FACTORS INFLUENCING UTILIZATION OF HEALTH INFORMATION DATA IN NAIROBI COUNTY PUBLIC HEALTH FACILITIES, KENYA

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

I dedicate this thesis to my Family who offered me unconditional love and support throughout the course of this thesis.

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ABBREVIATION AND ACRONYMS

CO	Clinical Officer
Df	Degree of Freedom
DHMIS	District Health Management Information Systems
DHMT	District Health Management Teams
DHS	Demographic and Health Survey
DR	Doctor
FGD	Focus Group Discussion
GOK	Government of Kenya
HC	Health Centre
HIO	Health Information Officer(s)
HIS	Health Information System(s)
HMIS	Health Management Information System(s)
KII	Key Informant Interviews
M&E	Monitoring and Evaluation
MO	Medical Officer
MOH	Ministry of Health
NGO	Non-Governmental Organization
SDGs	Sustainable Development Goals
SPSS	Statistical Package for Social Sciences
WHO	World Health Organization

ABSTRACT

Effective management of today's health systems depends on the critical use of data and information for policy formulation, planning, service monitoring, and decision-making. However, data use has been restricted and inadequate; resulting in vital health decisions frequently being based on political opportunism, donor demand, and infrequently repeated national studies that are insensitive to changes occurring over a shorter timescale. This study's objective was to investigate the factors that influence the utilization of Health information data. Specifically, assess the influence of data quality, establish the extent to which individual factors determines utilization of health information data, establish the level of staff involvement influences the utilization of health information data and identify organizational factors that influences the utilization of health information data in Nairobi County Public Health Facilities. A descriptive cross-sectional study employing quantitative methodology was conducted with at least 216 participants. Using a multistage sampling technique, the sample size of respondents was determined. Three public health facilities were sampled with proportional representation of respondents in each facility. Using SPSS version 25, quantitative data from structured questionnaires was entered, verified, cleaned, and analyzed. In the event of a relationship between categorical variables, the Chi-square test was applied. The majority of respondents were between the ages of 30 and 39, they were female, and were nurses. Majority also held a diploma as their highest level of education. Less than two-thirds of respondents (65.3%) used routine data for decision making on occasion. Additionally, (19.9%) and (14.8%) use routine data/health information for decision making infrequently and frequently, respectively. Level of education (p=0.025), gender of the health worker (p=0.010), cadre (p=0.001), participation in data discussion forums (p=0.013), training on data utilization (p=0.036), data collection (p=0.041), data analysis (p=0.032), data management (p=0.007), overall levels of competency (p=0.0001), access to routine data (p=0.001), access to a functional computer (p=0.023), and internet access (p=0.030). The researcher hopes that the study's findings will serve as a wake-up call for the management of public health facilities regarding the value of health information data in informing every decision made in the health facilities. The study recommends that County health management, in conjunction with the national level, provide training to improve health workers' skills, with a focus on routine data use, through on-the-job trainings and mentoring. It also recommended that the organizational context be improved by providing resources that support the use of information.

CHAPTER ONE: INTRODUCTION

1.1 Background Information

The World Health Organization (WHO) defines a Health Information System (HIS) as a system that integrates data collection, processing, reporting, and the use of information and knowledge to influence policy-making, programme action, and research. Health information is the foundation of health systems, and its availability will enable health workers to use it for better policy formulation, planning, implementation, monitoring, and evaluation of health initiatives (Tabesh, 2015). Routine health information has the ability to contribute in the development of indicators for public health care facilities such as decision making, planning, monitoring, and evaluation (Arumugam, et al 2016).

Globally, all countries have implemented the Health Information System, which has resulted in the production of high-quality and timely data, which is the foundation of the health system's functionality and informs decision-making in each of the five building blocks of the health care system, affecting quality health service delivery and health outcomes (World Health Organization [WHO], 2015). Despite differences in geopolitics, the district is the final fundamental unit of local government and administration (Afzal, 2017).

Improving the use of health information in all health-related institutions was judged vital by the government and non-governmental organisations in the United Kingdom in scaling up the delivery of good health care services. This is due to the fact that greater health information consumption needs higher data and information product quality, which necessitates improved health information systems (HIS) (Clancy & Cronin, 2015). Most African countries, particularly those in Sub-Saharan Africa, have experienced greater public sector engagement and interest in the role of the public for-profit sector in health service provision (Asiimwe, 2016). This is also true for the vast majority of poor and middle-income countries worldwide. Many countries have a vibrant and increasing public health system, which some argue is in response to inadequacies in public health. Health-care professionals are being challenged to provide treatments that are more accessible, affordable, and responsive to the needs and preferences of their patients (Adejumo, 2017).

In Uganda, health information dates back to 1985, when a central health information system (HIS) focused on morbidity and mortality was established (Asiimwe, 2016). In response to the need for more information influencing management elements, the system was reviewed in 1992, 2000, and 2004, culminating in the current human management information system. In light of the country's decentralisation initiative, one of the new system's goals was to improve the ability of health-related decision-making at the district level (Asiimwe, 2016).

Efforts were underway across Africa in the 1970s to improve health care and lower obstacles to service use, fuelled by the global health agenda (Dedan, 2011). In the early 1970s, Kenya's Ministry of Health (MOH) realised the need to develop health information systems (HIS), which are systems for gathering and processing data from various sources. The HIS was created from a variety of data sources. The information gathered was centred on the Ministry of Health's headquarters' demands. The information acquired was intended to aid in the creation of health policies, prioritisation, and assessment of health-care initiatives. The HIS built the Health Management Information System (HMIS), which was followed by the Vital Health Statistics Unit and the Evaluation and Research Unit (Mutemwa, 2016).

There has been a significant overall change of paper-based health record keeping and transmittal systems to an electronic system since the introduction of electronic health records (EHR) in the health sector (Routine Health Information Network [RHINO], 2019). Prior to the introduction of e-health, patients' health records were held manually in enormous volumes of printed folders, necessitating adequate records management methods to facilitate record storage and retrieval. It is widely acknowledged that health information or records are a key component of EHR system strengthening since health policies and planning are heavily reliant on accurate and timely information on various health issues, which improves a country's overall health status. Regardless, it is an important component for individual health organisations in controlling and enhancing healthcare delivery (WHO, 2019). Electronic Health Management Information Systems are one of the most significant ICT breakthroughs for organising and managing health information or records in order to boost any EHR system (e-HMIS). This e-HMIS is a facility-based data aggregation system designed to automate accurate and fast medical data collection, aggregation, storage, analysis, and evaluation for health-related decisions (RHINO, 2019). It is best described as an automated health information management system, which is made up of a collection of interconnected procedures and components that work together to generate health information and intelligence in order to monitor and manage people's health status and healthcare services in order to advance healthcare decisions at all levels (RHINO, 2019).

At Nairobi County, utilization of health information data in the district implementation plans, the utilization of data for operational plans and emerging issues is not clear. An evaluation of the nation's status on data utilizes demonstrated that this territory was extremely frail. Arranging was likewise not connected to health data and resource allocation did not depend on accessible proof. Checking and assessment of health programs and different intercessions should be founded on reports from the health information management information system. Information quality reviews done at the office by the supervisory group and different partners have demonstrated that information at Nairobi County is deficient, not promptly open, and is frequently not utilized in dynamic and the components affecting information use are no clear. The study seeks to emphasis importance of using health information data while making decision in health facilities by assessing the factors affecting utilization of health information data in the county through quality of data generated, individual factors, staff involvement and organizational factors.

1.2 Statement of the Problem

African countries need to be able to viably utilize information to screen examples of administration use through time so the effects of changes in arrangement and administration conveyance can be assessed. In spite of the fact that sub-province level directors routinely examine data, the utilization of data for operational plans and at hotspots for dynamic is restricted (Chikanda, 2016). In Kenya, 43% of information makers need information examination and understanding aptitudes, and 42% of wellbeing office chiefs break down and use information to impact the spending readiness cycle and arranging of clinical administrations (Scientific Symposium Report, 2016). Under 37% of gathered information is examined and utilized for dynamic (Ministry of Health,[MOH] 2016), subsequently the service is has a ton of information, not transformed into data and information to deliver results. One of the most suffering attributes of the data age is that we have zeroed in a lot on dominating exchange information and insufficient on transforming it into data and information that can prompt business results (Davenport et al., 2010; Karuri et al., 2014).

Nairobi County health facilities lack the necessary infrastructure, health products, and adequate personnel to manage and treat various medical conditions. In 2019 alone, the hospital had a workload of 348,116 new outpatients and 507,234 revisits. The admissions for the same period were100, 671 patients. The routine data that is generated is not used to detect drug stock-outs, disease trends, and allocation of resources to where there is a need. This leads to poor management of patients and inappropriate decisions that do not solve the patients' needs. Healthcare information lack importance unless it is used to inform decisions and the distribution of resources at all levels of healthcare. Thus, the need to study factors influencing utilization of Health Information data in Nairobi County Public Health Facilities.

1.3 Aim of the Study

The aim of this study was to examine the factors influencing utilization of health information data in Nairobi county Public Health Facilities, Kenya

1.4 Objectives of the Study

i. To assess the influence of data quality in the utilization of health information data in Nairobi County Public Health Facilities, Kenya.

ii. To establish the extent to which individual factors determines utilization of health information data in Nairobi county public health facilities, Kenya.

iii. To establish the level of staff involvement influences the utilization of health information data in Nairobi County Public Health Facilities, Kenya.

iv. To identify organizational factors that influences the utilization of health information data in Nairobi County Public Health Facilities, Kenya.

1.5 Research Questions

i. What is the influence of data quality in the utilization of health information data in Nairobi County Public Health Facilities, Kenya?

ii. What is the extent to which individual factors determines utilization of health information data in Nairobi county public health facilities, Kenya?

iii. What is the level of staff involvement influencing the utilization of health information data in Nairobi County public health Facilities, Kenya?

iv. What are the organizational factors that influence the utilization of health information data in Nairobi County public health Facilities, Kenya?

1.6 Justification

Due to unaddressed challenges in data collection, processing, and use at health facilities, it is still difficult to convert data into useful information in today's digitally connected world (MOH, 2016). When resources are limited, it is even more important to make decisions based on evidence, as pointed out by Pryse (2012). All of the major industries, from farming and fishing to shipping and transportation, rely heavily on collecting data and using that data to draw conclusions at the national and international levels; this practice should be emphasized to improve service quality. It is easier to ignore data for decision making and daily reporting to managers in the public sector, where profit maximization is not the primary objective, than in the private sector.

It is becoming increasingly clear that information systems are crucial for evaluating and expanding the range of healthcare provision. Curative care is giving way to preventative care on a global scale; hospital care is giving way to community and public health care; centralization is giving way to decentralization; and the focus on individual projects is giving way to an overarching sectorial strategy. The findings will help the County Health Management Team make better use of limited funds, implement programs supported by data, and boost health outcomes overall. Nonetheless, the research will add to the growing body of work on systematic methods to improve Kenyan hospitals' utilization of health information data for evidence-based decision making.

1.7 Significance of the Study

The researcher hopes that the study's findings will serve as a wake-up call for the management of public health facilities regarding the value of health information data that motivates dynamic, arranging, and evaluation. The analysis reveals how hierarchical components influence diverse factors such as behaviour and the specialized use of health information data in public health offices for evidence-based dynamics.

Once implemented, the study's findings will assist other health offices, such as private and religious health clinics, in appreciating the significance of introducing health data frameworks for better data. This will direct and alter the mentality of private health hospitals so that they no longer solely focus on the benefit thought process and instead position their conduct and practice towards better and enhanced assistance delivery.

The findings of this study can be used by researchers who want to do more research on the use of health data for other goals, such as asset accumulation, or in fields connected to the characteristics that influence the effective use of health information data by public and private health offices.

The study's recommendations may motivate the Ministry of Health and other relevant health authorities to strengthen limits and frameworks to improve the routine use of health data.

1.8 Assumptions

This study assumed that the respondents gave honest data that was founded on their insight.

1.9 Limitation

All research studies face a variety of obstacles. One of these constraints is the pressure of time. By limiting data collecting breaks, the researcher optimized the amount of time available. Given the private nature of the information sought, the researcher anticipated that respondents may purposefully offer inaccurate data or even hide information. The researcher reassured respondents that the information they provided were kept confidential. The researcher advised respondents that the questionnaires they received were unmarked and didn't require them to supply any information that might be used to identify them, such as phone numbers, names, or email addresses. Further, the researcher informed the respondents that the questionnaires will be completely destroyed after the information provided by the respondents are obtained. The researcher ensured that the language used in the questionnaires were of kind and comfortable for the reader. For instance, the introduction was worded to make the respondent at ease and create readiness to respond to the questions.

1.10 Delimitation of the Study

The purpose of this study was to investigate the factors that influence the use of health data in Nairobi City County Health Facilities. It concentrated on Nairobi County's health information management system. The study's scope was limited to data quality perception, individual variables, staff engagement, and organisational factors influencing health data consumption in Nairobi City County Health Facilities, Kenya.

1.11 Operational Definition of Terms

Data utilization: the degree to which health professionals use the information obtained for judgment

Data: These are evidence and details obtained in the original form used for reasoning or decision making

Decision making: the mechanism of choosing a reasonable choice or plan of action from the choices or available options. This is achieved to accomplish a particular goal or to perform a specific function.

Health/wellbeing facility: a venue that is designed or developed to serve patients and clients for a specific health state or events, such as a dispensary, clinic or hospital.

Health management information system: an effective compilation, collection, review and assessment policy, distribution and usage of information on individual patients, the community, the services used and the health effects of the intervention and the status and existence of the processes in which the intervention is carried out.

Health/wellbeing worker: is a person educated in the medical school/college involved in the operation, financial and day-to-day operation of a health facility or health services.

Routine data: these are information that is regularly reported without any particular study concerns, such as births, immunization reports, warnings of infectious diseases and deaths.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The literature that is discussed in this chapter is relevant to the guiding objectives of the study, which are as follows: identify the extent to which data are used; establish what technical factors; establish what organisational factors; and establish what behavioural factors influence the use of data for evidence-based decision making among health care workers in Nairobi County. The information that was gathered for this research came from a variety of sources, including textbooks, archives, the internet, and journals, and it was organised to correspond with the notes that were taken on the research topic.

2.2 Utilization of Health Information Data

Health information gathered utilizing HMIS is essential for arranging and assessing medical services administrations of wellbeing offices utilizing significant medical services pointers. Information the executives, ideal usage, and correspondence practices of wellbeing offices are extremely poor, for the most part in the creating. An investigation finding from South Africa showed that the general level of HMIS data utilize was 65percent (Yarinbab & Assefa, 2018). Studies of proof from Kenya Kihuba et al., (2014) and Mboro, (2017)uncovered that HMIS information use at medical care offices were poor. An examination finding from Cote d'Ivoire utilizing the Performance of Health information System Management (PRISM) structure (Nutley, et al., 2014) indicated a general wellbeing data usage score of 38% at medical care offices. Here, the PRISM contains a few schedules HIS pointers to portray the normal wellbeing data use status, and the general score was determined from those different markers.

A study done in India indicated that the most widely recognized sorts of choices detailed by respondents at the office, state, and local levels incorporated those identified with program the executives, arranging, and financial plans while staff working in wellbeing centres settled on choices about clinical and medication supply and arising epidemics. Health Management Information System (HMIS) information, local level studies, and state/area departmental reports were the frequently referred to information utilized for dynamic (Rexhepi, 2015). In another investigation in Tanzania, respondents detailed that they utilized wellbeing data to settle on choices with respect to clinical administrations, the requirement for staff preparing, and the improvement of authoritative strategies. Most of respondents referred to high remaining burden, absence of motivations, lacking specialized abilities, and inadequate information about existing information sources as a deterrent to wellbeing data use (Mukama, 2013).

A similar study done in Uganda by Asiimwe, (2016) demonstrated that staff in the vast majority of the offices detailed utilizing HMIS information for clinical stock and medication the executives, staffing choices, and administration improvement. HMIS information quality, nonetheless, was frequently undermined by being inadequate and erroneous; thusly, staff didn't generally depend on it for dynamic. Absence of PCs and incessant force disappointments decreased the staff's capacity to get to information and postponed the detailing cycle. Staff's ability to break down, decipher, and use information was restricted. Information exactness and practicality influenced information quality and along these lines use. The cycles of checking information precision and giving criticism on the submitted month to month reports were not executed, making it hard for staff to comprehend the significance of gathering information for improving their presentation as well as for the office or more elevated level or all in all (Oliver, 2013). Components adding to practical creation and utilization of good-quality information are specialized elements (for example information assortment sheets, measures), IT gadgets, information examination, ecological, authoritative, and social components (Ann, 2016).

