation coefficient was adopted. Subsequently each one of the variables was significantly correlated with

completeness of HMIS data the moment any correlation- existed with it's p-value less than 0.05.

According to table 4.3, there was a significant strong positive relationship between supportive supervision visits (r=0.598*), data quality assessments (r=0.714**) and completeness of HMIS data captured, analyzed and reported. The correlation coefficients were significant at 0.05 and 0.01 level of significance respectively. This implies that both factors play crucial roles in enhancing completeness of HMIS data among deliveries.

There was also a moderate positive relationship (r=.488) between HMIS trainings for frontline health workers and completeness of HMIS data among deliveries. However, the correlation coefficient was insignificant (p-value=0.108>0.05). This implies that while there appears to be a trend where more HMIS training for frontline health workers could be associated with better completeness of data, the evidence is not strong enough to draw definitive conclusions

Overall, the results of the correlation test done reveal a positive relationship between capacity building (r=0.6) and completeness of HMIS data captured, analyzed and reported in Regional Referral Hospitals.

Table 4. 3: Correlation analysis between capacity building and completeness

		Support supervision	completeness
Support supervision	Spearman's rho	1	.598*
	Sig. (2-tailed)		.040
	N	12	12
Completeness	Spearman's rho	.598*	1
	Sig. (2-tailed)	.040	
	N	12	12
		DQA	completeness
DQA	Spearman's rho	1	.714**
	Sig. (2-tailed)		.009
	N	12	12
Completeness	Spearman's rho	.714**	1
	Sig. (2-tailed)	.009	
	N	12	12
		HMIS trainings	completeness
HMIS Trainings	Spearman's rho	1	.488
	Sig. (2-tailed)		.108
	N	12	12
Completeness	Spearman's rho	.488	1
	Sig. (2-tailed)	.108	
	N	12	12
		Capacity building	**completeness**
Capacity building	Spearman's rho	1	.600*
	Sig. (2-tailed)		.453
	N	3	3
Completeness	Spearman's rho	.600*	1
	Sig. (2-tailed)	.453	
	N	3	3

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Source: Primary Data

4.2.1: Descriptive analysis related to capacity building and completeness.

Table 4.4 indicate 80.4% of study respondents agree with the statement that supportive supervisions are routinely conducted to boost capacity of staff in further understanding and widening their knowledge of HMIS data management. Only 19.6% disagreed that supportive supervisions are routinely carried out. Such statistics imply key stakeholders need to put strategies to ensure supervisions are effective and involve staff in each hospital department.

Furthermore, according to study respondents, routine data quality assessments were somehow key in influencing data quality with close to 79.3% indicating agreement to the statement and about 20.4% disagreeing with the same statement. For smooth implementation of HMIS and for quality assurance purposes it's recommended to have all health workers were routinely oriented on data management and provided with information on quality performance of data. According to one key informant;

> *"The Data Quality Assessments are conducted periodically (usually Quarterly) and by partners (NGOs) who mainly focus on a few data elements that meets their project goals and leave other data elements or units unverified for completeness and other quality dimensions" (Respondent, Key Informant 1 (Records)).*

About HMIS trainings, respondents were asked to rate their level of agreement. 62% of the respondents indicated that HMIS trainings do happen while 38% disagreed with the statement. Respondents revealed that the trainings are a good capacity development initiative and can do a lot in improving quality of data. They mentioned that since the MOH introduced new HMIS tools, staff still face

difficulties in understanding the variables in the tools and also filling of registers correctly was still a challenge to some.

> *"The HMIS 105 report forms for-instance are filled in triplicate for ease of reference but we are not told on how this is done and where the 3 copies should be distributed; more so the naming of data elements/indicators have been revised hence posing a challenge on how to understand them for timely gathering, processing and reporting; we believe this kind of information can be got through routine trainings" (Respondent, Key Informant 2).*

> *"Some health workers do not know how to accurately fill the register, make summaries on a daily basis for the clients they work on for each particular day, they end up leaving all this work un-done and wait for the Records Officer at the end of month to come and compile every-thing. Data collection for all facility data elements for monthly reporting is thus done or coordinated by the records officer(s), who ensures that all HMIS indicators are correctly entered in the digital system known as DHIS 2. When quality issues are discovered or observed, the Biostastician is made aware and takes necessary steps to address the issues" (Respondent, Key Informant 4)*

Table 4. 4: **Capacity building and completeness of HMIS data on deliveries**

Statement		Agree	Disagree	Total
Hospital/department receives regular supportive supervision visits	Freq	74	18	92
	%ge	80.4	19.6	100.0
Hospital/Department conducts routine Data Quality Assessments	Freq	73	19	92
	%ge	79.3	20.7	100.0
Hospital or department receive regular feedback on the quality of their submitted reports	Freq	29	63	92
	%ge	31.5	68.5	100.0
Hospital/partners organizes regular HMIS trainings targeting health facility staff?	Freq	57	35	92
	%ge	62.0	38.0	100.0
Staff understand what should be recorded in the source documents/registers	Freq	60	32	92
	%ge	65.2	34.8	100.0
Staff understand what should be included on the HMIS monthly report	Freq	74	18	92
	%ge	80.4	19.6	100.0
Staff understand when the reports are due and to whom the reports should be submitted	Freq	73	19	92
	%ge	79.3	20.7	100.0
In case of errors, responsible staff know how to communicate and effect changes in a report that was previously submitted	Freq	67	25	92
	%ge	72.8	27.2	100.0

Source: Primary Data

4.2.2: Analyzing frequency of supportive supervision visits, data quality assessments and HMIS trainings.

Table 4.5 below shows support supervision was reported as the mostly conducted quarterly (78.3%), followed by data quality assessments (79.3%) and then annual HMIS trainings (40.2%)

Table 4.5: Frequency of supportive supervision visits, data quality assessments and HMIS trainings conducted.

Period	Supportive supervision visits		Data Quality Assessment		HMIS trainings	
	n	**%**	**N**	**%**	**N**	**%**
Monthly	16	17.4	16	17.4	00	00.0
Quarterly	72	78.3	73	79.3	08	08.7
Bi-annual	04	04.3	03	03.3	29	31.5
Annual	00	00.0	00	00.0	55	40.2

Source: Secondary Data

4.2.3: Category of hospital staff who received HMIS training in the last 12 months.

The table below indicates that the majority of staff involved in HMIS activities reported having received brief training on data management, which primarily covered proper recording, data collection, and basic analysis or interpretation. However, a few staff members reported that they had not received any specific training beyond on-the-job training. On average, only 50% of the staff in the medical records department had received HMIS-related training in the past 12 months. Overall, 49% out of the Healthcare workers reported having received a training in HMIS in the last 12 months. The inadequacy of these trainings was attributed to things like absence of a hospital training plan, lack of financial resources to organize and facilitate training activities among others.

Table 4.6: **Category of hospital staff who received HMIS training in the last 12 months.**

Department	Number of staff	Number of staff trained	% trained
Medical Records	06	03	50%
Maternity	58	29	50%
Antenatal	28	14	50%
Family planning	22	09	41%
Total	114	55	49%

Source: Secondary Data

4.3: Effect of staffing levels on timeliness of HMIS data on maternal deliveries

The association between staffing levels (Biostatistician, HMIS focal person and Records Officers) and timeliness of maternal deliveries data was analyzed using spearman's Rank correlation coefficient. This form of non-parametric correlation statistic was opted because the variables were ordinal. Subsequently each one of the variables was significantly correlated with completeness of HMIS data the moment any correlation- existed with it's p-value less than 0.05.

Table 4.7, indicates a significant very strong positive relationship (r=.845**) between availability of Records Officer (s) and timeliness of data at 0.01 level of significance. The results implies that having Records Officers is highly effective in ensuring timely data for maternal deliveries. This kind of relationship was further supplemented by voices of key informants who emphasized the effort of records officers in ensuring quality HMIS Data.