2.3 Data Quality in Utilization of Health Information Data

A study on the planning and implementation of a data framework for executive wellness in Malawi was conducted. According to Chaulagai et al. (2015), the fulfilment of office-based health information was a significant problem in Malawi. In an investigation of data structures and information quality in three metropolitan Kenyan Ante Natal facilities, Ndegwa (2015) found that all analysed reports had limited completeness and precision. This was the case in offices supported by Information and Communication Technology (ICT) as well as offices employing manual structures. In the investigation, a variety of variables, including specialized, individual, and authoritative perspectives, constrained the quality of the data. It was expected that an intervention that encompasses all of these variables would be essential to turn the single direction frameworks into an integrated health framework with greater data quality and to encourage a culture of data use.

The accuracy of the data was evaluated by Afzal (2017), who conducted reviews in which he compared data from the DHIS with data from individual office records. Medical staff education on the value of health data, monthly information surveys and input, and regular information reviews were found to improve data completeness and accuracy used to evaluate Prevention of Mother-to-Child Transmission of HIV/AIDS (PMTCT) administrations in South Africa.

Ndegwa (2015) in an examination on data frameworks and information quality in three metropolitan antenatal facilities, seen that all analysed reports were of restricted precision. This has been with the case of Information Communication and Technology (ICT) upheld offices, just as the office utilizing manual structures. In the investigation, information quality was restricted by a wide range of elements including specialized, individual, and hierarchical angles. A methodical intercession that fuses every one of these viewpoints was expected to change the single direction frameworks into a coordinated wellbeing framework with higher information quality and to advance a culture of data use.

In evaluating the idealness of gathering, investigation, and scattering of data, Adejumo (2017)noted that most normal information were gathered for sure fire activities. The normal data frameworks require day by day accumulation of information on key components and prompt announcing of notifiable cases. Wellbeing offices are needed to refresh their month-to-month divider diagram and continually audit infection and administration inclusion patterns. Be that as it may, notwithstanding reliable subsequent meet-ups and updates, such practice had been set up as an order in scarcely 50% of the wellbeing offices.

Kimaro & Twaakyondo (2017) found that the usability of data was impacted by a lack of resources, a lack of knowledge and motivation, a significant amount of unfinished work, large datasets, and missing data. Their research examined the impediments to the utilisation of data and innovation for improving the effectiveness of the medical care delivery framework in Tanzania. The study's findings revealed that as the health system's level declined, so did people's understanding of the importance of the data they had collected.

2.4 Individual Factors Influencing the Use of Health Information Data

The certainty level of the wellbeing data supervisory crew additionally has the potential in impacting the degree of use of health information data by the general wellbeing offices. A large portion of the wellbeing office the executive’s individuals are certain to attempt HIS undertakings. They feel less sure about deciphering information and utilizing data, and more sure about checking information quality (Cheburet & Odhiambo-Otieno, 2016).

The skill of the working staff of the administration and specialized groups for the oversight of the general wellbeing offices and the use of health information data additionally impacts information use. Wellbeing office chiefs can achieve only 33% of the given HIS assignments. Further, they are gathering information without seeing totally why they are gathering that information and its utility has not been investigated and, in this way, likely make little thankfulness for gathering it (Dumont, 2012).

Insights and mentalities of senior administration towards information will affect the utilization of wellbeing data. In the event that ranking directors neglect to advance proof based dynamic and the utilization of data for straightforwardness and responsibility then a culture of data is probably not going to be cultivated. It is, in this way, significant to look at the discernments, mentalities, and estimations of ranking directors and other association individuals concerning data related capacities (Cheburet & Odhiambo-Otieno, 2016). To upgrade the utilization of wellbeing data in non-industrial nations, there is a need to fortify wellbeing labourers feeling of information proprietorship and wipe out the discernment that the wellbeing specialist's job closes when they gather information and communicate it to the following level. The utilization of automated information the executives instruments, for example, the DHIS is relied upon to improve the limit with respect to wellbeing labourers at all levels to dissect and decipher health information, and if this is combined with centred preparing around data utilized for dynamic it will prompt more possession, examination, understanding, and utilization of data at all levels (Mugenda, 2015). Kenya and other created nations that have actualized DHIS for the executives of their daily schedule and other wellbeing information are subsequently deliberately situated to move from divided and non-practical HIS to become good examples of ineffectual utilization of health information in low asset settings.

Among general wellbeing offices in non-industrial nations of Africa, limit working of Monitoring and Evaluation (M&E) groups has been actualized at all levels to advance full use of health information data in general wellbeing offices. Markers add to a generally speaking Monitoring and Evaluation methodology. In numerous nations, the in general monitoring and Evaluation plan and procedure are not satisfactory (for example goals are not SMART), so pointers are not all around planned and don't fill a reasonable need, and cut-off use of health information data. Some of the time Monitoring and Evaluation isn't successfully connected to the RHIS. For instance, pointers might be satisfactory, yet the information sources are not characterized, or the data framework gathers the marker in an organization that isn't promptly valuable to supervisors. The last point can be viewed as a fundamental issue also, as it might mirror an absence of correspondence among HIS, Monitoring and Evaluation, and the board capacities (Dumont, 2012).

Contentions as per Gopalan et al., (2013), arrangements and rules required on markers for determination, assortment, examination, and use, including standards for choosing pointers and the need to relate markers to issues, destinations, needs, and objectives are pivotal for boosting compelling use of health information data. Each nation requires great markers that address numerous issues yet should keep a sensible number. The dissatisfaction of working with broken frameworks with such a large number of markers to oversee has likewise been noted. Different nation models given incorporate where administrators need many pointers, and "achievement" is referred to as decreasing the quantity of markers to a reasonable level. The value of compiling a "base" list of basic indicators (info that is "preferred to have" as opposed to "required to know") is highlighted.

Similar to this, networks among parties involved in the management of health data make it easier for general health offices to use health information data. Sarkies et al. (2015) discovered that organisations are particularly likely for NGOs to boost performance by sharing data wisely in their research done in the United States. Similar to Food Rights and Uganda Land Alliance in Uganda, Asemahagn (2017) described CSO coalitions as a stage-smart process in which partners create a shared goal and work toward a more durable link. According to research done on the NGO manageability file (2008), supportability will require a small number of NGOs that are capable of offering assistance that consistently meets the problems, desires, and wishes of their people, as well as authoritative execution. The fundamental presumptions acknowledge that NGOs can provide assistance throughout a range of fields, products, and endeavours that represent the wants and needs of the wealthy to the underprivileged (Action Aid Country Strategic Paper III). Similar ties to other organisations are shared by CARE Uganda, World Vision, and the Uganda Red Cross Society. In 2011, CARE International Uganda looked into its partnerships with local charitable organisations, examining the factors that influence an organization's growth and management, and highlighting the differences between working with and through partners (Flingtorp, 2014).

2.5 Staff Involvement in Health Information Data Utilization

As indicated by Awowale (2017) in her investigation did on utilizing the data to settle on the choice, he takes note of that the intricacy of the framework configuration utilized in passage and recording of information is the main specialized factor influencing the usage of health information data by general wellbeing offices. Especially, in wellbeing offices where outside information frameworks specialists are employed for just planning and outlining the arrangement of information passage, it gets hard for the wellbeing labourers who are liable for every day schedule section to utilize and deal with the framework. The vast majority of the specialist staff for planning these frameworks will in general sell the new forms and releases of the information passage framework, for example, E-views and Sun Systems. These frameworks at that point require the work of an extraordinary individual for section of information and the board of the framework as it additionally requires remodel and update. Concerning the aforementioned, Shaw (2013) argues that the complexity of these systems makes it difficult for health care workers to use the system, leading them to rely on manual paper document recording, which causes data to be corrupted and poorly managed.

Notwithstanding the conversation of the specialized elements restricting use of health information data, Arumugam et al. (2016) found that a portion of the product for running the arrangement of information section and calculation is likewise scant, costly, and complex. The intricacy of the product likewise is a startling issue for general wellbeing offices to put a great deal of cash in such complex programming which is just accomplished for modernizing the wellbeing office not for rousing labourers in the framework.

Insufficient aptitudes in the nuts and bolts of M&E influence information quality as well as the capacity to utilize data in dynamic. The capacity to decipher wellbeing data and apply it to the automatic and strategy setting requires a range of abilities that is frequently never tended to in the pre-or post-administration preparing of wellbeing experts. Preparing in information the board and its significance at the office level may improve data use. Along these lines, the framework may turn into an advertiser for good quality information to be utilized in dynamic cycles (Teklegiorgis, 2014).

Over the span of contending the specialized components deciding use of the normal wellbeing data, the contentions made by Asemahagn (2017) in remarking because of IT unpredictability can't be overlooked. Afzal (2017) argues that IT uses and applications are another idea in present day organizations in non-industrial nations, especially in Africa. Institutions in Africa, even at the highest regional level, are predisposed to use manual information capturing systems, such as writing on paper and storing in cabinets. The employment of complex frameworks alone makes it necessary to replace the current working group with one that is proficient in the use and application of IT. Again, this requires additional planning because the current older population is not familiar with using IT. The current old working groups are tough to replace since they have a thorough understanding of the historical background of the health offices. Thus, the advancement of technology makes it harder and unpleasant to use conventional health data because it requires the use of computerised IT-based frameworks (Kohn, 2014).

Creating abilities in dissecting, deciphering, and dynamic advances data use. An investigation in Zambia found that an all-around planned Health Management Information System (HMIS) where wellbeing labourers were prepared as per globally archived rehearses added to the nature of information needed to help great choices (Abdusyakur, 2015). Preparing in information utilize should be led to fortify the limit of wellbeing labourers at the region and nearby levels to utilize wellbeing information for better administration and wellbeing administration conveyance.

Another study in in India indicated that lacking logical and information use aptitudes were the most normally revealed imperatives with a significant number of respondents communicating a requirement for additional preparation on information quality affirmation, investigation, and use. Curiously, scarcely any respondents concurred that helpless information quality was a genuine obstacle in spite of the fact that duplication of information and irregularities in the information assortment measure were seen boundaries to information use (Rexhepi, 2015). Also, health information data frameworks the executives should be decentralized to improve nearby utilization of wellbeing data. This happens when nearby level chiefs and wellbeing specialist co-ops are associated with planning information assortment and revealing instruments. At the area level, one assigned individual or group should be liable for the data. Also, data (counting crude information), should be made accessible to all potential data clients (Whitaker, 2018). Moreover, to improve maintainable interest for and utilization of information in dynamic individual limit in centre skills to request and utilize information should exist at all degrees of the wellbeing framework. Abilities remember aptitudes for information investigation, translation, blend, and introduction, and the improvement of information educated automatic proposals. Information clients frequently battle with an immature capacity to get examinations and decipher them in the automatic setting.

The usage of health information will be determined by top management's perceptions and attitudes toward data (Cheburet & Odhiambo-Otieno, 2016). If focused training on information use for decision making is combined with the use of computerised data management tools, such as the DHIS, it is anticipated that health workers at all levels will be better able to analyse and interpret routine health data. This will increase ownership, analysis, interpretation, and use of information at all levels (Mugendi, 2015). Kenya and other rich nations that have adopted DHIS for the management of their routine and other health data are thus strategically positioned to advance from fragmented and dysfunctional HIS to become leaders in the efficient use of routine health data in low resource situations. According to Asemahagn (2017), CSO alliances advance step by step as partners get a deeper understanding of one another and work to forge a more enduring bond, as is the case with Food Rights and Uganda Land Alliance in Uganda. The results of the 2008 NGO Sustainability Index analysis show that organisational performance and sustainability will both require a critical mass of NGOs that can effectively deliver services that consistently satisfy the needs, priorities, and expectations of their constituents. The underlying presumptions include that NGOs can offer services in a range of disciplines and can supply goods and services that correspond to the wants and needs of the pro-poor community. The third Action Aid Country Strategic Paper (Flingtorp, 2014).

In South Africa, modifications have been made to detect data requirements by the specialized group of the health data executive's framework in order to influence the extent of regular health data consumption. Throughout a wellness framework, data frameworks are developed to satisfy the needs of various information customers. Due to the diverse types of information consumers that access data frameworks and their varying requirements, the following information may not adequately address the specific data demands of all information consumers (Shaw, 2014). In addition, the vast amount of information may be overwhelming for prospective customers who are unable to investigate the available information resources. To promote information utilization, the focus should be on what partners need to know to effectively administering wellness initiatives, rather than what information is available to them (Clancy & Cronin, 2015).

2.6 Organizational Factors Influencing Use of Data

An organization's effectiveness is directly related to the performance of its personnel (Asemahagn, 2017). Rules, methods, and systems regulate the organisation. These principles, processes, and systems can help or hurt an individual's capacity to use data in decision making (Ann, 2016). An organisation that has structures and processes in place to improve the interaction of data users and producers, provide clear guidelines for data quality processes, and define roles and responsibilities related to data use, for example, will strengthen other interventions in place to improve data-informed decision making. Employee roles and responsibilities for data use should be specified in human resource documents. According to Asiimwe (2016), a study conducted in Uganda, organisational variables such as establishing a culture of knowledge and quality supervision were lacking. The adequacy of an association is straightforwardly connected to the presentation of its representatives (Asemahagn, 2017). The association is administered by rules, cycles, and frameworks. These standards, cycles, and frameworks can uphold or upset a person's capacity to utilize information in dynamic (Ann, 2016). For instance, an association that has structures and cycles for improving the connection of information clients and makers, giving clear rules to information quality cycles, and characterizing jobs and duties identified with utilizing information will reinforce different mediations set up to improve information educated dynamic. Human asset archives ought to indicate representative jobs and duties regarding information use. An investigation done in Uganda by Asiimwe (2016) indicated that hierarchical variables, for example, advancing a culture of data and quality management, were feeble. There was little proof of deliberate correspondence about execution targets, utilization of information for dynamic and backing, and sharing of examples of overcoming adversity (Oliver, 2013).

Data users work in an authoritative setting that impacts them through hierarchical standards, qualities, and practices. This hierarchical setting is the wellbeing administrations framework and can be overseen by general society or the public area. Authoritative considers, for example, deficiencies human and monetary assets, low administration uphold, absence of management, and initiative influencing RHIS execution are portrayed in the data framework writing(Rotich et al., 2013). The PRISM system considers hierarchical determinants critical for influencing execution and characterizes this classification as every one of those variables that are identified with authoritative structure, assets, methodology, uphold administrations, and culture to create, oversee and improve RHIS cycles and execution. All in all, individuals don't generally follow up on what they are advised to do yet follow up on sharing what is significant and esteemed in an association.

Notwithstanding society, input is viewed as a pointer of data use. Criticism is perceived as the methodology by the data clients to educate the information authorities regarding choices made and activities taken dependent on the information gathered. It could show up as verbal reports to gatherings, management of office activities, outline reports to yearly reports on a particular point. The input might be introduced as tables of month to month information, short program reports, diagrams, or quarterly or yearly reports (Nutley et al., 2012). Criticism is recognized as a zone where potential improvement would be advantageous for the lower level of obligation identified with both M&E, arranging, and dynamic exercises (Kihuba et al., 2014). To upgrade how information suppliers esteem data, input, incorporating relative criticism with neighbouring offices, is fundamental. Thusly, information suppliers will feel their information assortment adds to enhancements and change profiting both themselves and patients and make responsibility for information (WHO Regional Office for South-East Asia, 2018).

Gopalan (2013) contends in his study on the financial incentives for health area requests in Tanzania's low- and middle-income nations that the financial and human resource parts of the health data system also have an impact on how general health offices use health information data. To maintain information quality and collecting standards, assure correct data analysis, and ensure the proper use of data, the public sector needs qualified disease transmission specialists, analysts, and demographers. Health data personnel should be in charge of data collecting, detailing, and investigation at peripheral levels. These chores are frequently given to caregivers who are already overburdened and view them as a diversion from their main responsibilities. Tanzania's health care system is distinct from Uganda's, yet Gopalan's research was undertaken there (Scientific Symposium Report, 2016).

The way general health offices use health information data also depends on the state of the data system foundation. The health data system's infrastructure needs could be as straightforward as paper and pencils or as complicated as fully integrated, web-based ICT. The health data system must be able to store, document, dynamically update, and retrieve entries at the most basic level of record keeping. Many nations have reported flooded storage spaces filled with rotting hospital records, office logbooks, and disorganised, uninspected desk labour. Emerging innovations may aid countries in vastly increasing their capacity and execution limitations and shortening the preparation periods previously necessary. ICT can significantly enhance the accessibility, quality, dissemination, and consumption of health-related information. Rational limit functioning in electronic and HR across the health framework is unquestionably more powerful and cost-effective (Cheburet & Odhiambo-Otieno, 2016).

2.7 Theoretical Framework

The study is supported by Carbone's Evidence-Based Health Information System Theory (2009). According to the premise, any formative organisation needs evidence-based information regarding how daily schedule data is connected to planning and strategy information. According to Carbone (2009), it is important to consider relevant data framework assumptions while choosing new technologies for healthcare settings. The idea of evidence is not new to healthcare settings, but its application there is frequently limited to clinical endeavours, according to Carbone (2009). The results of this research and the relevant legal literature point out that when data framework use is immediately acknowledged and properly accepted, evidence should be the main conductor or setup route. The premises and conclusions given below serve as the foundation for the arguments.

The study also made the case that workers in the wellness industry, who make up the core workforce for dynamic companies, own and operate wellness environments (Carbone, 2009). Clinicians receive training in logic (exact discerning strategies). Observational data is in favour of the executive's new strategy. Exact sensible strategies impact clinical practise as a catalyst for societal change. There is evidence of care shortcomings in clinical practise in the nearby (electronic) health records. Using local knowledge (evidence) and observation to modify the executive's systems has a significant impact on changing behaviour. For development and subsequent change to be viable, evidence of accomplishment is necessary (Carbone, 2009).

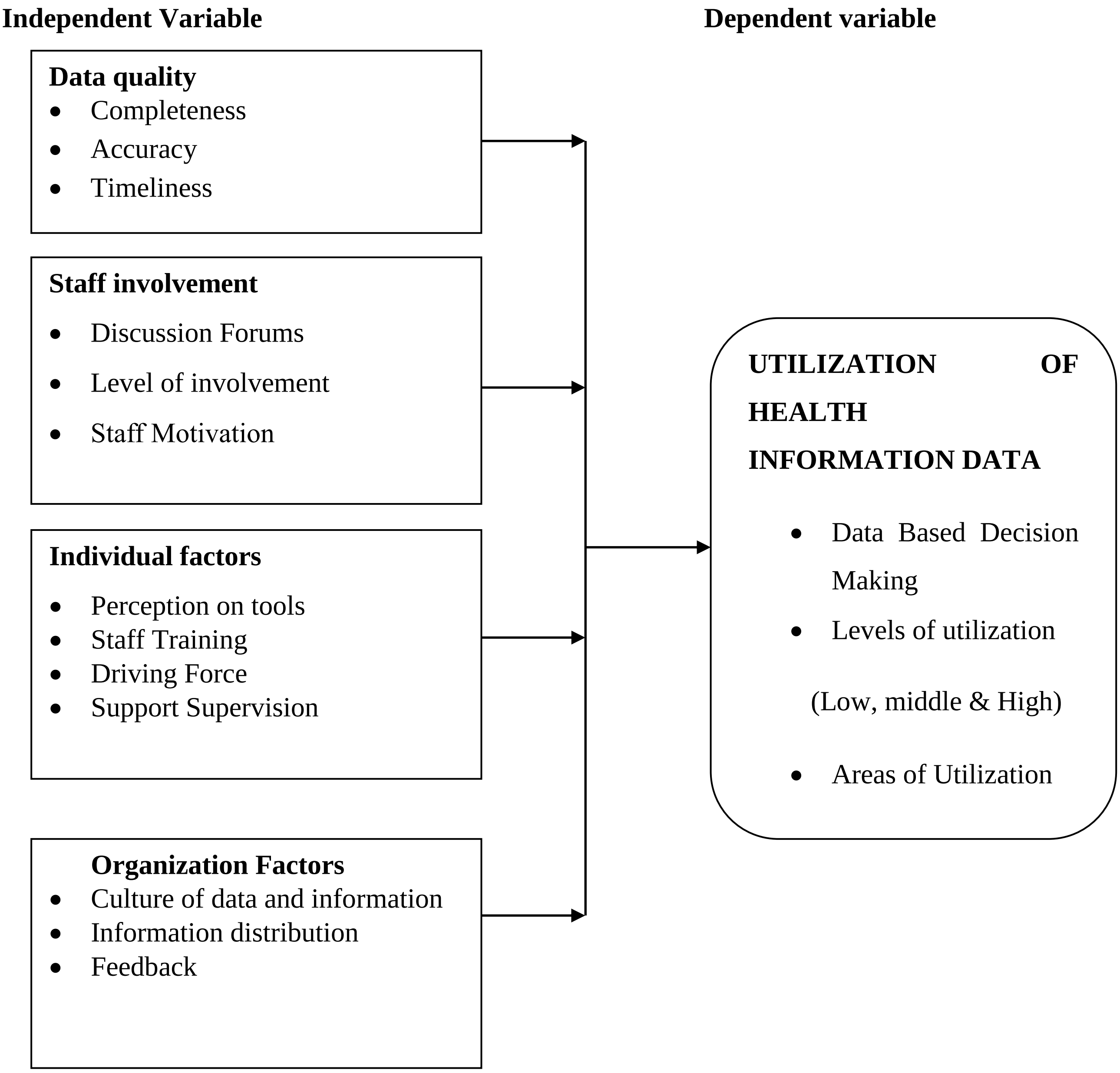
The administration, avoidance, or treatment of clinical issues in any healthcare setting constitutes the clinical errand (business) that should be improved or carried out (however, the application of data framework). This contrast with the evidence-based framework, which was developed to address the core business of healthcare (patient care), which is distinguished by its dual concern: input task (drivers) and output task (results). Such that it allays any lingering reservations regarding this notion. For a commercial model, "clinical enhancement of patient care" is the reality. The overall "clinical care" objective is propelled by the urge in conjunction with a working system. However, on the way (from contribution to yield), the impetus, like a working framework, should make sure that a circumstance or development takes place to allow the clinical (input) task-driven by the desire to improve the health of an individual or population to be satisfactorily completed (yield), also known as a clinical result in the health field (Oliver, 2013). The impetus (working framework) carries out a variety of responsibilities to make the evidence-based framework successful, including the following: For instance, to give a few examples of the likely sub-frameworks in healthcare settings, it should allow clinical group members to communicate with one another; it should ensure that an executive framework exists to catch patients who may miss clinical consideration; it should ensure that an executive framework exists to catch patients who may miss clinical consideration Evaluating the success of fulfilling this specific aim (improving health outcomes) is a crucial additional obligation (Kohn, 2014).

The connection between the human/labour force sub framework and the impulse is essential to understanding this concept. This relationship should be built on mutual respect and deliberate action between people who appear to share a common "ultimate goal" (wellbeing results upgrades). Since "person's momentary objectives" may not always be the same, it may not always be clear how the impetus and the health setting are related. For instance, the information system (IS) professional (impetus) may be more constrained to be financially and labour force-focused, despite the fact that both have the capacity to develop a logically modified and enhanced health data framework. This explanation is by no means comprehensive, but it starts to talk about the underlying uncertainties that support the developed connection (Sharma, et al., 2016).

2.8 Conceptual Framework

Figure 2. 1

Conceptual framework



Adopted and modified from the literature review(Hardee et al., 2015)**.**

2.9 Summary of Literature Review

The current writing has not indisputably settled the degree of health information data use. In any case, the writing uncovered a few potential issues that could impact the utilization of data, for example, insufficient aptitudes, helpless information quality, deficient admittance to hardware resembles PC, management, negative discernment and mentality of wellbeing labourers on information, and muddled jobs and duties on utilization of data to specify however not many.

Wellbeing data need esteem if not used to educate choices and the utilization regarding wellbeing data for dynamic is an excursion, not an objective. It is progressing information driven cycle that requires ceaseless assortment, examination and sharing since that is the lone manner by which patterns both positive and negative can be found and followed up on. Once more, a portion of the investigations which were accessible and looked into were obsolete and operationalized inside settings that may not be not like those inside the setting of this study.

CHAPTER THREE: METHODOLOGY

3.0 Introduction

This chapter elucidates and makes a case for the research strategy and technique used in the study. It describes the research instruments, the validity and reliability of the instruments, as well as the protocols for data collecting and analysis. It also describes the study design, the target population, the sample, and the sampling techniques.

3.1 Study Design

Study design is characterized as the framework or plan that is utilized to produce answers to explore issues. An examination configuration is viewed as a course of action of conditions for assortment and investigation of information in a way that plans to join importance with the exploration reason (Orodho, 2003). This study was descriptive cross-sectional study adopting quantitative research approaches. This design, presents procedures for collecting, analysing and linking the data in a single study (Eradio, 2015). Graphic plan is utilized when gathering data about individuals' perspectives, feelings, propensities, and other conceivable conduct (Orodho & Kombo, 2005). Kothari, (2004) and Okoth, (2012) portray the distinct plan as a strategy used to gather the nitty gritty depiction of existing marvels with the perspective on utilizing information to legitimize current conditions and rehearses or to make more wise arrangements for improving them.

3.2 Study Area

The research was carried out at several public hospitals in Nairobi County. It is the capital and biggest city of Kenya, as well as one of the most well-known urban areas in all of Africa and a vital economic hub in both the East and Central African Regions. Nairobi County is also one of the most identifiable metropolitan regions in the world. It serves as the headquarters for a large number of international associations and organizations, including the World Health Organization, the United Nations Habitat Program, and the United Nations Environmental Program. The city of Nairobi is the capital of the Republic of Kenya and acts as a centre for the administration of the country's affairs, as well as its economy and culture. It comprises more than half of Kenya's formal employment and contributes more than half of the country's gross domestic product. At a height of 1,660 meters above mean sea level, it may be found in the southern region of the nation. It is surrounded by the counties of Kiambu, Machakos, and Kajiado to the west, south, and east, respectively.

In Nairobi City, the months of July and August are often dry and cool, whereas the months of January and February are hot and dry. The city of Nairobi receives around 900 millimetres of precipitation on a yearly basis on average. April has the most amount of precipitation in a single month than any other month, while November sees the second-greatest amount. The coldest temperature varies from 14 degrees Celsius to 12 degrees Celsius, while the highest temperature ranges from 28 degrees Celsius to 22 degrees Celsius. Nairobi is home to a total of 782 medical institutions, including 14 maternity homes, 21 nursing homes, 49 VCTs, 176 dispensaries, 75 health centres, 401 medical clinics, 2 referral hospitals, 4 district hospitals, 176 health centres, 401 medical clinics, 14 maternity homes, and 21 nursing homes. The sector that encompasses network, social and individual administrations, as well as expert business administrations, is responsible for 52.1% of the overall revenue that the city generates. The agricultural and ranger service industry comes next, then the discount and retail exchange sector, the manufacturing sector, the tourist sector, and finally the assembly sector.

In the densely populated Embakasi Constituency of the City of Nairobi is where you'll find the Mama Lucy Kibaki Hospital, which is a level-5 facility. It is exactly located between Umoja-II and Komarock Estates, 11 kilometres east of the city centre, at the junction of Kangundo road and Kayole Spine road. In other words, it is a crossroads. The majority of the land in this region is zoned for residential use, and it also has a number of unauthorized communities. The medical facility contains a total of 120 beds, including 18 in the critical care unit (ICU). The Mutu-ini Hospital is a level 4 county hospital that can be found in the neighbourhood of Dagoretti South in Mutu-ini, which is situated in Nairobi County. Beginning in 2021, a significant amount of money is being invested on the facility's infrastructure so that it may be upgraded to level 5 hospital statuses.

Formerly known as the Infectious Diseases Hospital (IDH) under the aforementioned King George VI Hospital, which is now known as Kenyatta National Hospital, Mbagathi Hospital is now known as Kenyatta National Hospital. The hospital was built in the 1950s to treat infectious illnesses that required patients to be quarantined, such as TB, measles, meningitis, and leprosy. Today, the hospital is still used for same purposes. In 1995, Kenyatta National Hospital was renamed IDH and converted into an autonomous District Hospital serving the city of Nairobi. Despite having few facilities and only a small number of employees, IDH was able to fulfil its new role. Since that time, Mbagathi County Hospital has undergone expansion in order to provide medical services that are on par with those provided by other county hospitals around the country. The bulk of the hospital's patients come from low-income backgrounds, since Mbagathi County Hospital covers a broad catchment area that includes nearly one million people. The major health care facility can be found at Kenyatta/Golf Course, which is located in the Dagoretti Division of the Nairobi West District. The Kenyatta National Hospital, the Kenyatta City Council Market, the Forces Memorial Hospital, the Kenya medical Research Institute, and the Kibera slums are all located nearby. It is the sole public health facility in Nairobi, and the Ministry of Health depends on it to alleviate strain on the Kenyatta National Hospital, which is responsible for processing referral patients. The Ministry of Health relies on it to ease pressure. Mbagathi County Hospital is now classified as a level 5 facility and is recognized as an internship training institution by the Kenya Medical Practitioners and Dentists Council.

3.3 Study Population

Nairobi County has several public health facilities out of this 3 are considered to have high volume of data information due to their status as County referral hospitals. Mbagathi hospital has 151 health workers, Mutu-ini hospital has 103 health workers and Mama Lucy Kibaki hospital has 142 health workers. The study population included departmental clinicians who have ordinary contact and give care to patients; these included nurses, midwives, medical officers, clinical officers, pharmacy staff, and laboratory technologists. There are approximately 396 health care staffs in selected health facilities.

3.4 Sample Size Determination

Daniel (1999) sample calculation is an approach to decide the example size for an investigation. It is the best technique to utilize. The population under study is less than 5000 and it is a simple formula to determine the adequate sample size that estimates the population prevalence with good precision.

The Daniel formula is:

$$n = \frac{NZ^2pq}{e^2(N-1) + Z^2pq}$$

Where:

- Z is the standard deviation of the normal distribution at the desired confidence interval. In this instance, a 95% confidence interval was utilized, yielding a Z value of 1.96.
- N is the population of the study, which is less than 5000

- n represents the sample size
- e is the desired level of precision (i.e., the margin of error); • p is the (estimated) percentage of data utilization that is 50%.
- q is 1 – p.

$$n = \frac{396 * 1.96^2 * 0.5 * (1 - 0.5)}{0.05^2(396 - 1) + 1.96^2 * 0.5(1 - 0.5)}$$

= the calculated sample size is 196

In order to take into consideration non-responses, lost surveys, incomplete questions, and questionnaires that were not completed for unclear reasons, an additional 10% of 196 was added. The total number of people in the sample was consequently 216.

3.5 Sampling Technique

This research adopted multistage sampling techniques; purposive sampling was employed to select one Kenyan County with Nairobi County selected. The purposive sampling method was used to select Mama Lucy Kibaki, Mbagathi, and Mutu-ini hospital due to their high level of data. Proportionate stratification was utilized to choose the sample size per hospital. In proportionate, an arbitrary example from every sample size is taken in a number corresponding to the sample size when contrasted with the populace. These layers subsets are then pooled to frame an arbitrary example. The procedure of drawing this defined example is known as separated inspecting. The quantities of respondents selected per healthcare are shown below:

Table 3. 1

Proportionate Sampling

Health facility	Healthcare workers	Sample size
Mbagathi sub-county hospital	151	82
Mama Lucy Kibaki hospital	142	77
Mutu-ini hospital	103	56
Total	**396**	**216**

The quantity of respondents in every health facility was dispensed relatively utilizing the quantity of respondents. The chose number of respondents was examined advantageously in every hospital through an efficient inspecting procedure.

3.6 Variables

The dependent variable was the use of health information data, independent variables are socio-demographic characteristics, data utilization, factors influencing the use of health information data such as data quality, individual factors, staff involvement, and organization influences of data utilization.

3.7 Selection Criteria

3.7.1 Inclusion Criteria

Healthcare workers:

- working in selected public health facilities,
- with work experience of 6 or more months
- who were available during the data collection period and
- who were willing to participate in the study

3.7.2 Exclusion criteria

Healthcare workers:

- Who were on sick off, study leave, maternity leave, paternity leave, etc.
- Who did not volunteer to participate in the study were excluded from the study
- Those who did not sign consent form.

3.8 Study Procedure

3.8.1 Pre-Testing

10% of the sample size was utilized for pre-testing at the Mathari National and Teaching Hospital, and the responders were excluded from the research. This was done to validate the validity of the survey and to verify that addresses were readily identifiable, as well as to analyse the development of components in the survey, challenges in data collection, and other key factors, and to make the required modifications to suit the research. A preliminary test was conducted weeks before the real information collection began to ensure consistency. By conducting the pre-testing study in a different health facility, this sample was excluded from the actual study. It allowed the researcher to check questionnaires for ambiguities and unclear questions so they could be corrected. Mathari hospital was chosen for pre-test due to status as referral hospital in Nairobi County but it is managed by National government and also high numbers of patients attended in this facility.

3.8.2 Participants' Recruitment and Data Collection.

When the information assortment instruments are pre-tried and surveyed, the examination collaborators were prepared and situated to comprehend the investigation targets, study unit, and information assortment devices. The focused-on hospitals were educated in about fourteen days advance so that focused staff to be found at the office. The examiner was available for quantitative information assortment at the wellbeing offices every day. Re-arrangements was made for those health workers that won't be accessible or occupied. Self-organization of the survey was permitted after the careful direction of the wellbeing labourers on noting the device, and cross-checking the culmination of the appropriate responses was inspected when picking the apparatus. The central agents were by and by be engaging interviewees who was searched out purposively. The Key witnesses was drawn closer and mentioned on the off chance that they would partake in the investigation. For the individuals who concurred, educated agree and authorization to record the meetings was gotten and a prelude expressing the recent concern was disclosed to the witnesses. A meeting aide was utilized in the conversation. The conversation was held in broad daylight places, for example, their workplaces for simplicity of recording and furthermore to guarantee classification.