"…at the end of each month, a Records staff member, with support from a nurse or midwife, compiles data from all unit registers to complete the monthly HMIS report forms. The Records Officer, assisted by the Biostatistician, aggregates the data from the daily registers and enters the figures into the HMIS monthly form. The Biostatistician then updates the data in the online system (DHIS-2). If there are any significant discrepancies in the data elements, the Records Officer consults with the relevant departmental head to resolve the issues" (Respondent 2).

A moderate positive relationship (r=0.488) between availability of a Biostatistician and timeliness of HMIS data reports existed. The correlation coefficient was however insignificant at 0.01 level of significance. This implies that having a biostatistician may contribute to more timely data reporting.

There was a week positive insignificant relationship (r=0.255) between availability of HMIS focal person and timeliness of HMIS Data reports. This implies that having an HMIS focal person does not have a strong or reliable impact on the timeliness of data reporting.

Overall, results reveal a moderate positive relationship between staffing levels (r=0.53) and timeliness of HMIS data.

Table 4. 7: **Correlation analysis between staffing levels and timeliness**

		Biostatistician	Timeliness
Biostatistician	Spearman's rho	1	.488
	Sig. (2-tailed)		.108
	N	12	12
Timeliness	Spearman's rho	.488	1
	Sig. (2-tailed)	.108	
	N	12	12
		HMIS F/P	Timeliness
Timeliness	Spearman's rho	1	.255
	Sig. (2-tailed)		.424
	N	12	12
HMIS FP	Spearman's rho	.255	1
	Sig. (2-tailed)	.424	
	N	12	12
		Records staff	Timeliness
Timeliness	Spearman's rho	1	.845**
	Sig. (2-tailed)		.001
	N	12	12
Records staff	Spearman's rho	.845**	1
	Sig. (2-tailed)	.001	
	N	12	12
		Staffing levels	**Timeliness**
Staffing levels	Spearman's rho	1	.530
	Sig. (2-tailed)		.248
	N	3	3
Timeliness	Spearman's rho	.530	1
	Sig. (2-tailed)	.248	
	N	3	3

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Primary Data

4.3.1: Descriptive analysis related to staffing levels and timeliness.

According to table 4.8, 97.8% of respondents confirmed that the hospital employs a full-time Biostatistician through the Ministry of Health, while 2.2% were unaware of the presence of a full-time Biostatistician at the hospital.

On whether the hospital and Arua District at large has a full time HMIS focal person, 96.7% of the responded agreed that there's such a person while the remaining 3.3% Disagreed.

Regarding whether each hospital department has a Records Officer assigned to handle the daily collection and reporting of HMIS data, 67.4% of respondents agreed, while 32.6% disagreed. The analysis of the data in addition highlighted two main strengths for the hospital with regard to availability of Records Officers. Firstly, though the policy provides for one Records Officer to manage the entire Health information, this was not the case at Arua Regional as reflected in the qualitative response below:

> *Here at Referral Hospital: "Yes – we do have at least a records officer assigned in each of the critical departments like Maternity and HIV/ART, they support Nurses in the units to properly document, compile, review and submit reports" (Key Informant 1)*
>
> *Secondly, "much of the data aggregation and reviewing is led by the Records Officer assigned to a particular department: The Healthcare workers (Nurses and midwives) do much of day-to-day filling of registers with patient information" (Key Informant 2).*

Table 4. 8: Staffing levels and timeliness of HMIS data for maternal deliveries

Statement		Agree	Disagree	Total
Arua District has a full time Biostatistician employed by the Ministry of Health	freq	90	02	92
	%ge	97.8	2.2	100.0
Arua District has a full time HMIS focal person	freq	89	03	92
	%ge	96.7	3.3	100.0
Hospital has a functional records department with staff responsible for routine HMIS related tasks	freq	54	38	92
	%ge	58.7	41.3	100.0
Every Hospital Department is assigned Records Officer in-charge of collecting and reporting HMIS data	freq	62	30	92
	%ge	67.4	32.6	100.0
Staff in your health facility or department are trained on routine (HMIS)	freq	41	51	92
	%ge	44.6	55.4	100.0
Designated staff are responsible for reviewing periodic reports before submission to next level	freq	29	63	92
	%ge	31.5	68.5	100.0
Hospital or District has staff trained in data analysis and interpretation	freq	54	38	92
	%ge	58.7	41.3	100.0
Hospital or District has staff who takes lead in analysis and interpretation of HMIS data	freq	57	35	92
	%ge	62.0	38.1	100.0

Source: Primary Data

4.4: Effect of technology on accuracy of HMIS data for maternal deliveries

The association between technology and level of accuracy of HMIS data among deliveries was analyzed using spearman's Rank correlation coefficient. This form of non-parametric correlation statistic was opted because the variables were ordinal. Subsequently each one of the variables was significantly correlated with technology of HMIS data the moment any correlation- existed with it's p-value less than 0.05.

According to Table 4.9, the correlation analysis using Spearman's Rank correlation coefficient produced output statistics that revealed some form of relationship between technology in general by studying each of the attributes independently against quality of HMIS data (accuracy of data) as further explained below;

A significant strong and positive relationship (r=.775**) existed between DHIS 2 access and accuracy of HMIS data captured, analyzed and reported. The correlation coefficient was significant at 0.01 level of significance. Results indicate that having access to the DHIS 2 system is strongly associated with improved HMIS data accuracy.

There was a moderate insignificant positive relationship (r=0.522) between availability of computers and accuracy of HMIS data. This suggests a trend that more access to computers might be associated with improved data accuracy.

There was also a very weak positive insignificant relationship (r=0.111) between availability and access to internet and accuracy of HMIS data. This implies that internet access has a minimal and unreliable effect on data accuracy.

Of all the technology attributes (DHIS2 access, computers and internet) studied, access to DHIS2 was found to be significantly correlated with accuracy of data at 0.01 level of significance. It can thus be noted that access to DHIS 2 is very critical in guaranteeing data accuracy (one of the parameters of data quality) followed by access to computers.

Although seemingly there is a high positive correlation between accuracy and access to computers (r=0.522); it's important to note that this relationship is insignificant at 0.01level of significance

Overall, results reveal a weak positive relationship between technology (r=0.47) and accuracy of HMIS data.

Table 4. 9: **Correlation analysis between technology and accuracy**

		DHIS 2 Access	Accuracy
DHIS 2 Access	Spearman's rho	1	.775**
	Sig. (2-tailed)		.003
	N	12	12
Accuracy	Spearman's rho	.775**	1
	Sig. (2-tailed)	.003	
	N	12	12
		Internet	Accuracy
Internet	Spearman's rho	1	.111
	Sig. (2-tailed)		.731
	N	12	12
Accuracy	Spearman's rho	.111	1
	Sig. (2-tailed)	.731	
	N	12	12
		Computer	Accuracy
Computer availability	Spearman's rho	1	.522
	Sig. (2-tailed)		.082
	N	12	12
Accuracy	Spearman's rho	.522	1
	Sig. (2-tailed)	.082	
	N	12	12
		Technology	**Accuracy**
Technology	Spearman's rho	1	.470
	Sig. (2-tailed)		.272
	N	3	3
Accuracy	Spearman's rho	.470	1
	Sig. (2-tailed)	.272	
	N	3	3

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Primary Data

4.4.1: Descriptive analysis related to technology and accuracy.

Table 4.10 presents an analysis of related statements were rated by respondents based on their understanding and how they see things related to technology.

When asked whether the hospital and its departments have access to DHIS 2, 55.5% of respondents agreed, while 43.5% disagreed. Over-all many study respondents confirmed that hospital has access to DHIS2 system of managing HMIS data. For those that indicated otherwise, it could be that they were not holding tasks of data reporting at the time of this study. The hospital administration however indicated that all staff charged with HMIS data reporting have all access to DHIs 2.