3.9 Research Instruments

The study employed use of questionnaire as tool to collect data from the field. The questionnaire was used due to detailed information required to help in-depth analysis of the problem. This tool was chosen because it is fast, efficient, cost saving and assuring respondent of anonymity thereby giving accurate response on questions asked.

3.9.1 Validity

Validity is the extent to which an exploration instrument guesses what it intends to measure and performs as anticipated. Using criterion validity, it was ensured that the purposeful elements are indeed what is to be measured and no other variable. My supervisor, a professional in the subject, examined the validity of the instrument to see if it matches the objectives of the research and whether the question reflects the ideal response. Prior to the allocation of the actual collection of data, the validity was strengthened. In addition, a pre-testing study was conducted in order to modify the poll as necessary.

3.9.2 Reliability

In order to determine the instrument's level of dependability, a procedure called the half-split test was carried out. The items on the exam were divided into two halves, each of which included content-related objects, and the results of the test were graded independently. The results on both sides should have a strong correlation with one another if the test is valid (Cohen et al., 2007).

$$\textit{Reliability of the overall test} = \frac{2\ x\ reliability\ for\ ½\ tests}{1 + reliability\ for\ ½\ tests}$$

Correlation between Product Moment and Pearson When assessing reliability, the coefficient was taken into consideration. For the purposes of determining the reliability of the instruments, a correlation coefficient of 0.75 would be acceptable. According to Mugenda & Mugenda (2003), a significant association between two variables is indicated by a correlation coefficient that is larger than or equal to 0.8. When developing the questionnaire for the research, significant consideration was given to the aims of the investigation. In addition, the examination was carried out using Cronbach's Alpha, with the Alpha coefficient ranging from one to five, with the lower values being more reliable than the higher ones. The results of the pre-testing research were used to evaluate how the poll should be altered in light of the 0.7 hypothesis proposed by Cronbach. In spite of the fact that, in general, the higher the score, the more trustworthy the created scale is, it has been proved that a coefficient of 0.7 is worthy of consideration.

The Cronbach Alpha Reliability Coefficient test revealed that the reliability results for the questionnaire as an instrument for socio-demographic characteristics was 0.814, for the extent of use of data for service improvement it was 0.778, and for data quality perception in utilization of HMIS it was 0.790. Additionally, the test revealed that the reliability results for staff attitude influencing use of data was 0.800, staff participation in data utilization was 0.732, and for organizational factors influencing use of data it was 0.800. It was determined that all of the variables were sufficient, and the reliability of the instruments was approved.

Table 3. 2

Cronbach Alpha Reliability Coefficient

Variables	Cronbach Alpha Coefficient
Socio-demographic characteristics	0.814
The extent of use of data for service improvement	0.778
Data quality perception in utilization of HMIS	0.790
Individual factors influencing use of data	0.800
Staff involvement in data utilization	0.732
Organizational factors influencing use of data	0.838

3.10 Data Management and Analysis

3.10.1 Data Storage

The details were keyed in and stored in an examination exercise manual, the Microsoft Word and Excel programming on a personal computer, and either a glimmer/outside circle or rewritable CD as a backup.

3.10.2 Statistical Analysis

The factual programming in SPSS was used to carry out the analysis of the collected data. Quantitative data was encoded and arranged with the assistance of SPSS form 25.0. Informative metrics such as frequencies, standard deviations, and means were applied in the process of summarizing, organizing, and reorganizing the data that was obtained. We investigated the link between needed factors and autonomous factors via the use of connection analysis. The value of 0.05 was chosen as the centrality threshold. Using a method called bivariate analysis; each of the independent factors was correlated with the dependent variable in order to establish which of the variables had the most significant connection. The strength of the link between independent factors and dependent variables was analysed with the use of the Odds Ratio (OR) and the 95% Confidence Interval (CI). Both of these statistics were calculated using the CI. The level of statistical significance that was deemed acceptable was established at

= 0.05, and for the correlation analysis, a two-sided p-value with 95% confidence intervals (CI) was indicated. In a multivariate analysis, all of the independent variables that were investigated simultaneously in a bivariate analysis were those that were shown to be fundamentally related with one another. Calculations in binary were used to attain this goal. The strength of the link between the independent variable that was maintained constant and the variable that was being studied was determined by calculating changed odds ratios (AOR) and their associated 95% confidence intervals (CI).

3.11 Ethical Consideration

The proposal for this study was submitted to the Kenya Methodist University-Ethical Review Committee for ethical approval prior to its implementation. The National Commission of Science, Technology, and Innovation (NACOSTI) were asked for permission to conduct research, and the County government was also cited. Members' educated consent was created and managed. Respondents were given a new opportunity to participate in the survey, and this was deemed consistent throughout the test. Respondents were informed that they may choose whether or not to participate in the investigation, as well as withdraw from the investigation at any time. This had no effect on the administrations they were carrying out. No actions or prizes were offered to participants in exchange for participation in the study. Privacy and confidentiality were consistently safeguarded. The information collected was processed, dissected, and detailed in configurations that do not permit the individual member's ID. No identifying information was captured in voice or video without the consent of the respondents. No intrusive procedures were performed on the participants, so no real risks were encountered.

CHAPTER FOUR: FINDINGS AND DISCUSSION

4.0 Introduction

This chapter presents the findings of the study, as well as an analysis of those findings. The findings are, in essence, the product of the combination of quantitative research tools that were used throughout the data gathering process. It is structured according to the general characteristics of the respondents, the extent to which data is used, the influence of data quality on the utilization of health information data, the extent to which individual factors determine the utilization of health information data, the level of staff involvement that influences the utilization of health information data, and the organizational factors that influence the utilization of health information data in Nairobi City County Public Health Facilities, Kenya.

4.1 Response Rate

The needed sample size was met with a response rate of one hundred and sixteen percent, which means that a total of 216 structured questionnaires were sent out into the world. Since none of the questionnaires were left unfinished, this indicates that the response rate was enough. This is enough to provide sufficient and reliable information in order to answer the research questions. According to Brick and Williams (2013), a low response rate might result in possible bias. As a consequence, in this research, a high response rate was related with a high degree of informational dependability. In addition, Pike (2017) said that survey researchers have long held the belief that obtaining a high response rate is the best approach to acquire unbiased estimates, and he mentioned that this belief has been around for a long time. On the other hand, the vast majority of researchers have started to cast doubt on the long-held notion that low response rates always result in biased findings.

4.2 Socio-Demographic Characteristics

The study involved 216 health workers. Of these, respondents between 30-39 years were 84 (38.9%). As shown in the table 4.1, females were 111 (51.4%), with nurses 58 (26.9%) contributing the highest number, HIO 7 (3.2%) and medical officers 5 (2.3%) were the least healthcare workers (Table 4.1). Table 4.1 shows that most 118 (54.6%) of the respondents had diploma as their highest attained education level followed by 57 (26.4%) had degree. Regarding work experience, 123 (56.9%) had a working experience from 5 years and 90 (41.4%) have been working in selected health facilities between 3-4 years during the time of the study.

Table 4. 1

Socio-Demographic Characteristics

Characteristics		Frequency	Percent
Age group	20-29 years	58	26.9
	30-39 years	84	38.9
	≥ 40 years	74	34.3
Gender	Male	105	48.6
	Female	111	51.4
Professional training	Medical officer	5	2.3
	Clinical officer	41	19.0
	Nurse	58	26.9
	Pharmaceutical technologist	35	16.2
	Lab technologist	50	23.1
	Radiologist	10	4.6
	Nutritionist	5	2.3
	Orthopedics	5	2.3
	HIO	7	3.2
Highest education attained	Certificate	1	0.5
	Diploma	118	54.6
	Higher Diploma	40	18.5
	Degree	57	26.4
Working experience	Less than 1 year	19	8.8
	1-2 years	23	10.6
	3-4 years	51	23.6
	≥ 5 years	123	56.9
Duration at health facility	Less than 1 year	25	11.6
	1-2 years	44	20.4
	3-4 years	90	41.7
	≥ 5 years	57	26.4

4.3 Utilization of Health Information Data.

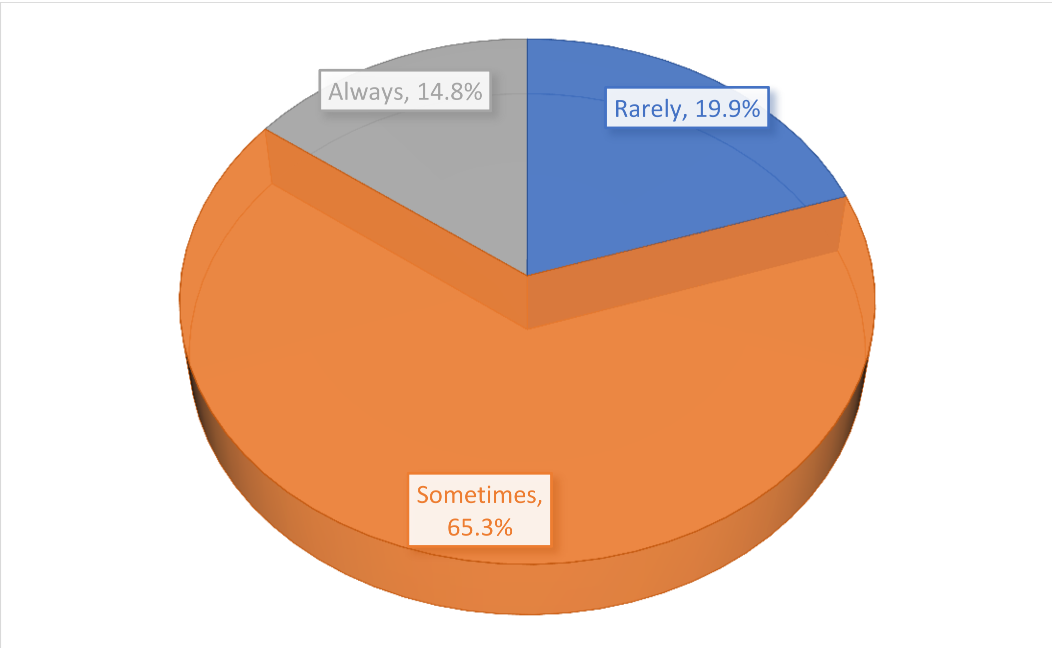
4.3.1 Overall Routine Data Use

The percentage use of the health information data generated for decision making was determined in each hospital and presented an overall data use. Less than two-third of respondents 141 (65.3%) sometimes used routine data for decision making. Additionally, 43

(19.9%) and 32 (14.8%) rarely and always use the routine data/health information generated for decision making as presented in Figure 4.1.

This is consistent with a South African study by Yarinbab and Assefa (2018), which found that the average use of HMIS information was 65 percent. A Cote d'Ivoire study utilizing the Performance of Health information System Management (PRISM) framework (Nutley et al., 2014) revealed that 38% of healthcare facilities utilized health information. The study concurs with Nicole et al. (2017), who emphasized that few of the vast amounts of data collected are utilized by data collectors and local health management at the health facility or district level. A health information data is achieved when all decision-makers demand facts and clear indicators. A positive health information data is characterized by the frequent utilization of information.

Figure 4. 1
Routine Data Use among Healthcare Workers



4.3.2 Extent of Routine Data Use for Decision Making

In the study respondents self-rated the extent to which they use data for decision making in each of the eight areas in a scale of 1 to 4 with a rating score of 0% to 100% where 1 meant rarely with a rating score of (0 – 25 %), 2 meant sometimes with a rating score of (26 – 50 %), 3 meant often with a rating score of (51 – 75 %), and 4 meant always with a rating score of (76 – 100%). According to analysis results shown on Table 4.2, use of health information for formulation of planning had a mean 3.12 (77.3%), identification of emerging epidemics 2.91 (75.8%) and medical supply & drug management 2.77 (74.8%). The overall routine data use index was calculated by taking the mean of all eight dimensions which come to 73.6%. This is consistent with Ndegwa (2015) that noted most of healthcare workers utilize routine data for planning and epidemiology. Multiple factors, such as technological, individual, and organizational constraints, were found to limit data quality, as determined by the study. To transform the one-way systems into an integrated health system with better data quality and to foster an information-use, a comprehensive intervention addressing all of these issues was required.

Table 4. 2

Extent of Routine Data Use for Decision Making

Are of data use	Mean	Percentage score
Day-to-day program management	2.669	73.0
Medical supply & drug management	2.765	74.8
Formulating plan	3.121	77.3
Human resources management	2.635	72.7
Monitoring key objectives and policy	2.705	74.1
Identification of emerging epidemics	2.913	75.8
Data use index	**2.564**	**73.6**

4.3.3 Socio-Demographic Characteristics Influencing Routine Data Use

Further analysis with an aid of chi-square test was carried out in order to establish association between respondent's socio-demographic characteristics and use of routine data for decision making. The Pearson chi-square in Table 4.3 shows a statistically significant association between level of education (Fischer exact test, p=0.025), gender of the health worker (χ^2=9.116; df 2; p=0.010) and professional trainings (Fischer exact test; p=0.001) with routine data use for decision making. This may be explained by the fact that these professionals are the one mostly spent more time patients at the hospital. On the other hand, the study results showed that, age, duration at the facility and working experience of the health worker were not significantly related to use of routine data for decision making.

Age (χ^2=6.761; df 4; p=0.149), duration at the facility (χ^2=10.684; df 2; p=0.099) and working experience (Fischer exact test, p=0.763) had no statistical relationship to use of routine data for decision making, p>0.05, thus does not influence utilization of routine data (Table 4.3).

Table 4. 3

Socio-Demographic Characteristics Influencing Routine Data Use

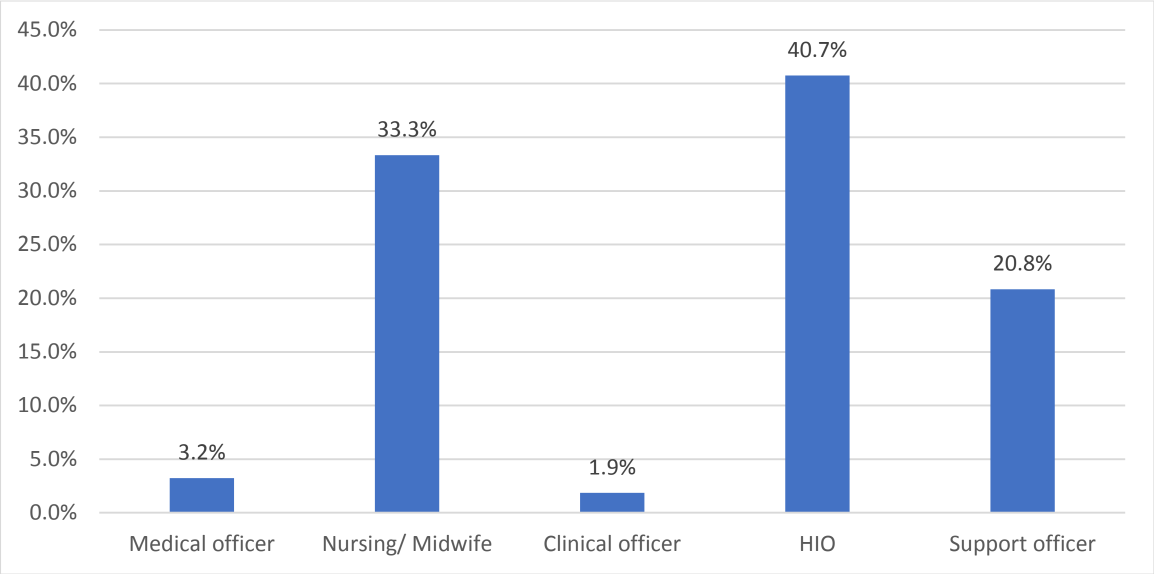
Variables		**Rarely**	**Sometimes**	**Always**	**Significance**
Age group	20-29 years	15(25.9%)	36(62.1%)	7(12.1%)	χ^2=6.761; df 4; p=0.149
	30-39 years	10(11.9%)	62(73.8%)	12(14.3%)	
	≥ 40 years	18(24.3%)	43(58.1%)	13(17.6%)	
Gender	Male	22(21.0%)	60(57.1%)	23(21.9%)	χ^2=9.116; df 2; p=0.010
	Female	21(18.9%)	81(73.0%)	9(8.1%)	
Professional training	Medical officer	1(20.0%)	3(60.0%)	1(20.0%)	Fischer exact test p=0.001
	Clinical officer	8(19.5%)	28(68.3%)	5(12.2%)	
	Nurse	13(22.4%)	41(70.7%)	4(6.9%)	
	Pharm tech	9(25.7%)	22(62.9%)	4(11.4%)	
	Lab tech	8(16.0%)	35(70.0%)	7(14.0%)	
	Radiologist	1(10.0%)	5(50.0%)	4(40.0%)	
	Nutritionist	1(20.0%)	4(80.0%)	0(0.0%)	
	orthopedic	2(40.0%)	3(60.0%)	0(0.0%)	
	HIO	0(0.0%)	0(0.0%)	7(100.0%)	
Highest education attained	Certificate	0(0.0%)	1(100.0%)	0(0.0%)	Fischer exact test p=0.025
	Diploma	25(21.2%)	81(68.6%)	12(10.2%)	
	Higher Diploma	9(22.5%)	28(70.0%)	3(7.5%)	
	Degree	9(15.8%)	31(54.4%)	17(29.8%)	
Working experience	Less than 1 year	3(15.8%)	12(63.2%)	4(21.1%)	Fischer exact test p=0.763
	1-2 years	4(17.4%)	14(60.9%)	5(21.7%)	
	3-4 years	13(25.5%)	33(64.7%)	5(9.8%)	
	≥ 5 years	23(18.7%)	82(66.7%)	18(14.6%)	
Duration at health facility	Less than 1 year	5(20.0%)	15(60.0%)	5(20.0%)	χ^2=10.684; df 2; p=0.099
	1-2 years	8(18.2%)	27(61.4%)	9(20.5%)	
	3-4 years	20(22.2%)	65(72.2%)	5(5.6%)	
	≥ 5 years	10(17.5%)	34(59.6%)	13(22.8%)	

4.3.4 Filling Monthly Reports/Data

Health information officer 88 (40.7%), nursing/midwife 72 (33.3%), support staff 45 (20.8%), clinical officers 4 (1.9%) and medical officers 7 (3.2%) filled the monthly reports/data in the selected facilities (Figure 4.2).

Figure 4. 2

Filling Monthly Reports/Data



This concurs with Ndegwa (2015) study in three metropolitan antenatal facilities which found that most of health data are mostly responsibility of health record officers. This has been with the case of Information Communication and Technology (ICT) upheld offices, just as the office utilizing manual structures. In the investigation, information quality was restricted by a wide range of elements including specialized, individual, and hierarchical angles. A methodical intercession that fuses every one of these viewpoints was expected to change the single direction frameworks into a coordinated wellbeing framework with higher information quality and to advance a culture of data use.

4.4 Influence of Data Quality in the Utilization of Health Information Data

4.4.1 Data Accuracy

The responses of respondents are summarized in table 4.4 below. More than half of respondents (61.6% and 56.0%, respectively) disagreed with the statements that they had come across wrong data when making judgments and that faulty data prohibited them from utilizing data frequently to make decisions. In addition, 64.8% and 65.7% of respondents agreed that they did not depend on health information data to make choices, and that they did take remedial action to resolve stated data accuracy concerns prior to using the data. All of the analysed reports were discovered to be inaccurate and lacking, according to the conclusions of Ndegwa's (2015) investigation into information systems and the calibre of data at three metropolitan Kenyan Ante Natal clinics. Regardless of whether a facility used information and communication technology (ICT) or manual forms, this was the scenario at all of them. The quality of the data was compromised during the research process due to a wide range of technological, organisational, and human issues. A comprehensive intervention that included each of these components was necessary to promote an information-use culture and convert the one-way systems into an integrated health system with greater data quality. In order to convert the one-way systems into an integrated health system, this was also necessary.

Table 4. 4

Data Accuracy

Data accuracy		Frequency	Percent (%)
Encountered inaccurate data	Strongly disagree	13	6.0
	Disagree	120	55.6
	Neutral	10	4.6
	Agree	73	33.8
	Strongly agree	0	0.0
Inaccurate data has made it difficult to use data to make decisions on a regular basis.	Strongly disagree	13	6.0
	Disagree	108	50.0
	Neutral	17	7.9
	Agree	78	36.1
	Strongly agree	0	0.0
Before using the data, take corrective action to fix any data accuracy issues that have been identified.	Strongly disagree	0	0.0
	Disagree	58	26.9
	Neutral	18	8.3
	Agree	136	63.0
	Strongly agree	4	1.9
To make decisions, we used/relied on other data sources rather than health information data.	Strongly disagree	7	3.2
	Disagree	47	21.8
	Neutral	20	9.3
	Agree	142	65.7
	Strongly agree	0	0.0

4.4.2 Data Completeness

A summary of respondents' opinions is shown in Table 4.5. The majority (93.1%) agreed that the reported data includes all necessary data set reports, and 93.5%, 84.3%, 64.4%, and 53.2% agreed that the reported data is sufficient for our needs, that the health information data is irrelevant for my current needs for data analysis and aggregation, and that there is no added benefit from combining inconsistent data.

Table 4. 3
Data Completeness

Data Completeness		Frequency	Percent (%)
All of the essential dataset reports are included in the reported data.	Disagree	3	1.4
	Neutral	12	5.6
	Agree	188	87.0
	Strongly agree	13	6.0
The data that was reported is adequate in meeting our requirements.	Disagree	25	11.6
	Neutral	9	4.2
	Agree	176	81.5
	Strongly agree	6	2.8
The data that was reported provides a summary of the work that the department did.	Disagree	7	3.2
	Neutral	7	3.2
	Agree	192	88.9
	Strongly agree	10	4.6
My present requirements for data analysis and aggregation do not need me to have access to health information data.	Strongly disagree	12	5.6
	Disagree	42	19.4
	Neutral	23	10.6
	Agree	139	64.4
There is no added value due to aggregating inconsistent data	Strongly disagree	13	6.0
	Disagree	73	33.8
	Neutral	15	6.9
	Agree	115	53.2

4.4.3 Data Timeliness

The thoughts of respondents are reflected in the table included in the 4.6 section. The following are some of the thoughts that respondents had in response to the claim that the facility always produces reports on time: disagree 22 (10.2%), neutral 24 (11.1%), and agree 170 (78.7%). 151 respondents (77.8%) agreed with the statement, while 30 (13.9%) expressed their disagreement with the statement. The results were as follows: disagree 21 (9.7%), neutral 22 (10.2%), and agree 173 (80.1%). Regarding the claim that we always utilize current data when making decisions: disagree 21 (9.7%), neutral 22 (10.2%), and agree 173 (80.1%). The following are the replies that were given in regard to the argument that one must always utilize data while making decisions: 15 (7%) disagreed, 27 (12.5%) were indifferent and 174 (80.6%) agreed.

The results are similar with those of research that was carried out in India and Uganda. That study came to the conclusion that the quality of the data was often jeopardized due to inaccuracy and incompleteness. As a result, staff members did not always depend on it for decision making (Hardee et al., 2015; Asiimwe, 2016). In addition, the low quality of the data makes it more difficult for stakeholders to use information in order to make decisions that are supported by evidence. Those who have a poor opinion of the quality of the data are less inclined to actively seek it out in the future for the purpose of making decisions. For information to be used in a manner that is consistent, the data must be of a high quality. This gives users the confidence that the information they are consulting is correct, comprehensive, and up to date.

Table 4. 5

Data Timeliness

Data Timeliness		Frequency	Percent (%)
There is never a delay in the timely delivery of reports from the facility.	Strongly disagree	4	1.9
	Disagree	18	8.3
	Neutral	24	11.1
	Agree	120	55.6
	Strongly agree	50	23.1
Always, corrective measures are carried out within a suitable amount of time.	Strongly disagree	5	2.3
	Disagree	25	11.6
	Neutral	18	8.3
	Agree	133	61.6
	Strongly agree	35	16.2
When making choices, we constantly take into account the most recent data.	Strongly disagree	5	2.3
	Disagree	16	7.4
	Neutral	22	10.2
	Agree	124	57.4
	Strongly agree	49	22.7
The necessary data is always and promptly accessible for decision making.	Strongly disagree	3	1.4
	Disagree	12	5.6
	Neutral	27	12.5
	Agree	125	57.9
	Strongly agree	49	22.7

4.5 Staff Involvement Influences the Utilization of Health Information Data

4.5.1 Involvement in Data Discussion Forums

Table 4.7 shows that more than half of respondents 87 (62.1%) were sometimes been involved in data discussion forum at the facility with 28 (20.0%) always involved in data discussion forums. Additionally, involvement in data discussion forums (Fischer exact test, p=0.013) was significantly associate with utilization of health information data for service delivery. This is similar to study by Ndegwa, (2015) that indicated lack of enough computers and training on data use among health managers as main challenges in Kenyan health facilities. According to Arumugam et al. (2016), some of the software needed to run the data entry and computing system is also hard to come by, expensive, and complex. It is concerning that public health facilities would invest a significant sum of money in such challenging software. This is not done to reward system employees; rather, it is done to modernise the healthcare facility. Lack of understanding of management and evaluation principles may have a detrimental influence on both the quality of the data and the ability to use it for decision-making. The skill set essential to analyse health information and apply it to the programmatic and policy context is rarely covered in pre-service or post-service training for health professionals. The provision of training in data management and the utility of data at the facility level may enhance the use of information. Therefore, the system has the potential to promote the utilisation of high-quality data in the decision-making process (Teklegiorgis, 2014).

Table 4. 6
Involvement in Data Discussion Forums

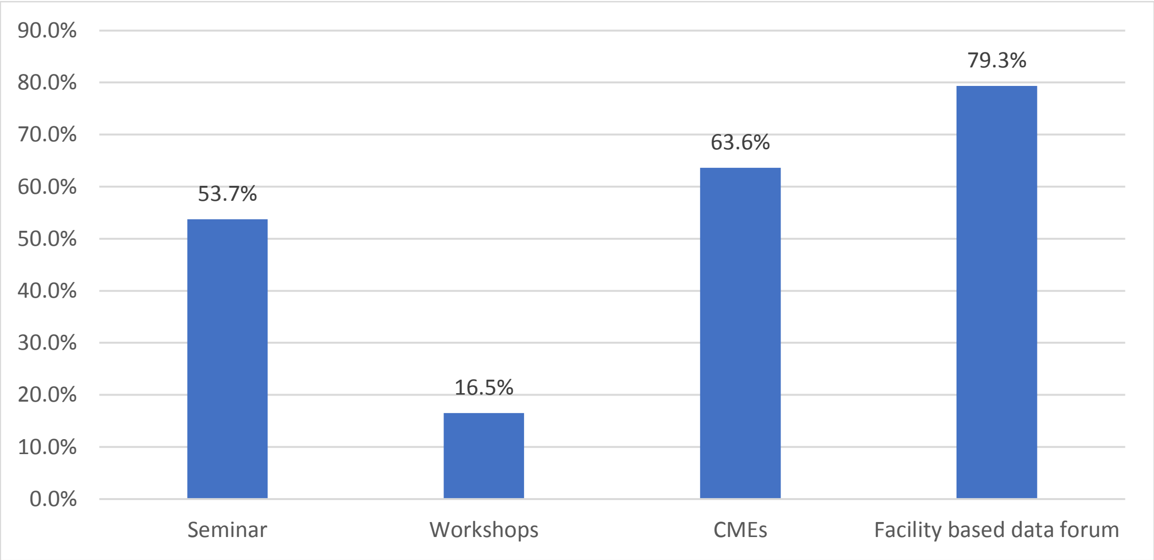
Variables		Rarely	Sometimes	Always	Significance
Data discussion forum	Yes	25 (17.9%)	87 (62.1%)	28 (20.0%)	Fischer exact test p=0.017
	No	18 (23.7%)	54 (71.1%)	4 (5.3%)	

4.5.2 Data Discussion Forums

Facility based data forum (79.3%), continuous medical education (63.6%), and seminars were most data discussion forums utilized by respondents.

Figure 4. 3

Data Discussion Forums

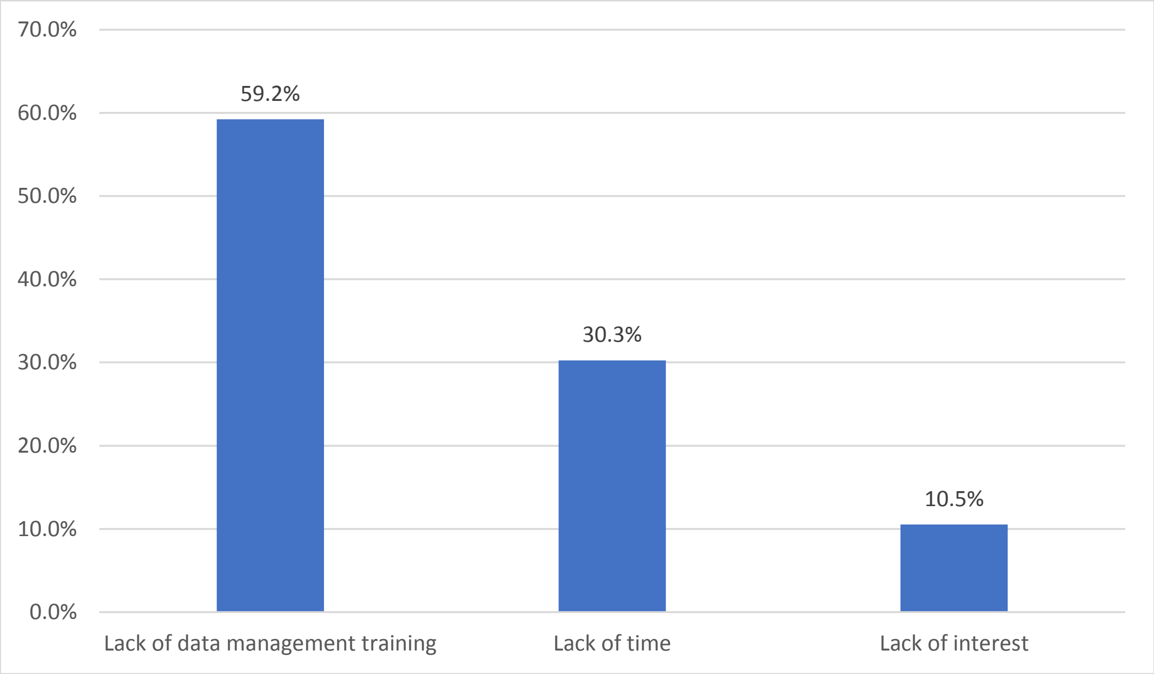


4.5.3 Hindrances for Involvement in Data Discussion Forums

At least 45 (59.2%) of facility workers wanted to take part in a data discussion forum but couldn't because they lacked the necessary expertise in data administration (Figure 4.4). Inadequate analytic and data usage skills were the most often stated barriers, with many respondents in the India survey citing a need for more education and training in the areas of data quality assurance, analysis, and application. Few respondents, however, thought that poor data quality was a major barrier, while many thought that duplicate data and irregularities in the data gathering process were problems (Rexhepi, 2015). To further enhance local use of health information, the administration of health information systems should be decentralized. This happens when local administrators and healthcare professionals work together to create systems for recording and analysing information. Information management should be handled by a single person or group at the district level.

Figure 4. 4

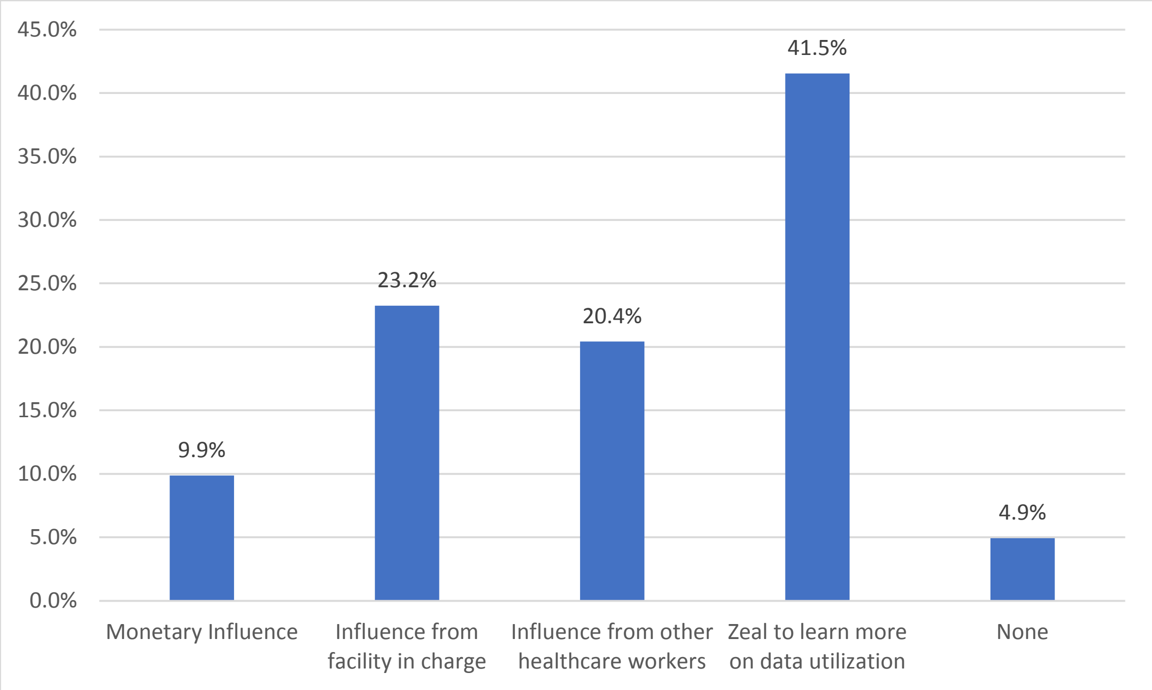
Hindrances for Involvement in Data Discussion Forums



4.5.4 Influences in Involvement in Data Utilization

Zeal to learn more on data utilization (41.5%), influence from facility in charge (23.2%), and influence from other healthcare workers (20.4%) influenced healthcare workers involvement in data utilization at the facility (Figure 4.5).