> *"The primary role of data aggregation and reporting in the system (DHIS 2) is primarily for the Records Team and occasionally to a few carefully selected staff. All those assigned such roles are provided with DHIS 2 user name and pass-word to be able to access the system to check the status of reporting and provide timely feedback to the frontline healthworkers (nurses and midwives)", Respondent 4*

About whether the Hospital has access to computers and computerized system for reporting and analyzing HMIS Data, 53.2% agreed with the statement that such computers are available, while 46.7% disagreed. 45.7% agreed the hospital has access to internet connectivity and 54.3% disagreed.

Table 4. 10: Technology and accuracy of HMIS deliveries data

Statement		Agree	Disagree	Total
Hospital has and consistently uses standardized national HMIS tools for reporting in the DHIS2	freq	73	19	92
	%ge	79.3	20.7	100.0
The Hospital has access to DHIS2	freq	52	40	92
	%ge	55.5	43.5	100.0
Staff have the skills to perform DHIS 2 related tasks such as data entry, analysis and interpretation	freq	50	42	92
	%ge	54.3	45.7	100.0
DHIS2 allows tracking of unique individual clients within and across Service Delivery Points to avoid double counting	freq	52	40	92
	%ge	56.6	43.4	100.0
Hospital has computerized system for reporting and analyzing HMIS data	freq	49	43	92
	%ge	53.2	46.7	100.0
The hospital has access to internet connectivity for ease of HMIS data management	freq	42	50	92
	%ge	45.7	54.3	100.0
SOPs/ Job Aids/Guidelines are available that describe how DHIS 2 should be implemented	freq	77	15	92
	%ge	83.7	16.3	100.0
Data archiving/storage system at the Hospital is adequate	freq	41	51	92
	%ge	44.6	55.4	100.0

Source: Primary Data

CHAPTER FIVE: SUMMARY OF FINDINGS AND DISCUSSIONS

5.0 Introduction

This chapter presents a summary of key study findings and discussions.

5.1 Demographics

The study collected and analyzed data on five demographics which included sex composition, staff's department, cadre, education level and period of employment.

The demographic variables above were included in the study for purposes of ensuring inclusivity but also to make it possible to triangulate finding by the report users. Inclusivity as an approach of making sure all respondents are included in the study for purposes of generating diverse response is further emphasized by Ministry of Health, (2021) under the HMIS implementation manual.

Findings indicate a higher proportion of females compared to males, which aligns with the fact that there are more females admitted to the nursing profession compared to men. These results are consistent with the data from the Uganda National Household Survey (UNHS, 2020).

Maternity, family planning, antenatal, records departments were considered for the study due to their contribution to the overall quality of data about deliveries for Arua RRH. The Administration takes key decisions regarding staffing, learning and development which are very instrumental in ensuring quality of deliveries. The antenatal unit provides early maternal related support to mothers

right from the 1st ANC visit throughout 4th ANC and beyond (MOH 2019). The results of the study indicate a higher representation of midwives compared to other professions within the departments examined. This can be attributed to the fact that the maternity unit serves as a primary department for admitting and receiving mothers with maternal illnesses.

While period of service alone does not guarantee high-quality data, longer periods of service generally correlate with improved data quality due to accumulated experience, familiarity with the system, and adherence to established protocols.

Research highlights that higher educational attainment among health professionals is associated with improved quality HMIS data in Uganda, as better-educated staff are more likely to adhere to data collection standards and accuracy (Mugisha et al., 2020). Therefore, enhancing educational qualifications, particularly beyond the diploma level, could significantly improve the reliability and effectiveness of HMIS data.

5.2: Effect of capacity building on completeness of HMIS data for maternal deliveries

Study findings revealed completeness of HMIS deliveries data depends on capacity building i.e supportive supervision visits, DQAs and HMIS trainings conducted and involving frontline healthcare workers in regional referral hospitals. A strong positive relationship (r=0.6) existed between capacity building and completeness of HMIS data, which was significant at 0.01 level of significance. The results relate with Nass et al., (2019) that highlighted a positive

significant relationship between capacity building and completeness of HMIS data on deliveries; he emphasized the role of capacity building to hospital staff to build relationships, monitor performance, and enhance problem-solving skills among the team involved in healthcare service delivery.

A correlation analysis test revealed, a significant positive mild correlation ($r=0.598^{*}$, p value=0.040) between supportive supervision visits and completeness of HMIS deliveries data at 0.01 level of significance. This is because engaging stakeholders, such as districts, in support supervision proves beneficial in several ways. Firstly, it helps in identifying and resolving issues effectively. Additionally, it enhances workplace morale, motivation, job retention, and overall satisfaction, which in turn leads to improvements in infrastructure, staff management, service delivery, and record-keeping. In addition, it improves technical competencies and standard-driven health care (Suh et al. 2007). These findings agree with (Snowdon et al. 2017) that showed supportive supervision to contribute positively to completeness of health facility deliveries data, competency, adherence with protocols, and reducing patient complications. Furthermore, the findings align with Silas (2017), who identified a significant positive relationship between supervision visits for HMIS activities and performance in his study in Kenya. Similarly, Hotchkiss et al. (2010) found that supportive supervision was significantly associated with data quality in their evaluation of the PRISM framework in Uganda. Correlation analysis demonstrated a strong positive relationship between DQAs and the completeness of HMIS delivery data ($r = 0.714^{**}$, $p = 0.009$), with statistical significance at the 0.01 level. The R-squared

value of 0.509 indicates that, controlling for all factors, DQAs account for 51% of the variation in the completeness of HMIS data. According to Leonard et al. (2021), in their study on data utilization and factors affecting the performance of health management information systems in Tanzania, over half (72.1%) of health facility respondents reported that the district team had conducted a DQA, with just under half indicating they had received training within the same year.

HMIS trainings were found to have a weak and insignificant relationship with completeness of HMIS data (r=0.488, p value=0.108). To further discuss this, the R-Square value of (R^2=0.238) simply means that if all factors are controlled, only about 24% of the variations in completeness of HMIS data is because of HMIS trainings. For these trainings to be impactful on quality of maternal deliveries data, they should be integrated to include all key stakeholders in the health sector and more so observation checklists utilized to supplement the questionnaire whenever carrying out supervision visits. Simba and Mwangu (2006).

A research report by Ndabarora et al., (2013) re-emphasized the positive contribution of DQAs, trainings and supervisions in ensuring quality of hospital data as part of the routine health information systems among HIS researchers. Silas (2017) in his study in Kenya about factors affecting performance of routine HMIS; there was an insignificant positive relationship between trainings of staff and quality of HMIS deliveries data.

5.3: Effect of staffing levels on timeliness of HMIS data for maternal deliveries

Study findings revealed that quality of HMIS data among deliveries to some extent depends on staffing levels related attributes of availability of a full time Biostatistician, availability of an HMIS focal person and availability of Records Staff in Regional Referral Hospitals. There was a moderate positive relationship (r=0.5) between staffing levels and timeliness of HMIS data. The nature of the relationship or dependency was different in terms of magnitude or strengths across each of the mentioned attributes.

The findings were consistent with Silas (2017), who, in his study on factors influencing the performance of routine health information systems at selected health facilities in Kenya, found a significant positive relationship between the availability of and adequate staffing for HMIS. The relationship was specifically found to exist between medical records officers and timelines of HMIS data elements on Babies born before arrival and maternal deliveries in unit.

Correlation analysis revealed a positive, albeit mild, relationship between the availability of a Biostatistician and the timeliness of HMIS data. However, this relationship was statistically insignificant at the 0.05 level ($r = 0.488$, $p = 0.108$). To further discuss this, the R-square value of (R^2=0.238) simply means that if all factors are controlled, only about 24% of the variations in timeliness of HMIS data (for instance submission of reports in the DHIS 2 by the deadline) is because of having a Biostatistician in place. This justifies Biostatistician alone is not key

in influencing quality of HMIS data; with or without a Biostatistician, not much may happen on quality of HMIS data on deliveries.