Figure 4. 5
Influences in Involvement in Data Utilization



4.6 Individual Factors Influencing the Use of Health Information Data

4.6.1 Continuous Professional Training

The extent of continuous professional training in aspects of routine data use, that is, HMIS, survey, data utilization, data analysis, planning and computer software. The findings revealed that 156 (72.2%), 154 (71.3%), 152 (70.4%) and 155 (71.8%) of healthcare workers had training on data collection, data analysis, data management and data utilization respectively. Further analysis was done to establish whether the extent of training in various areas had any statistically significant association with routine data use by use of chi-square test of independence and results were displayed in Table 4.8. The results indicate statistically significant association between extent of training on data utilization (Fischer exact test, p=0.039), data collection (Fischer exact test, p=0.044), data analysis (Fischer exact test, p=0.037), and data management (Fischer exact test, p=0.011) with utilization of health information data among the health workers participated in the study. This concurs with a study by Cheburet and Odhiambo-Otieno, (2016) showed training on data quality assurance, and analysis were positively correlated with utilization of health information data. Insufficient analytic and data usage abilities were the most often reported restrictions, according to a survey conducted by Rexhepi (2015). A substantial number of respondents expressed a need for extra training in data quality assurance, analysis, and application. It is interesting to note that just a small percentage of respondents said that poor data quality was a major barrier. However, respondents believed that duplicate data and irregularities in the data gathering process were barriers to the use of data.

Table 4. 7

Continuous Professional Training

Variables		Use data			Significance
		Rarely	Sometimes	Always	
HMIS	Yes	19(14.8%)	83(64.8%)	26(20.3%)	χ^2=10.466 df 2 p=0.005
	No	24(27.3%)	58(65.9%)	6(6.8%)	
Data collection	Yes	29(18.6%)	98(62.8%)	29(18.6%)	Fischer exact test p=0.044
	No	14(23.3%)	43(71.7%)	3(5.0%)	
Data analysis	Yes	29(18.8%)	96(62.3%)	29(18.8%)	Fischer exact test p=0.037
	No	14(22.6%)	45(72.6%)	3(4.8%)	
Data utilization	Yes	29(18.7%)	97(62.6%)	29(18.7%)	Fischer exact test p=0.039
	No	14(23.0%)	44(72.1%)	3(4.9%)	
Data management	Yes	28(18.4%)	94(61.8%)	30(19.7%)	Fischer exact test p=0.011
	No	15(23.4%)	47(73.4%)	2(3.1%)	
HMIS software's	Yes	17(14.5%)	72(61.5%)	28(23.9%)	Fischer exact test p=0.0001
	No	26(26.3%)	69(69.7%)	4(4.0%)	
Data presentation	Yes	12(12.6%)	56(58.9%)	27(28.4%)	χ^2=26.743 df 2 p=0.0001
	No	31(25.6%)	85(70.2%)	5(4.1%)	

4.6.2 Competence in Routine Data/Information Management Tasks

On overall level of competence in health information data management tasks, 98 (45.4%) rated to be moderate, 23 (10.6%) low and 4 (1.9%) very high (Table 4.9). Additionally, 55 (25.5%) said it's not easy to access routine data/information whenever needed. There is a statistically significant relationship between overall levels of competence (p=0.0001) and access to routine data (p=0.001) and the usage of health information data for service delivery, as shown in Table 4.9. This is consistent with the findings of studies conducted in Kenya, Zambia, and India, which concluded that a well-designed HMIS does not automatically equate to high-quality data and effective use of information, but that constant capacity development is essential (Mutemwa, 2016; Tabesh, 2015). The study demonstrates a statistically significant relationship between training in data presentation and the health worker's utilization of information. Inadequate technical skills and understanding of data administration restrict the use of information. The training of health professionals in analytic and information usage abilities has been considered as a technique of boosting their capacity to utilize health information to enhance facility management and service delivery.

Table 4. 8

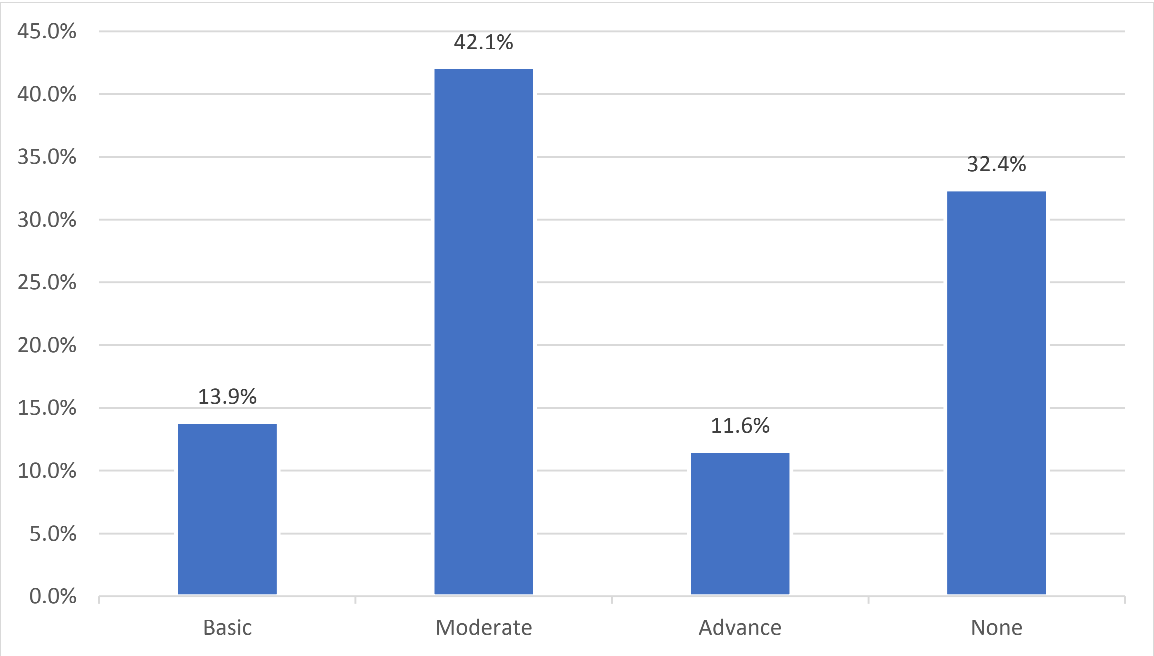
Competence in Routine Data/Information Management Tasks

Variables		Use routine data			Fischer Exact
		Rarely	Sometimes	Always	
Level of competence	Low	4(17.4%)	19(82.6%)	0(0.0%)	p=0.0001
	Moderate	26(26.5%)	66(67.3%)	6(6.1%)	
	High	13(14.3%)	56(61.5%)	22(24.2%)	
	Very high	0(0.0%)	0(0.0%)	4(100.0%)	
Easy to access routine data	Yes	27(16.8%)	102(63.4%)	32(19.9%)	p=0.001
	No	16(29.1%)	39(70.9%)	0(0.0%)	

4.6.3 Acquired Information Technology

Slightly less than half (42.1%) had moderate knowledge of information technology with 13.9% and 11.6% had basic and advance knowledge respectively. Users frequently struggle with an insufficient capacity to comprehend, analyse, and interpret information in a programmatic context. Competence or skill in performing a task is a significant motivator for information use. When asked to rate their ability to perform HMIS tasks such as calculating percentages, plotting graphs, explaining findings and their implications, and using information to identify gaps and set goals, 44.4% rated themselves as having a good ability. In contrast, they felt less confident in interpreting data and making decisions based on information.

Figure 4. 6
Acquired Information Technology

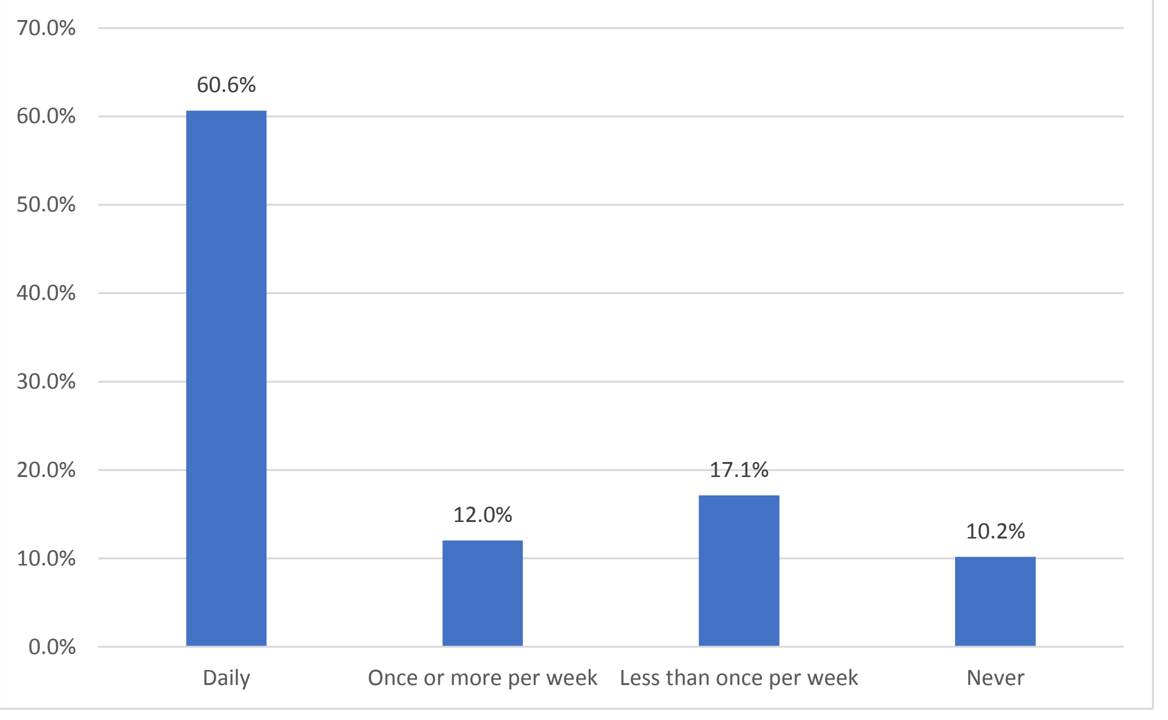


4.6.4 Frequency of Computer Use

More than half (60.6%) use a computer on daily services for certain tasks at work with 17.1% and 10.2% use less than once per week and do not use it at all respectively (Figure 4.7).

Figure 4. 7

Frequency of Computer Use

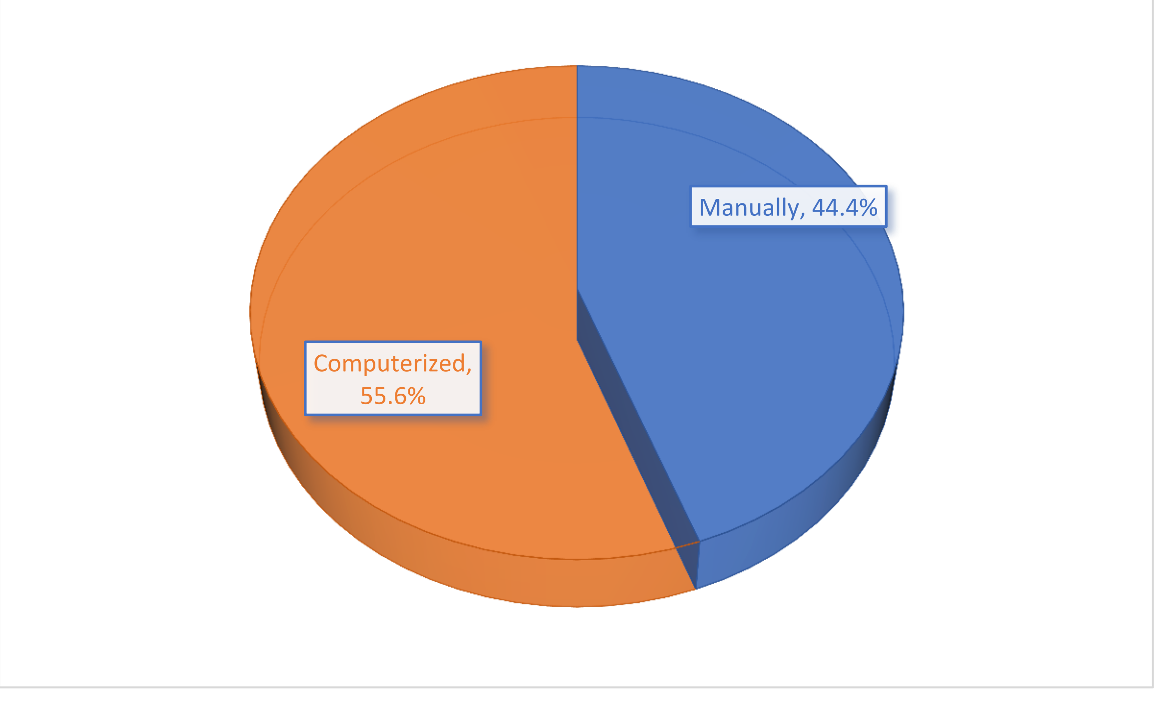


4.6.5 Routine Data Collection

Figure 4.8 shows that slightly more than half 120 (55.6%) use computers for data analysis and storage while 96 (44.4%) use manual methods.

Figure 4. 8

Routine Data Collection

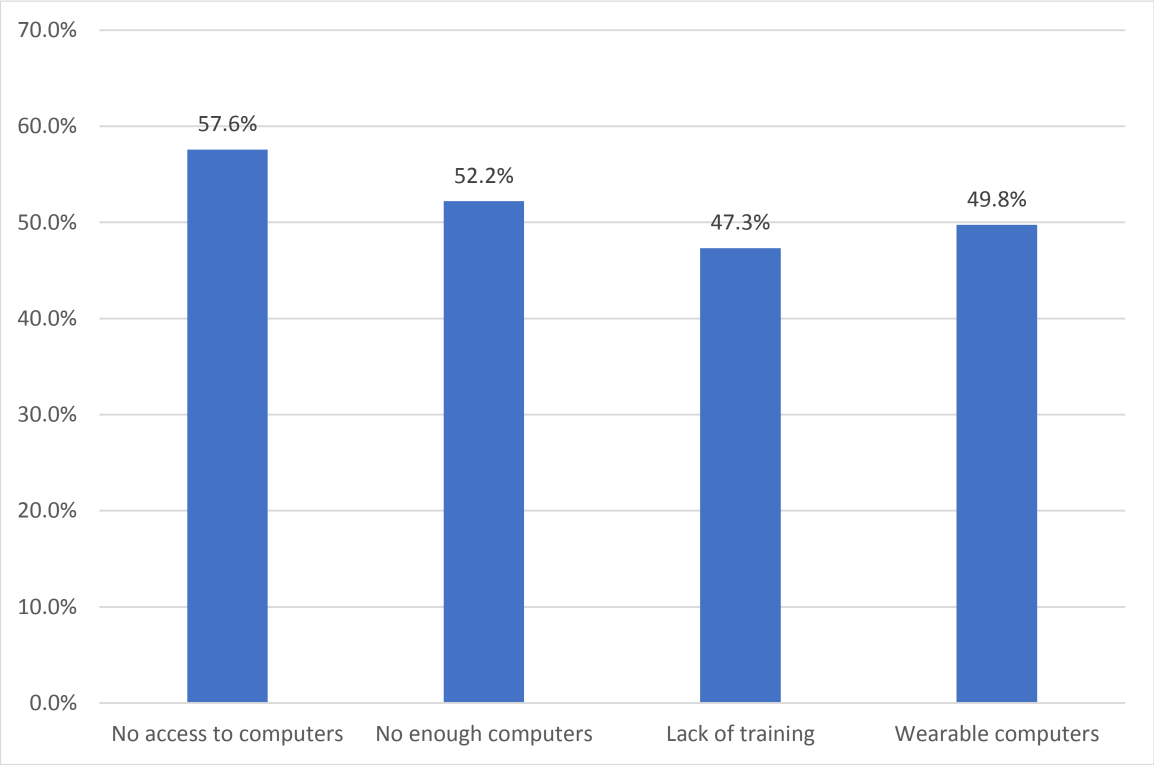


4.6.6 Difficulties in Using Computers

Inaccessibility to computers (57.6%) and inadequate computers (52.2%) were main difficulties experienced by healthcare workers.