The study findings indicated that a full-time HMIS focal point person is present, as confirmed by 96.7% of the respondents. It was noted that this HMIS focal person was not a specialist in health information. The absence of staff with core competencies in data management and analysis has been identified as a major weakness affecting data quality in various studies (Leonard et al., 2021). Similar observations were made by Yusof et al. (2008) in their evaluation framework for health information systems. Also, study findings align with the guidelines on staffing for Districts Health Offices and Regional Referral Hospitals by the Health Service Commission (2018), that provides for each district to have a fulltime Biostatistician and HMIS focal person with minimum qualifications of a bachelor's degree who oversees the implementation of HMIS and ensures quality of data collected and reported through HMIS.

Furthermore, upon running a correlation analysis, it was found out that a very weak positive relationship existed between availability of an HMIS focal person and timeliness of HMIS data. The relationship was statistically insignificant at 0.05 level of significance (r=0.255, p value=0.424). To further discuss this, the R-square value of (R^2=0.065) simply means that if all factors are controlled, only about 6.5% of the variations in timeliness of HMIS data is as a result of having a HMIS focal person in place. This justifies the conclusion that a HMIS focal person alone is not key in influencing quality of HMIS data; with or without a HMIS focal person, not much may happen on the quality of HMIS delivery data.

These findings agree with a study done in Uganda about evaluation of the performance of routine information system management (PRISM) framework reported that presence of HMIS focal person may not heavily influence quality of HMIS data (Hotchkiss et al., 2010).

Further analysis revealed that Records Officers are available although not adequate and this was confirmed by (67.4%) of the study respondents. Furthermore, a correlation analysis indicated that a very strong positive and significant relationship existed between availability of records staff and timeliness of HMIS data ($r=0.845^{**}$, p value=0.001). This probably is because of their day-to-day obligation of data collection, entry, analysis and disaggregation. This further implied that Records staff contribute heavily to the quality of HMIS data much more than a Biostatistician and an HMIS focal person. Infact the R-square value of ($R^2=0.714$) simply means that if all factors are controlled, 71% of the variations in timeliness of HMIS data is as a result of Records Staff. This kind of relationship was also demonstrated by Silas (2017) in his study in Kenya about factors influencing the performance of routine health information system; there was a significant positive relationship between adequate staffing for HMIS tasks, and quality of routine health information system data.

Overall findings agree with the findings of a study that was done in Ethiopia that found out that availability of skilled human resources including Records Officers, Health Biostatistician, HMIS focal persons increased the likelihood of achieving data quality (Teklegiorgis et al., 2019).

5.4: Effect of Technology on accuracy of HMIS data for maternal deliveries

Study findings revealed that accuracy of HMIS delivery data to a less extent depends on technology related attributes, which include; access to DHIS2, availability of a computerized system for analyzing and reporting and availability of internet connectivity in Regional Referral Hospitals. There was a weak positive relationship (r=0.47) between technology and accuracy of HMIS data.

The weak relationship was because of the inefficient utilization of available systems like DHIS2, computers and internet to gather, analyze and report maternal deliveries data as required by the line ministry. These findings agree with Kiberu et al., (2020); that data quality issues continue to occur, and these are largely attributed to poor access to DHIS 2 and computers and internet access. They suggested that for the quality issues to be addressed, there is a need to scale-up DHIS2 and computer utilization to lower-level health facilities to improve accuracy of HMIS data among deliveries collected at that level before they are submitted to the district and national levels.

More than half of the study respondents (55.5%) revealed that the hospital has access to DHIS2 (both user-name and password). According to the study respondents, these credentials are only known and kept by the Medical Records team. The log-in details are usually changed on an annual basis to avoid possible hackers. According to a Kimaro, (2020), the adoption of DHIS2 aimed to facilitate data access and stimulate usage.

Furthermore, a correlation analysis showed that a strong positive relationship existed between having access to DHIS2 and accuracy of HMIS data. The

relationship was statistically significant at 0.01 level of significance ($r=0.775^{**}$, p value=0.003). To further discuss this, the R-Square value of ($R^2=0.600$) simply means that if all factors are controlled, about 60% of the variations in accuracy of HMIS data is as a result of having access to DHIS2 in place. This justifies the conclusion that access to DHIS 2 is very key in influencing Quality (most especially accuracy) of HMIS data. These study findings relate to a study done by Divya (2015) on the impact of technology on primary healthcare information management in India, it was discovered that access to DHIS 2 serves as an efficient enabler that reduces manual documentation practices by ably connecting to available computers and databases much more easily. It was as such found out that access to DHIS 2 is positively correlated with accuracy of institutional new-born deliveries, thus providing an e-health solution for improving maternal and child health.

There is limited access to internet connectivity by the hospital departments and this was confirmed by (54.3%) of the study respondents. It should be noted that although much of the HMIS data collection and aggregation can be done manually, much of the entry and verification in the system (DHIS 2) requires stable and adequate internet.

Furthermore, upon running a correlation analysis, it was found out that a very weak positive relationship existed between access to internet and accuracy of HMIS data. The relationship was statistically insignificant at 0.05 level of significance (r=0.111, p value=0.731). To further discuss this, the R-Square value of ($R^2=0.012$) simply means that if all factors are controlled, only about 1.2% of

the variations in accuracy of HMIS data is as a result of having access to internet in place. This justifies the conclusion that access to internet alone is not key in influencing accuracy of HMIS data among deliveries.

Findings revealed that computers are available in selected departments, and this was confirmed by (53.2%) of the study respondents. Computers play a significant role in minimizing errors during data entry as opposed to manually doing it.

Furthermore, upon running a correlation analysis, it was found out that a somehow mild positive relationship existed between access to computers and accuracy of HMIS data. The relationship was statistically insignificant at 0.05 level of significance (r=0.522, p value=0.082). To further discuss this, the R-Square value of (R^2=0.272) simply means that if all factors are controlled, only about 27% of the variations in accuracy of HMIS data is as a result of having access to computers in place. This implies that access to computers alone is not key in influencing accuracy of HMIS data.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.0 Introduction

This section presents major conclusions, recommendations for further action and areas for further study.

6.1 Major conclusions

The study notably found out that a relationship existed between capacity building, staffing levels and technology and quality of HMIS data among deliveries specifically completeness, timeliness and accuracy among deliveries. HMIS was found to enhance the accuracy of data on maternal deliveries, primarily because the HMIS implementation includes access to DHIS2, which is utilized for reporting healthcare data. It is worth noting that HMIS remains a vital source of healthcare information in Uganda and globally for reasons emanating to its ability to integrate all health care indicators and programs and availing this information digitally.

Each of the study variables influenced data quality differently and as a result requires unique interventions to address noticeable gaps existing for improved quality of data. The study for instance revealed a mild positive relationship between supportive supervision visits and quality of HMIS data meaning that as much as supportive supervision visits were being conducted, they were not adequate to strongly guarantee quality of data especially among deliveries. To make these visits impactful, the frequency may be increased as a mitigation measure but also the methodology (who, how, where and why) of conducting the visits may be revisited/re-thought.

6.2 Recommendations for further action

For HMIS to ably achieve it's purpose of generating quality data that is complete, timely and accurate to influence programming and decision making by stakeholders, collaborative efforts must suffice. The study proposes the following recommendations.

Need to emphasize clear responsibilities in data management to address issues like incorrect register filling. This effort should also aim to ensure skilled staff with HMIS capacities are recruited to implement HMIS. This will further make data management an integral role for all departments hence guaranteeing complete, timely and accurate delivery data.

The hospital should roll-out inclusive training sessions involving junior staff and promotes enhanced data sharing and dissemination practices to strengthen data quality assurance processes.

The hospital should strengthen the existing feedback mechanisms for health information by utilizing the already existing digital system (DHIS 2) to collect real time feedback from all hospital departments.

6.2.1 Areas of further study

For purposes of additional study, potential study areas are proposed to the scholars to further contribute to what already is existing in the areas of HMIS and data quality. The proposed study areas may include;

- Study the influence/contribution of other associated factors on quality of HMIS data across different healthcare levels including District hospitals, HCIVs, HCIIIs.
- Additional research can be conducted to determine the existing gaps in midwives and nurses' training, which would involve reviewing their training curriculum.
- Examine how the period of service of hospital staff members influences the quality of HMIS data. The study can be expanded to look at the influence of nurses and or midwives or other healthcare professionals on quality of HMIS data in hospitals.

REFERENCES

AbouZahr C and Boerma T (2019). Health information systems: The foundations of public health. Bull World Health Organization.

AbouZahr, C. (2021). Health information systems: The foundations of public health. Bulletin of the World Health Organization, 83(8), 578–583

Anyangwe SCE, Mtonga C (2012). Inequities in the Global Health Workforce: The Greatest Impediment to Health in Sub-Saharan Africa. Int. J. Environ. Res. Public Health, 4(2):93100.

Bailey P., Nayunja M., Nzabanita a., Marjoola R. (20216). Development of HMIS in least Developed Country Settings: The case of Uganda. Retrieved May 17, 2016, fromahima.org: www.library.ahima.org/doc?oid-58653

Bhattacharya AA, Umar N, Audu A, Felix H, Allen E and Schellenberg JRM (2019). Quality of routine facility data for monitoring priority maternal and newborn indicators in DHIS2: a case study from Gombe State, Nigeria. PLoS ONE. 2019;14(1): 0211265.

Bill, G. (2011). Research methods. Quantitative and qualitative. Acts Press

Carbone (2008): Elaboration of data by United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects

Chaulagai CN, Moyo CM, Koot J, Moyo HBM, Sambakunsi TC, Khunga FM, Naphini PD (2015): Design and implementation of a health management information system in Malawi. Health Policy Plan. 20 (6): 375-384. 10.1093/heapol/czi044.

Cheburet, S.K., & Odhiambo-Otieno.G. (2022): State of data quality of routine Health management Information System: Case of Uasin Gishu county referral Hospital, Kenya. International Research Journal of Public and Environmental Health.

Creswell, J.W. (2003) Research Design-Qualitative, Qualitative and Mixed Methods Approaches. London: SAGE Publications

Divya Kanwar Bhati (2015). "Impact of Technology on Primary Healthcare Information Management: A Case of North India" Perspectives in Health Information Management (International issue).

Earl-Babbie, M. (2013). The Practice of Social Research, 10th edition, Wadsworth, Thomson Learning Inc., ISBN 0-534-62029

Glele Ahanhanzo, Y., Ouedraogo, L. T., Kpozèhouen, A., Coppieters, Y., Makoutodé, M., & Wilmet- Dramaix, M. (2014). Factors associated with data quality in the routine health information system of Benin. Archives of Public Health, 72(1), 25.

Green. (2015). Task shifting to tackle health worker shortages. Retrieved December 2, 2015.

Health Metrics Network. (2005). HMN. Issues in health information.

HIS Hub (2013). Prioritizing data sources to strengthen health information systems in the Asia Pacific region. The University of Queensland.

Hiwot et al., (2019. Evaluation of Health Management Information Systems-A Study of HMIS in Kerala.

Hotchkiss A, Musominali S, Baganizi M, & Paccione, G (2010). A process evaluation of performance-based incentives for village health workers. Human Resources for Health, 12(1), 19.

Isabalija S.,MayokA GK., Rwashana A.S., and Mbarika V.W. (2011). Factors Affecting Adoption, Implementation and Sustainability of Telemedicine Information Systems in Uganda. Journal of Health Informatics in Developing Countries, 299 -316. Retrieved March 18, 2017, from http://www.jhidc.org/index.php/jhidc/article/view/72

Jhpiego (2020). Framework and Standards for Country Health Information Systems. World Health, 2nd Editio(January), 72.

Karengera I, Onzima RAD, Katongole S-P, Govule P, (2022). Quality and Use of Routine Healthcare Data in Selected Districts of Eastern Province of Rwanda. International Journal of Public Health Research.

Karuri J, Waiganjo P, Orwa D, Manya A (2014). DHIS2: The Tool to Improve Health Data Demand and Use in Kenya. J. Health Informatics in Developing Countries, 8(1):38–60.

Kiberu V.M., Matovu J.K.B., Makumbi F., Kyozira C., Mukooyo E., and Wanyenze R. K. (2020). Strengthening district-based health reporting through the district health management information software system: the Ugandan experience. BMC medical Informatics and Decision making, 1--9. Retrieved June 12, 2017,

Kiberu VM, Matovu JK, Makumbi F, Kyozira C, Mukooyo E, et al. (2019) Strengthening district based health reporting through the district health management information software system: the Ugandan experience. BMC medical informatics and decision making 14: 40.

Kimaro H.C, (2020). Analysing the hindrance to the use of information and technology for improving efficiency of health care delivery system in Tanzania.Tanzan Health Res Bull, ,New York, USA, McGraw-Hill Publishers.

Kimaro HC, Nhampossa JL, (2019). The challenges of sustainability of health information systems in developing countries: comparative case studies of Mozambique and Tanzania. J Health Inform Dev Ctries. 2007;1(1):1–10 http://www.jhidc.org/index.php/jhidc/article/view/3.

Kothari, C.R (2004).Research Methodology: Methods and Techniques, 2nd Edition. New Delhi: New Age International Publishers.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and psychological measurement, 30(3), 607-610.

Little, J. W. (2019). Inside health information systems: Representations of community health practice. Health facility workers Record, 105(6), 913–945.

Lorenzi, S. D. (2018). Assessing the quality of data aggregated by antiretroviral treatment clinics in Malawi.Bull World Health Organ 2011

Leonard et al., (2021): Data utilisation and factors influencing the performance of the health management information system in Tanzania

Makumbi FE, Okello C, Mutebi A, Wabwire-Mangen F (2016): Health Sector HIV/AIDs Response Review. Kampala: Uganda,

Mboya. (2017). Constructing Social Research: The Unity and Diversity of Method, Pine Forge Press, 2017, ISBN 0-8039-9021-9

MEASURE Evaluation (2010). A Review of Constraints to Using Data for Decision Making Recommendations to Inform the Design of Interventions.

MEASURE Evaluation (2012). How can routine health information systems improve health systems functioning in low and middle-income countries? assessing the evidence base. Advances in Health Care Management.

MEASURE Evaluation (2017): eHMIS (Electronic Health Management Information System) User Guide. HMIS Scale-up Project with support from the United States Agency for International Development (USAID)

Ministry of Health. (2017). Health Sector Strategic Plan Iii. Kampala. Retrieved June 17, 2017, from http://www.health.go.ug/docs/HSSP_III_2017.pdf

Ministry of Health (MoH) Uganda (2016) Health Management Information System Resource Center.

Ministry of Health (MoH), 2019, National Electronic Health Information Management System (eHMIS) User Acceptance Testing Report

Ministry of Health, Health Systems 20/20, Makerere University School of Public Health: Uganda Health Systems Assessment. 2011, Kampala, Uganda and Bethesda, MD: Health Systems

Ministry of Health, MoH (2018): The State of Regional Referral Hospitals in Uganda

Ministry of Health. (2020) Annual Health Sector Performance Report, Ministry of Health.

Mishra, A., Vasisht, I., Kauser, A., Thiagarajan, S., & Mairembam, D. S. (2017). Determinants of Health Management Information Systems performance:Lessons from a district level assessment. BMC Proceedings.