Figure 4. 9

Difficulties in Using Computers



4.6.7 Quality of Routine Data

Data quality affects demand and information use in all level of health care delivery. The healthcare workers were of diverse discipline and this influence their perception on data quality dimensions. In table 4.10, most of respondents rated data quality characteristics as poor /fair especially in terms of accuracy (51.2%), and completeness (52.2%). Additionally, none of variable was significantly associated with utilization of health information data for service delivery among the healthcare workers.

Table 4. 9

Quality of Routine Data

Variables		Use routine data: Rarely	Sometimes	Always	Significance
Timeliness	Very good	17(22.1%)	18(27.3%)	14(22.6%)	χ^2=1.379; df 6 p=0.967
	Good	22(28.6%)	17(25.8%)	16(25.8%)	
	Bad	19(24.7%)	17(25.8%)	19(30.6%)	
	Poor	19(24.7%)	14(21.2%)	13(21.0%)	
Accuracy	Very good	18(23.4%)	17(25.8%)	16(25.8%)	χ^2=7.990; df 6 p=0.239
	Good	13(16.9%)	16(24.2%)	20(32.3%)	
	Bad	19(24.7%)	19(28.8%)	11(17.7%)	
	Poor	27(35.1%)	14(21.2%)	15(24.2%)	
Reliability	Very good	23(29.9%)	12(18.2%)	14(22.6%)	χ^2=5.478; df 6 p=0.484
	Good	22(28.6%)	20(30.3%)	13(21.0%)	
	Bad	17(22.1%)	15(22.7%)	16(25.8%)	
	Poor	15(19.5%)	19(28.8%)	19(30.6%)	
Completeness	Very good	20(26.0%)	14(21.2%)	13(21.0%)	χ^2=5.363; df 6 p=0.498
	Good	20(26.0%)	11(16.7%)	18(29.0%)	
	Bad	19(24.7%)	17(25.8%)	16(25.8%)	
	Poor	18(23.4%)	24(36.4%)	15(24.2%)	
Relevancy	Very good	17(22.1%)	15(22.7%)	19(30.6%)	χ^2=5.013; df 6 p=0.542
	Good	25(32.5%)	16(24.2%)	13(21.0%)	
	Bad	14(18.2%)	14(21.2%)	16(25.8%)	
	Poor	21(27.3%)	21(31.8%)	14(22.6%)	
Credibility	Very good	22(28.6%)	23(34.8%)	17(27.4%)	χ^2=4.772; df 6 p=0.573
	Good	15(19.5%)	17(25.8%)	19(30.6%)	
	Bad	23(29.9%)	12(18.2%)	13(21.0%)	
	Poor	17(22.1%)	14(21.2%)	13(21.0%)	

4.6.8 Challenges of Routine Data Use

The main difficulties that healthcare workers encounter when using data are performance indicators with new additions but no deletions (54.2% of the time), technical skills with inadequate data training (51.4% of the time), a lack of understanding of the benefits of data use

(49.5% of the time), time: a lot of time is spent in reporting (48.6% of the time), and indicators that are output-oriented (48.6% of the time) (Table 4.11).

Table 4. 10

Challenges of Routine Data Use

Challenges		Frequency	Percent (%)
Technical skills: poorly trained in data	Yes	111	51.4
	No	105	48.6
Motivation/ No feedback to initiate corrective measures	Yes	101	46.8
	No	115	53.2
Time: the reporting process takes up a significant amount of time.	Yes	105	48.6
	No	111	51.4
Work load: Overworked staffs	Yes	97	44.9
	No	119	55.1
Lack of Incentives	Yes	100	46.3
	No	116	53.7
A lack of awareness on the advantages of data use	Yes	107	49.5
	No	109	50.5
Many Reporting levels	Yes	90	41.7
	No	126	58.3
Too much information asked	Yes	95	44.0
	No	121	56.0
Duplication	Yes	100	46.3
	No	116	53.7
Indicators are output oriented	Yes	105	48.6
	No	111	51.4
There have been new additions made to the list of performance indicators, but none have been taken away.	Yes	117	54.2
	No	99	45.8

4.7 Organizational Factors

4.7.1 Access to Functional Equipment at Workplace

Routine data use is determined by access to functional resources. Among the health workers who participated in the study 97 (44.9%) and 97 (44.9%) reported to have access to computer and internet respectively. Table 4.12 shows chi-square analysis results that indicates statistically significant association between access to functional computer (χ^2=9.913; df 2; p=0.023) and access to internet (χ^2=7.046; df 2; p=0.030) with utilization of health information data. Culture of sharing information may be encouraged or discouraged by the organization. The use of information in the process of decision-making is a defining characteristic of the culture of information (Aljunid *et al.*, 2017).

Table 4. 11

Access to Functional Equipment at Workplace

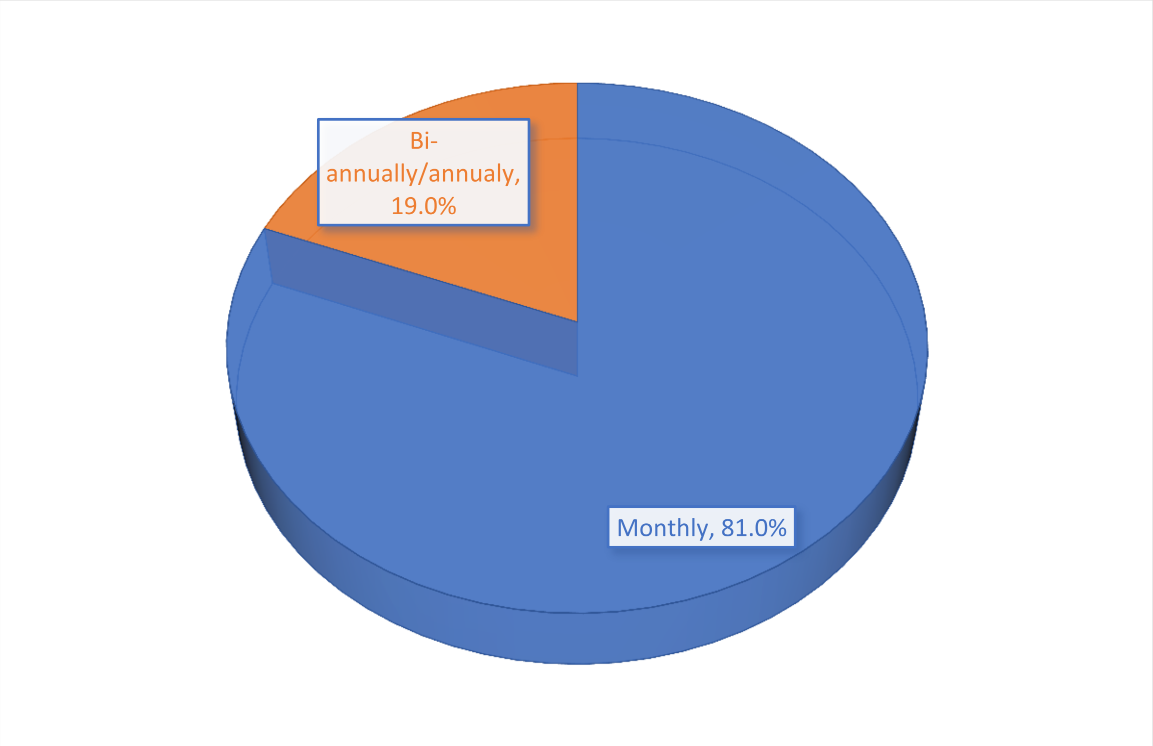
		Rarely	Sometimes	Always	Significance
Computer	Yes	22(22.7%)	56(57.7%)	19(19.6%)	χ^2=9.913; df 2 p=0.023
	No	21(17.6%)	85(71.4%)	13(10.9%)	
Printer	Yes	7(24.1%)	18(62.1%)	4(13.8%)	Fischer Exact Test p=0.413
	No	36(19.3%)	123(65.8%)	28(15.0%)	
Calculator	Yes	14(22.6%)	40(64.5%)	8(12.9%)	χ^2=1.832; df 2 p=0.400
	No	29(18.8%)	101(65.6%)	24(15.6%)	
Data backup units (e.g. flash disc, CD etc.)	Yes	9(26.5%)	20(58.8%)	5(14.7%)	χ^2=2.135; df 2 p=0.344
	No	34(18.7%)	121(66.5%)	27(14.8%)	
Access to internet	Yes	21(21.6%)	65(67.0%)	11(11.3%)	χ^2=7.046; df 2 p=0.030
	No	22(18.5%)	76(63.9%)	21(17.6%)	

4.7.2 Managerial or Administrative Meetings

Slightly less than half 175 (81.0%) hold monthly meetings for reviewing managerial or administrative matters (Figure 4.10).

Figure 4. 10

Managerial or Administrative Meetings



4.7.3 Topics Discussed During Meetings

Patients' utilization 165 (76.4%), service coverage 145 (67.1%), and medicine stock out 143 (66.2%) were common topic discussed during meetings (Table 4.13).

Table 4. 12

Topics Discussed During Meetings

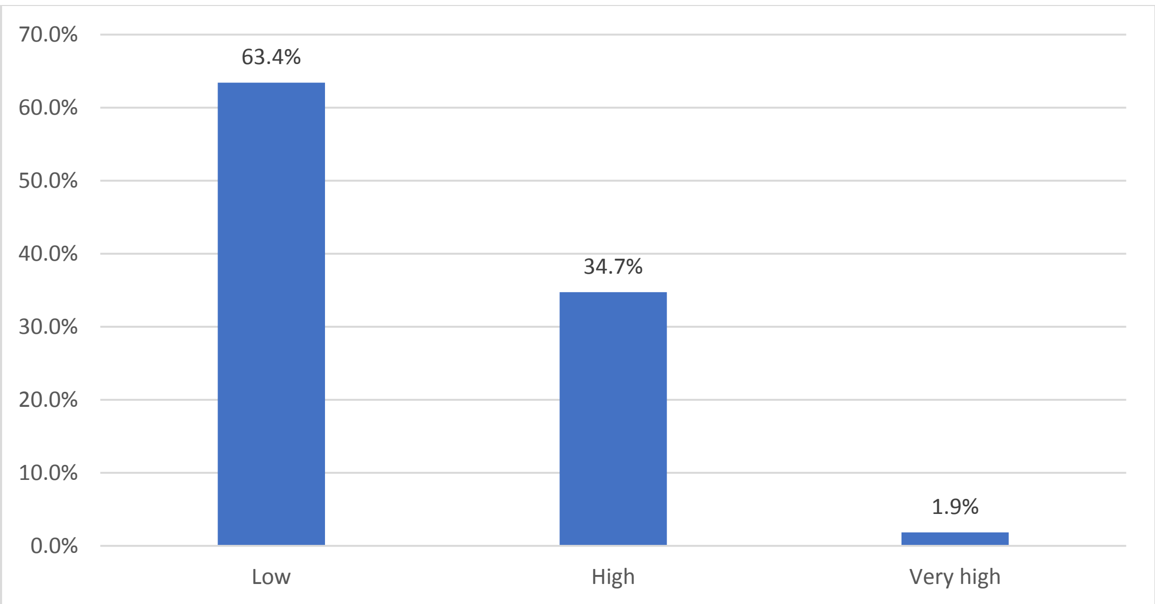
Characteristics		Frequency	Percent (%)
Administration of regular data such as quality, reporting, or adherence to deadlines	Yes	114	52.8
	No	102	47.2
The results of commonly collected data, such as illness statistics,	Yes	112	51.9
	No	104	48.1
Service coverage,	Yes	145	67.1
	No	71	32.9
Medicine stock out	Yes	143	66.2
	No	73	33.8
Patient utilization	Yes	165	76.4
	No	51	23.6

4.7.4 Level of Support Data/Information Management

Figure 4.11 demonstrates that 137 (63.4%) of those in charge of data/information management had low levels of support, while 75 (34.7%) and 4 (1.9%) had high and very high levels of support, respectively. Similarly, Scientific Symposium Report (2020) found that in Uganda, a lack of organizational variables including establishing a culture of knowledge and quality oversight contributed to their findings. Some respondents cited the absence of departmental meetings as a reason for not discussing and reviewing management issues. Asemahagn et al. (2017) and Whitaker et al. (2018) found that a lack of regular systems to support M&E activities for local level health workers, such as not holding meetings, negatively impacted the perceived significance of health information use. Feedback is considered an indicator of information utilization. When data collectors receive feedback, they believe their data collection contributes to improvements and changes that benefit themselves and patients, and they develop a sense of ownership over the data (Sharma *et al.*, 2016).

Figure 4. 11

Level of Support Data/Information Management



4.7.5 Basis for Decision Making at Health Facility

Table 4.14 displays the weight given to various considerations in arriving at the conclusion that data will be used for decision making at specified facilities. Decisions were based on health needs (43.5%), cost (39.8%), personal liking (38.9%) and superiors' directives (38.0%). This conforms to Asiimwe, (2016) that lack of computer reduced staff ability to access and use information.

Table 4. 13

Basis for Decision Making at Health Facility

Basis		Frequency	Percent (%)
Comparing data with strategic health objectives	Agree	71	32.9
	Neutral	46	21.3
	Disagree	99	45.8
Considering costs	Agree	86	39.8
	Neutral	39	18.1
	Disagree	91	42.1
Evidence/facts	Agree	77	35.6
	Neutral	47	21.8
	Disagree	92	42.6
Health needs	Agree	94	43.5
	Neutral	39	18.1
	Disagree	83	38.4
International NGOs/donor	Agree	47	21.8
	Neutral	47	21.8
	Disagree	122	56.5
Personal liking	Agree	84	38.9
	Neutral	38	17.6
	Disagree	94	43.5
Political interference	Agree	42	19.4
	Neutral	45	20.8
	Disagree	129	59.7
Superiors' directives	Agree	82	38.0
	Neutral	40	18.5
	Disagree	94	43.5

4.7.6 Correlation of Health Information Data

From the analysis of table 4.15 below, there is a statistically significant relationship between data quality with Individual factors; staff involvement; organization factors, as indicated by correlation coefficients of ($r = 0.310$), ($r = 0.308$), and ($r = 0.294$), respectively. This indicates that for the utilization of health information data, the data quality should incorporate all the sectors in the health facility from individual factors, involvement in training, data collection, data analysis, and data presentation as well as organization factors.

Analysis has also shown that there is a substantial positive association between individual factors and staff engagement ($r = -0.399$, p-value = 0.048), as well as a relationship between individual factors and organization factors ($r = -0.214$, p-value = 0.033). Further, there was strong significant association between staff involvement and organization factors, indicated by correlation coefficients of ($r =-0.485$, p-value = 0.003).

Table 4. 14

Correlation between Variables

		Data quality	Staff attitude	Staff involvement	Organization factors
Data quality	r	1	0.310**	0.308*	0.294**
	Sig. (2-tailed)		0.002	0.039	0.003
	N	216	216	216	216
Staff attitude	r	0.310**	1	0.399*	0.214*
	Sig. (2-tailed)	0.002		0.048	0.033
	N	216	216	216	216
Staff involvement	r	0.308*	0.399*	1	0.485
	Sig. (2-tailed)	0.039	0.048		0.003
	N	216	216	216	216
Organization factors	r	0.294**	0.214*	0.485*	1
	Sig. (2-tailed)	0.003	0.033	0.003	
	N	216	216	216	216

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

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

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This chapter summarizes all the independent variable used in the study and how each influences utilization of health information data by pointing out areas where more focus and strengthening is required. From the findings all the variables do affect utilization of health information data in diverse way hence need to be addressed.

5.1.1 Influence of Data Quality in the Utilization of Health Information Data

Less than two-thirds of respondents (65.3%) occasionally made decisions using routine data. Numerous factors, including technical, individual, and organizational factors, hampered data quality. The study revealed that all examined reports were incomplete and inaccurate to varying degrees. In order to transform the one-way systems into an integrated health system, a systematic intervention is required. Inaccessibility to computers (57.6%) and inadequacy of computers (52.2%) were the most significant obstacles encountered by healthcare professionals.

5.1.2 Individual factors influencing the Use of Health Information Data

This study revealed that the majority of healthcare professionals utilized health information data for service enhancement, with the majority using it for formulation of planning, identification of emerging epidemics, and management of medical supply and drugs. Some decisions were made based on health needs, cost, personal preference, and directives from superiors, rather than on facts, which may have led to inefficiency and poor health outcomes

5.1.3 Staff involvement influencing the Use of Health Information Data

The study found that lack of data management training accounted for 45 (59.2%) of the facility's data discussion forum participation barriers. Furthermore, to enhance the local use of health information, the administration of health information systems should be decentralized. This happens when local administrators and health-care providers work together to build data gathering and reporting tools. One individual or team should be selected as the district's information manager.