Mphatswe, W., Mate, K. S., Bennett, B., Ngidi, H., Reddy, J., Barker, P. M., & Rollins, N. (2012). Improving public health information: a data quality intervention in KwaZulu-Natal, South Africa. Bulletin of the World Health Organization, 90(3), 176–82.

Mucee, E. M., Otieno, O., Kaburi, L. W., & Kinyamu, R. K. (2019). Routine Health Management Information Use in the Public Health Sector in Tharaka Nithi County, Kenya. Imperial Journal of Interdisciplinary Research (IJIR).

Mugenda, O. M., & Mugenda, A. G. (2003). Research Methods: Quantitative and Qualitative approaches. Nairobi: Acts Press.

Muriithi, J., Seki, D., & Kamau, M., 2020. Integrating Evidence-Based Health Information Systems in Kenya: Enhancing Data Quality and Health Service Delivery. Journal of Health Informatics in Africa, 12(2), 45-59

Mutale, W., Chintu, N., Amoroso, C., Awoonor-Williams, K., Phillips, J., Baynes, C., Michel, C., Taylor, A., & Sherr, K. (2020). Improving health information systems for decision making across five sub-Saharan African countries: Implementation strategies from the African Health Initiative. BMC Health Services Research. BioMed Central Ltd.

Mwebaza, J., Kizito, K., & Opendi, P., 2020. Availability of Computers in Ugandan Health Facilities: Challenges and Recommendations. Journal of Health Informatics in Africa, 15(2), 78-86

Namazzi, G., Nambuya, A., & Kirunda, J., 2020. Infrastructure and Technological Challenges Affecting Maternal Health Data Quality in Uganda. International Journal of Health Informatics, 98, 102-110

Nass, J., Damberg, C., Ryan, A., Agres, T., Schwartz, a, & Dentzer, S. (2019). Health Policy Brief. Health Affairs, 19, 1–5.

Ndabarora, E., Chipps, J. a., & Uys, L. (2013). Systematic review of health data quality management and best practices at community and district levels in LMIC. Information Development, 30(2), 103–120.

Nshimyiryo and Sayinzoga, (2020). Health management information system (HMIS) data verification: a case study in four districts in Rwanda. PLoS ONE. 2020;15(7): 0235823.

Nyamtema, Harriet. (2015). Bridging the gaps in the Health Management Information System in the context of a changing health sector. BMC Medical Informatics and Decision Making.

Odhiambo-Otieno G.W. and Wilson W.O. (2005) Evaluation criteria for the district health management information systems: Lessons from the Ministry of Health, Kenya Afr Health Sci; 5(1): 59–64.

Opendi, P., Mwebaza, J., & Kizito, K., 2021. Challenges in Data Quality for Maternal Deliveries in Uganda: Systemic and Operational Factors. BMC Health Services Research, 21(1), 212-223

Ouedraogo M, Kurji J, Abebe L, Labonté R, Morankar S, Bedru KH, (2019): A quality assessment of Health Management Information System (HMIS) data for maternal and child health in Jimma Zone, Ethiopia. PLoS ONE. 2019;14(3):e0213600.

Renner, P. (2020). Why Most EMR Implementations Fail. Available: http://www.streamlinemd.com/Data/Sites/58/assets/StreamlineMD_WhitePaper_1 B.p df [Accessed February 2015].

Shaw, V. (2019). Health information system reform in South Africa: developing an essential data set. Bull World Health Organ. New York,USA: McGraw-Hill.

Shrestha and Bodart, (2012): Health Sector Strategic and Investment Planning. Alma-Ata, USSR, 6-12

Simba, D. O., & Mwangu, M. A. (2006). Factors influencing Quality of Health Management Information System (HMIS) data:The case of Kinondoni District in Dar es Salaam Region,Tanzania. East African Journal of Public Health.

Simba, S. (2005). Health services delivery: Cooperation in strengthening national health information systems.

Silas. (2017). Case Study Research Design and Methods. London: SAGE Publications.

Snowdon W.A, Rern H.S and Winter A. (2017). When Information Technology meets Healthcare in West Africa:A literature review. Journal of health Informatics in Africa, 2(2), 29 -35. Retrieved February 10, 2017, from https://jhia-online.org/index.php/jhia/article/view/104

Suh P, Najunja M, Nzabanita A, Magoola R (2007) Development of HMIS in least developed country settings: the case for Uganda. WHO Country Office for Uganda, Ministry of Health, Uganda.

Suzan et al. (2020). Can performance-based financing be used to reform health systems in developing countries? Bulletin of the World Health Organization, 89(9), 695–698.

Teklegiorgis Kidist, Gebremariam Kidane, Mirutse Gebrameske and Lerebo Wondwossen (2019): Level of data quality from Health Management Information Systems in a resources limited setting and its associated factors, eastern Ethiopia

Teklegiorgis, K., Tadesse, K., Mirutse, G., & Terefe, W. (2021). Level of data quality from Health Management Information Systems in a resource limited setting and its associated factors. South African Journal of Information Management.

UNICEF (2019): Innovating Application of Mobile Technologies with Routine Health Information Systems.

Witter, S., Toonen, J., Meessen, B., Kagubare, J., Fritsche, G., & Vaughan, K. (2013). Performance based financing as a health system reform: mapping the key dimensions for monitoring and evaluation. BMC Health Serv Res, 13, 367.

Xiao Y, Bochner AF, Makunike B, Holec M, Xaba S and Tshimanga M, (2021): Challenges in data quality: the influence of data quality assessments on data availability and completeness in a voluntary medical male circumcision programme in Zimbabwe. BMJ Open.

APPENDICES

Appendix 1: Survey Questionnaire

SECTION 1: INTRODUCTION
My name is Julius Ahimbisibwe, a student of Master of Public Health at Kyambogo University. In partial fulfillment of the requirements for the award of Master of Public Health, I am required to conduct a research in an area of my interest. I would like to ask you to participate in a one-to-one interview on "Assessing the influence of capacity building, staffing levels and technology on Quality of Health Management Information System (HMIS) data among deliveries in Arua Regional Referral Hospital". The survey will last for less than 30 minutes. Please answer all the questions truthfully. You will not be judged on your responses; you may refuse to answer any question and you may choose to stop the discussion at any time. There is no direct benefit, money or compensation to you in participating in this study

SECTION 2: CONSENT FOR RESPONDENTS' PARTICIPATION IN DATA COLLECTION	
2.1 You have been sampled to participate in this study and the information you give will be used strictly for academic purposes and will never be used against you or your office. The information got from you will be kept confidential. Your consent to participate is implied by your decision to respond to the Survey Questions. Do you consent to participate in this study? If the person responds NO, go to **CONCLUSION.**	1 = Yes 2 = No

SECTION 3: RESPONDENT'S CHARACTERISTICS	
3.1 Sex of Respondent	1=Male 2=Female
3.2 Respondent's Department/ward	1=Administration 2=Medical Records 3=Maternity 4=Antenatal 5=Family Planning 8=Other, specify
3.3 Respondent's Cadre	1=Biostatistician 2=HMIS focal person 3=Records Officer 4=Medical Director 5=Human Resource Officer 6=Cashier 7=Midwife 8=Nurse 9=Medical Doctor 10=Clinician 11=Other, specify
3.4 Respondent's Highest Education level	1=Certificate 2=Diploma 3=Degree 4=Postgraduate Certificate 5=Postgraduate Diploma 6=Masters 7=Other, specify
3.5 Duration of employment in the department	1=Less than 5 years 2=5-9 years 3=10-15 years 4=over 15 years
3.6 Duration of employment in current position	1=Less than 5 years 2=5-9 years 3=10-15 years 4=over 15 years

Section 4:

Capacity Building and Completeness of Health Management Information System Data

In your opinion, please rate the extent to which you agree with the following statements. Please use tick (√) for the appropriate answer.

Statement	Strongly disagree	Disagree	Agree	Strongly agree
1. Your Hospital/department receives regular supportive supervision visits from district and/or MoH team and/or other NGOs according to the guidelines				
2. Your Hospital/Department conducts routine Data Quality Assessments				
3. The Hospital or department receive regular feedback on the quality of their submitted reports?				
4. The Hospital/partners organizes regular HMIS trainings targeting health facility staff? *Probe for trainings done and duration*				
5. Staff understand what should be recorded in the source documents/registers				
6. Staff understand what should be included on the HMIS monthly report.				
7. Staff understand when the reports are due and to whom the reports should be submitted.				
8. In case of errors, responsible staff knows how to communicate and effect changes in a report that was previously submitted to the district.				

All cadres

Period	# of Hospital staff	# of Hospital Biostats	# of HMIS Focal persons	# of records staff	HMIS 105 Reporting rate
Jan-20					
Feb-2020					
Mar-2020					
April-2020					
May-2020					
June-2020					
July-2020					
Aug-2020					
Sept-2020					
Oct-20					
Nov-20					
Dec-20					

Section 5:

Staffing Levels and Timeliness of HMIS data

In your opinion, please rate the extent to which you agree with the following statements. Please use tick (√) for the appropriate answer.

Statement	Strongly disagree	Disagree	Agree	Strongly agree
1. Arua District has a full time Biostatistician employed by the Ministry of Health?				
2. Arua District has a full time HMIS focal person employed by the Ministry of Health for over-seeing the implementation of HMIS across the District?				
3. Your Hospital has a functional records department with staff responsible for routine Health Management Information System (HMIS) related tasks?				
4. Every Hospital Department is assigned Records Officer in-charge of collecting and reporting HMIS data.				
5. Staff in your health facility or department are trained on routine Health Management Information System (HMIS)				
6. There are designated staff responsible for reviewing periodic reports prior to submission to the next level?				
7. Hospital or District has staff trained in data analysis and interpretation.				
8. Hospital or District has staff who takes lead in analysis and interpretation of HMIS data				

All cadres

Period	# supportive supervison visits conducted	# DQAs conducted?	# HMIS trainings conducted?	Reported data is complete?
Jan-20				
Feb-2020				
Mar-2020				
April-2020				
May-2020				
June-2020				
July-2020				
Aug-2020				
Sept-2020				
Oct-20				
Nov-20				
Dec-20				

Section 6:

Technology and Accuracy Health Management Information System data

In your opinion, please rate the extent to which you agree with the following statements. Please use tick (√) for the appropriate answer.

Statement	Strongly disagree	Disagree	Agree	Strongly agree
1. The Hospital has and consistently uses standardized national HMIS forms/tools for reporting in the DHIS2				
2. The Hospital has access to DHIS2				
3. Staff have the skills to perform DHIS 2 related tasks such as data entry, analysis and interpretation				
4. The DHIS2 allows tracking of unique individual clients within and across Service Delivery Points to avoid double counting.				
5. The Hospital has computerized system for reporting and analyzing HMIS data.				
6. The hospital has access to internet connectivity for ease of HMIS data management				
7. SOPs/ Job Aids/Guidelines that describe how e HMIS should be implemented clearly written and accessible to all staff				
8. Data archiving/storage system at the Hospital is adequate				

All cadres

Period	Access to DHIS 2 available?	Access to internet connectivity?	Computers are available for records staff to manage data?	# computers available
Jan-20				
Feb-2020				
Mar-2020				
April-2020				
May-2020				
June-2020				
July-2020				
Aug-2020				
Sept-2020				
Oct-20				
Nov-20				
Dec-20				

Section 7:

Quality of Health Management Information System data

In your opinion, please rate the extent to which you agree with the following statements. Please use tick (√) for the appropriate answer.

Statement	Strongly disagree	Disagree	Agree	Strongly agree
Accuracy				
Data reported in the health facility monthly reports is similar to the data in the health facility registers				
Monthly data available in the DHIS2 is similar to the data on monthly reports submitted to records office				
Completeness				
Expected monthly reports are submitted to the health records office				
Data elements in the expected monthly reports are completely filled				
Timeliness				
Hospital departmental reports (ANC/Maternity/FP/Nutrition) are compiled in a timely manner				
Monthly reports are submitted by the specified deadline to the Records Office for timely reporting in to the DHIS2				

All cadres

CONCLUSION
Provide any other comments

Thank you for your time. I assure you that information shared in this discussion will be treated with utmost confidentiality

Documentation Review 1:

Review of HMIS Registers, Monthly HMIS reports and reported data in DHIS2-Accuracy & Completeness

Indicator	Primary Data Source (Registers) & Data for Aggregation	Secondary Data Source (HMIS Summary Reports)	Period	Onsite Count	Reported Monthly Outputs in the HMIS	Reported Monthly Outputs in the DHIS2	Percentage Deviation of HMIS Report from Joint Count	Percentage Deviation of DHIS2 Report from Joint Count
1) Number of deliveries at health unit in the quarter of October to December 2020.	HMIS FORM 072: Intergrated Maternity Register (**Deliveries at unit**)	HMIS 105: Health Unit Outpatient Monthly Report - 2. Maternal and Child Health (MCH) -2.2 Maternity – MA04a	Jan-20					
			Feb-2020					
			Mar-2020					
			April-2020					
			May-2020					
			June-2020					
			July-2020					
			Aug-2020					

			Sept-2020					
			Oct-20					
			Nov-20					
			Dec-20					
			TOTAL					

Documentation Review 2:

Review of DHIS2 for Reporting Rates-Timeliness

Indicator	Data source	Period	%ge of reporting/100%	Comments
1) HMIS 105 Reporting rate for the period Jan – Dec 2020	DHIS 2	Jan-20		
		Feb-2020		
		Mar-2020		
		April-2020		
		May-2020		
		June-2020		
		July-2020		
		Aug-2020		
		Sept-2020		
		Oct-20		
		Nov-20		
		Dec-20		
		TOTAL		

Appendix 2: Hospital interview guide-

1. **Facility Code: ___________________________________**

2. **Name of Key Informant: ___________________________________**

3. **Role/position of Key informant?**

4. **Contact of Key Informant: ___________________________________**

5. **Facility Department: ___________________________________**

Section A: Health Management Information System (HMIS)

1. Please tell me your understanding of the term HMIS?

Probes:

a) Origin of hospital HMIS

2. How has the implementation of HMIS been?

3. Who is responsible for implementation of HMIS and overall data quality?

Probes:

a) Challenges for HMIS implementation
b) Achievements

Section B: Data Quality

1. What is your understanding of data quality?

2. Do you know any data quality mechanisms? Please describe.

3. How do you ensure data quality in the Hospital?

4. What can you say are the possible factors influencing quality of HMIS data?

Probes:

a) How staffing levels affect data quality
b) How Technology affect data quality
c) How capacity building affect data quality

Appendix 3: Table for determining sample size from a given population

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	**92**	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.— *N* is population size and *S* is sample size.