5.1.4 Organizational Factors Influencing Utilization of Health Information Data

The performance of an organization's employees is directly proportional to its effectiveness. Information culture is defined by the use of information whenever decisions are made. 76.7 percent of respondents agreed that decisions were based on health requirements, cost, and personal preference. Feedback is considered an indicator of information utilization. When data collectors receive feedback, they believe their data collection contributes to changes and improvements that benefit both themselves and patients, and they develop a sense of ownership over the data.

5.2 Conclusion

Inadequate technical skills and data management knowledge hinder the use of information. A well-designed HMIS does not automatically result in high-quality data and effective use of generated information, but continuous capacity building is essential. Training health workers in analytical and information-use skills has been viewed as a means of enhancing their capacity. The results also revealed a statistically significant correlation between levels of competency and access to routine data and the decision-making use of routine data. Therefore, the researcher concluded that to increase the demand for and use of information in decision making, core competencies in various aspects of information management must be developed at all levels of the health care system, and information must be readily available whenever users desire it.

The majority of respondents were concerned about poor data quality (inaccurate, untimely, incomplete, and unreliable), which led to negative perceptions, an attitude shared by all health care professionals. The results also revealed that performance indicators have new additions but no deletions, technical skills: poorly trained in data, lack of knowledge of the benefits of data use, time: a great deal of time is spent on reporting, and indicators are output-oriented were the most significant obstacles encountered by healthcare workers when it comes to utilizing data.

Among the respondents who participated in the study had received minimal training at all in information areas like data analysis, data utilization, and HMIS software. Moreover, a quarter of the health workers at selected health facilities said it’s not easy to access routine data/information whenever needed.

The study also demonstrated poor access to functional equipment like computer and internet which jeopardize health information utilization. Most of staff had low support from in-charge on matters pertaining to data/information management of which most had low level of support respectively. Even though they were holding departmental meetings to share performance on key indicators, the meetings were irregular.

5.3 Recommendations

For the purpose of making decisions based on the best available evidence at all levels of healthcare, the county health management team should raise the demand for and use of high-quality health information data.

Hospital management, donors, and other stakeholders must give healthcare workers on-going training with a focus on using health information data through on-the-job trainings, mentoring for those already employed, and strengthening the curriculum in health training institutions by integrating HMIS modules into all cadres.

In order to institutionalise proactive information quality assurance mechanisms to identify and address data flaws and strengthen the feedback process in which information consumers and producers communicate with one another to share information needs and challenges encountered, county government must include health workers in various level health information data meetings and discussions at the facility level.

By providing tools, computers, skilled workers, automation, connectivity, as well as targeted regular support supervision, review meetings, and job descriptions outlining information roles and responsibilities, the county government can strengthen organisational resources that support information use at all levels.

5.4 Areas of further Research

Additional research is needed in the following areas:

1. Similar research must be conducted in other counties to generate more supporting evidence.
2. Researchers should compare public and private health facilities to gain an understanding of the routine use of data and to provide information for policy adjustments and creation.

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APPENDICES

Appendix i: Consent Form

Kenya Methodist University
P. 0 Box 267-60200
MERU, Kenya

SUBJECT: INFORMED CONSENT

Dear Respondent,

My name is **Duncan Njuguna** I am a M.Sc. student from Kenya Methodist University. I am conducting a study titled: **FACTORS INFLUENCING UTILIZATION OF HEALTH INFORMATION DATA IN NAIROBI CITY COUNTY PUBLIC HEALTH FACILITIES, KENYA** the findings will be utilized to strengthen the health systems in Kenya and other Low-in-come countries in Africa. As a result, countries, communities and individuals will benefit from improved quality of healthcare services. This research proposal is critical to strengthening health systems as it will generate new knowledge in this area that will inform decision makers to make decisions that are research based.

Procedure to be followed

Participation in this study will require that I ask you some questions and also access all the hospital's department to address the six pillars of the health system. I will record the information from you in a questionnaire check list.

You have the right to refuse participation in this study. You will not be penalized nor victimized for not joining the study and your decision will not be used against you nor affect you at your place of employment.

Please remember that participation in the study is voluntary. You may ask questions related to the study at any time. You may refuse to respond to any questions and you may stop an interview at any time. You may also stop being in the study at any time without any consequences to the services you are rendering.

Discomforts and risks.

Some of the questions you will be asked are on intimate subject and may be embarrassing or make you uncomfortable. If this happens; you may refuse to answer if you choose. You may also stop the interview at any time. The interview may take about 40 minutes to complete.

Benefits

If you participate in this study you will help us to strengthen the health systems in Kenya and other Low-in- come countries in Africa. As a result, countries, communities and individuals will benefit from improved quality of healthcare services. This field attachment is critical to strengthening the health systems as it will generate new knowledge in this area that will inform decision makers to make decisions that are research based.

Rewards

There is no reward for anyone who chooses to participate in the study.

Confidentiality

The interviews will be conducted in a private setting within the hospital. Your name will not be recorded on the questionnaire and the questionnaires will be kept in a safe place at the University.

Contact Information

If you have any questions you may contact the following supervisors:

1. **Miss. Lillian Muiruri** 2.**Dr. Kezia Njoroge**, Chair Department of Health Systems Management of Kenya Methodist University, Nairobi campus.

Participant's Statement

The above statement regarding my participation in the study is clear to me. I have been given a chance to ask questions and my questions have been answered to my satisfaction. My participation in this study is entirely voluntary. I understand that my records will be kept private and that I can leave the study at any time. I understand that I will not be victimized at my place of work whether I decide to leave the study or not and my decision will not affect the way I am treated at my work place.

Name of Participant…………………………………………. Date…………………………..

Signature……………………………………….

Investigator's Statement

I, the undersigned, have explained to the volunteer in a language s/he understands the procedures to be followed in the study and the risks and the benefits involved.

Name of Interviewer………………………………………………Date…………………….

Interviewer Signature…………………………………………

Appendix ii: Questionnaire

TITLE: FACTORS INFLUENCING UTILIZATION OF HEALTH INFORMATION DATA IN NAIROBI CITY COUNTY PUBLIC HEALTH FACILITIES, KENYA

INSTRUCTION:

Instructions: ***Do not write your name or any other personal data on the questionnaire.***

Please follow instructions while answering questions in each area.

The information given here will remain confidential.

1	**Study Number**	
	Name of Health facility	

SECTION A: SOCIO DEMOGRAPHIC CHARACTERISTICS

1.	What is your age in complete years?	……………………….	
2.	What is your gender?	a) Male -1 b) Female-2	
3.	What is your professional training?	a) MO - 1 b) RCO - 2 c) Nurse - 3 d) Pharmacy - 4 e) Lab – 5 f) Others specify………..	
4.	What is your highest education attained?	a) Certificate - 1 b) Diploma-2 c) HND - 3 d) Degree – 4 e) Masters -5 f) PhD-6	
5.	What is your working experience since your first graduated?	a) Six months but < 1 year-2 b) One year but < 3 years-3 c) Three years but < 5 years-4 d) ≥ 5 years -5	

6.	For how long have you been working at this health facility?	a) Six months but < 1 year-2 b) One year but < 3 years-3 c) Three years but < 5 years-4 d) ≥ 5 years -5	

7. What kind of Information Technology have you acquired?

A) Basic ( ) B) Moderate ( ) C) Advance ( )

SECTION B: DATA QUALITY

1. Data Accuracy:

Please rate the performance of your facility/department on the stated data accuracy domains. Please choose your preferred response by ticking only one box per question.

[Key: 1= strongly disagree, 2= Disagree, 3= Neutral, 4=Agree, 5= strongly agree]

	1	2	3	4	5
I have encountered inaccurate data during decision making process					
Inaccurate data has hindered me from routinely using data to make decisions					
I take corrective action to address noted data accuracy issues before use					
I have used/relied on other data sources and not health information data to make decisions					

2.Data Completeness

Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question.

Key: 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	1	2	3	4	5
Reported data includes all the necessary dataset reports					
Reported data is sufficiently complete for our needs					
Reported data summarizes the work of the department					
Health information data is not relevant to my current data analysis and aggregation needs					
There is no added value due to aggregating inconsistent data					

3.Data Timeliness:

Please rate the timeliness of health information data from your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question.

Key: 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	1	2	3	4	5
Reporting from the facility is always on time (according to the set national reporting timelines)					
Corrective actions are always taken within reasonable time					
When making decisions, we always use current data					

Data is always available on time for decision making					

SECTION C: STAFF INVOLVEMENT

1. Have you ever been involved in data discussion forum in your facility?

   Yes [ ]   No [ ]

a) If the answer in question 1 above is yes, then what forum have you been involved in?

   A. Seminars [ ]

   B. Workshops [ ]

   C. Continuous Medical Examinations [ ]

   D. Facility based data forum [ ]

b) If the answer in question 1 above is No, then what might be the hindrances?

   A. I have not been trained in data management [ ]

   B. My job is tasking hence no time for data discussion [ ]

   C. I have no interest [ ]

2. What has influenced your involvement in data utilization in your facility?

   A. Monetary Influence [ ]

   B. Influence from facility in charge [ ]

   C. Influence from other healthcare workers [ ]

   D. Zeal to learn more on data utilization [ ]

   E. None of the above [ ]

SECTION D: INDIVIDUAL FACTORS			
1.	Have you received any continuous professional training in the following areas? | | YES | NO | a) HMIS b) Data collection c) Data analysis d) Data utilization a) Data management f) HMIS software Other data related areas (specify).......................................		If yes, Duration (*in weeks/months or years)*
2.	How would you describe your overall level of competence in routine data/information management tasks?	a) Low ---1 b) Moderate--2 c) High ----3 d) Very High-----4	

	YES	NO
a) HMIS		
b) Data collection		
c) Data analysis		
d) Data utilization		
a) Data management		
f) HMIS software		

3.	Do you find it easy to access routine data/information whenever you need it?	a) Yes -----1 b) No ------2	

4.	How frequently do you use a computer for certain tasks at work? a) Daily ….1 b) Once or more per week but NOT daily…..2 c) Less than once per week……3 d) Never……4	
5.	How is the collected data analysed and stored (Please show the exact way used)	

	a) Manually----1 b) Computerized ---2		
6.	What difficulties do you face in using Computers? a) No access to computers……1 b) No enough computers……...2 c) No training in computer……3 Others (Specify) ………………4		
7.	How would you rate the quality of health information data/information generated by this facility in terms of?		

	Very good	Good	Bad	Poor
A. Timeliness				
B. Accuracy				
C. Reliability				
D. Completeness				
E. Relevancy				
F. Credibility				

8.	What specific challenges have you experienced among your staff when it comes to using data? **Please rank them in order of severity-1,2,3 etc** a) Technical skills: poorly trained in data b) Motivation/ No feedback to initiate corrective measures c) Time: A lot of time taken in reporting d) Work load: Overworked staffs e) Lack of Incentives f) Lack of knowledge of benefit of data use g) Many Reporting levels	

	h) Too much information asked i) Duplication j) Indicators are output oriented k) Performance indicators have new additions but no deletions l) Others (specify)..	

SECTION E: ORGANIZATIONAL FACTORS

1.	Which of the following **functional** equipment's do you have **access to** in your office/workplace?	a) Computer--1 b) Printer--2 c) Calculator…3 d) Data backup units (e,g flash disc, CD etc)…4 e) Access to internet…5	
2.	What is your experience in usage of the computers?	a) Low …..1 b) Medium …..2 c) High …..3	
3.	How often do you have meetings for reviewing managerial or administrative matters?	a) Monthly…….1 b) Bi annual/ Annually…2	
4.	Is an official record of meetings maintained? **(If yes please check the meeting records for the last three months)**	a) Yes -----1 b) No ------2	
5.	What topics were discussed and recorded during the meeting?		

	YES	NO
Management of routine data like quality, reporting or timeliness		
Findings of routine data like disease data,		
Service coverage,		
Medicine stock out		
Patient utilization		

Other related areas (specify).......................................

6. Please be frank and choose your answers honestly. To what extent, do you agree with th following on a scale of 1-5 with 1=strongly agree, 2=Agree, 3=Neutral, 4=Disagree 5=Strongly disagree? **In health system decisions are based on**

	1	2	3	4	5
Comparing data with strategic health objectives					
Considering costs					
Evidence/facts					
Health needs					
International NGOs/donor					
Personal liking					
Political interference					
Superiors' directives					

What level of support from your in-charge on matters pertaining to data/information management do you receive?	a) Very low -1 b) Low -2 c) High -3 d) Very high -4

SECTION F: UTILIZATION OF DATA

1.	How often do you use the routine data/health information generated for decision making?	b) Never -1 c) Rarely -2 d) Sometimes -3 e) Always-4	
2.	Please indicate the extent to which you use data generated for: - On a scale of 1-4, where 1 means never, 2 means rarely, 3 means sometimes and 4 Always:		

	1	2	3	4
Day-to-day program management				
Medical supply & drug management				
Formulating plans				
Review financial statement and Budget preparation				

	Deciding budget reallocation					
	Human resources management					
	Monitoring key objectives and policy					
	Identification of emerging epidemics					
3.	Who fills the monthly reports/data?	a) Medical officer….1 b) Nursing/ Midwife…2 c) Clinical Officer….3 d) HIO………4 e) Support Staff…….5 f) Other (Specify)………6				

Thank you very much for your participation and completing this questionnaire

Appendix iii: Introduction

KENYA METHODIST UNIVERSITY

P. O. Box 267 Meru - 60200, Kenya
Tel: 254-064-30301/31229/30367/31171
Fax: 254-64-30162
Email: deanrd@kemu.ac.ke

DIRECTORATE OF POSTGRADUATE STUDIES

June 25, 2021

Commission Secretary,
National Commission for Science, Technology and Innovations,
P.O. Box 30623-00100,
NAIROBI.

Dear sir/ Madam,

DUNCAN NJGUNA (HSM-3-2533-1/2014)

This is to confirm that the above named is a bona fide student of Kenya Methodist University, Department of Health Systems Management undertaking a Degree of Master of Health Systems Management. He is conducting research on, **'Factors influencing utilization of health information data in Nairobi City County public health facilities, Kenya'.**

We confirm that his research proposal has been defended and approved by the University.

In this regard, we are requesting your office to issue a permit to enable him collect data for his research.

Any assistance accorded to him will be appreciated.

Thank you.

22 JUN 2021

Dr. John Muchiri, PHD.
Director Postgraduate Studies
Cc: Dean SMHS
COD, Public Health
Postgraduate Co-ordinator
Supervisors

Appendix iv: Ethical Clearance

KENYA METHODIST UNIVERSITY

P. O. BOX 267 MERU - 60200, KENYA FAX: 254-64-30162
TEL: 254-064-30301/31229/30367/31171 EMAIL: serc@kemu.ac.ke

June 21, 2021 KeMU/SERC/HSM/33/2021

Duncan Njuguna
Kenya Methodist University

Dear Duncan,

SUBJECT: FACTORS INFLUENCING UTILIZATION OF HEALTH INFORMATION DATA IN NAIROBI CITY COUNTY PUBLIC HEALTH FACILITIES, KENYA

This is to inform you that Kenya Methodist University Scientific Ethics and Review Committee has reviewed and approved your above research proposal. Your application approval number is KeMU /SERC/HSM/33/2021. The approval period is 21st June 2021 – 21st June 2022.

This approval is subject to compliance with the following requirements

I. Only approved documents including (informed consents, study instruments, MTA) will be used.

II. All changes including (amendments, deviations, and violations) are submitted for review and approval by Kenya Methodist University Scientific Ethics and Review committee.

III. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to KeMU SERC within 72 hours of notification.

IV. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to KeMU SERC within 72 hours.

V. Clearance for export of biological specimens must be obtained from relevant institutions.

Appendix v: NACOSTI Approval

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **167636**

Date of Issue: **09/July/2021**

RESEARCH LICENSE

[redacted]

This is to Certify that Mr.. Duncan Chege Njuguna of Kenya Methodist University, has been licensed to conduct research in Nairobi on the topic: FACTORS INFLUENCING UTILIZATION OF HEALTH INFORMATION DATA IN NAIROBI CITY COUNTY PUBLIC HEALTH FACILITIES, KENYA for the period ending : 09/July/2022.

License No: **NACOSTI/P/21/11619**

167636

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY &
INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document,
Scan the QR Code using QR scanner application.

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is Guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014

CONDITIONS

1. The License is valid for the proposed research, location and specified period
2. The License any rights thereunder are non-transferable
3. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research
4. Excavation, filming and collection of specimens are subject to further necessary clearence from relevant Government Agencies
5. The License does not give authority to tranfer research materials
6. NACOSTI may monitor and evaluate the licensed research project
7. The Licensee shall submit one hard copy and upload a soft copy of their final report (thesis) within one year of completion of the research
8. NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice

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