Source: Krejcie &Morgan (1970)., "Determining Sample Size for Research Activities", Educational and Psychological Measurement

Appendix 4: Capacity building and related attributes data

Summary data about capacity building and related study attributes										
Period (Jan-Dec'2020)	supportive supervison visits conducted?	# supportive supervison visits conducted	Supervision reports available and accessible?	DQAs conducted?	# DQAs conducted?	HMIS trainings conducted?	# HMIS trainings conducted?	# Deliveries-on site count	# Deliveries-DHIS-2	Reported data is complete?
Jan	Yes	4	No	Yes	1	Yes	1	547	548	No
Feb	No	0	No	No	0	No	0	449	449	Yes
Mar	No	0	No	No	0	No	0	572	587	No
Apr	No	0	No	No	0	No	0	483	472	No
May	Yes	3	Yes	Yes	1	No	0	411	411	Yes
Jun	No	0	No	No	0	No	0	513	513	Yes
Jul	No	0	No	No	0	No	0	521	519	No
Aug	No	0	No	No	0	No	0	579	579	Yes
Sep	Yes	3	Yes	Yes	1	No	0	580	580	Yes
Oct	No	0	No	No	0	No	0	556	564	Yes
Nov	No	0	No	No	0	No	0	546	551	No
Dec	No	0	No	No	0	No	0	462	461	Yes

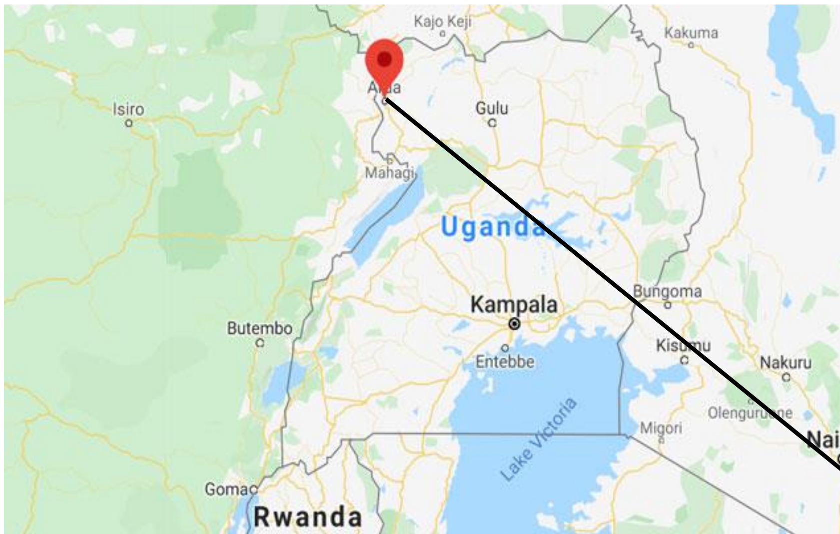
Appendix 5: Staffing levels and related attributes data

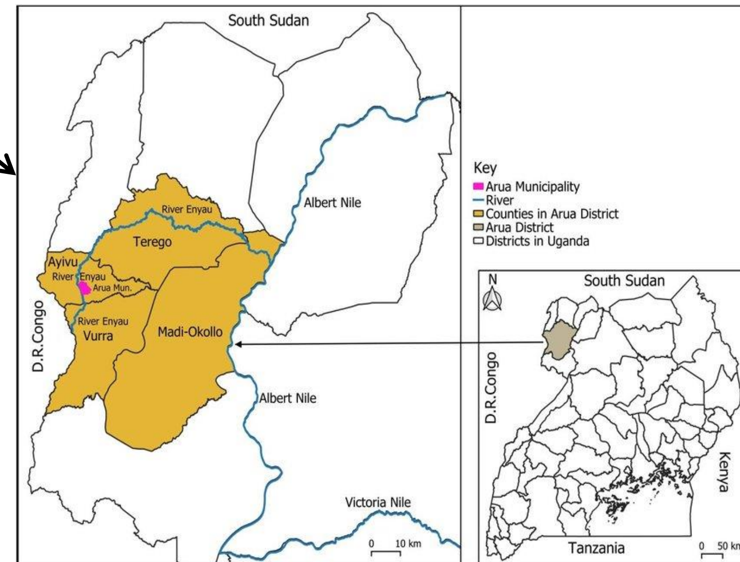
Summary data about staffing levels and related study attributes									
Period (Jan-Dec'2020)	# of Hospital staffs	# of Hospital Biostat available?	# of HMIS FP available?	# of records staffs	Reporting rate	Reports submitted in/on time?	# Deliveries-on site count	# Deliveries-DHIS-2	Discrepancy
Jan	110	3	2	5	100%	Yes	547	548	1
Feb	110	3	2	4	93%	No	449	449	0
Mar	110	1	1	5	95%	Yes	572	587	15
Apr	115	1	1	6	99%	Yes	483	472	-11
May	115	1	1	3	85%	No	411	411	0
Jun	115	1	1	5	96%	Yes	513	513	0
Jul	118	1	3	4	91%	No	521	519	-2
Aug	118	1	4	6	100%	Yes	579	579	0
Sep	118	1	3	4	89%	No	580	580	0
Oct	120	1	3	5	96%	Yes	556	564	8
Nov	120	2	3	3	80%	No	546	551	5
Dec	117	1	2	6	98%	Yes	462	461	-1

Appendix 6: Technology and related attributes data

Summary data about technology and related study attributes							
Period (Jan-Dec'2020)	Access to DHIS 2	Access to internet	Availability of computers for data management	# computers available	# Deliveries- on site count	# Deliveries- DHIS-2	Data accuracy?
Jan	Yes	Yes	Yes	6	547	548	No
Feb	Yes	Yes	Yes	4	449	449	Yes
Mar	No	No	No	5	572	587	No
Apr	No	No	No	3	483	472	No
May	Yes	Yes	Yes	6	411	411	Yes
Jun	Yes	Yes	Yes	2	513	513	Yes
Jul	Yes	No	Yes	3	521	519	No
Aug	Yes	Yes	Yes	1	579	579	Yes
Sep	Yes	Yes	Yes	4	580	580	Yes
Oct	Yes	Yes	Yes	1	556	564	No
Nov	Yes	Yes	Yes	3	546	551	No
Dec	Yes	Yes	Yes	2	462	461	Yes

Appendix 7: Map showing study area





Appendix 8: Work plan and timeframes

Proposed Research Work-plan																						
Activity	**Dec’20**	**Jan’21**	**Feb’21**	**Mar’21**	**Apr’21**	**May’21**	**Jun’21**	**Jul’21**	**Aug’21**	**Sep’21**	**Oct’21**	**Nov’21**	**Dec'21**	**Jan'22**	**Feb'22**	**Mar'22**	**April'22**	**May'22**	**Jun'22**	**Jul'22**	**Aug'22**	**Status**
Research concept development																						Completed
Proposal development & preesentation at the department																						Completed
Working on comments & feedback from supervisors																						Completed
Designing of Datacollection tools & upload onto KOBO server																						Completed
Attending MSC seminar series																						On-going
Presenting approved proposal at the Faculty-1st round																						Completed
Inco-operating comments following presentation at the Faculty																						Completed
Submission of final proposal																						Completed
Data collection & entry (both qualitative and Quantitative)																						Completed
Data cleaning, coding, analysis and interpretation																						Completed
Progress reporting																						On-going
Writting a Draft Research report																						Completed
Inco-operating comments, writing a final report and submission																						On-going
Conducting validation/dissemination workshop																						

Appendix 9: The budget

Table 2: The budget forecast

No	Particulars	No. of days	Frequency	Unit cost (UGX)	Total Amount (UGX)
1. Data collection fees					
1	Transport to & from Arua	5	2	60000	120,000
2	Transport with in Arua	5	5	6000	30,000
3	Accommodation	5	6	50000	300,000
4	Meals	5	5	10000	50000
Sub-total					**500,000**
2. Other costs					
1	Internet costs (lumpsum)-40GB		2	50,000	100,000
2	Airtime (lumpsum)		5	10,000	50,000
3	Stationery costs incl printing (lumpsum)				50,000
4	Miscellaneous				100,000
Sub-total					**300,000**
Grand total					**800,000**

Budget Notes:

1) The researcher used a mobile questionnaire through KOBO toolbox, which reduced the high costs associated with printing data collection tools, while also streamlining data entry processes to save time and resources.
2) The researcher utilized their own mobile tablet equipped with KOBO toolbox to administer the survey questionnaire. The KOBO form included robust validation checks such as skip logic and mandatory responses to ensure quality of data.
3) Data collection at the hospital was scheduled for five (5) days. Costs for transport, accommodation, and meals were calculated based on the actual days of data collection.

4) All other expenses were consolidated into a lump sum covering the entire research period.
5) A miscellaneous budget line was included to address unforeseen expenses that arose during the research process.