ASSESSMENT OF FACTORS INFLUENCING EFFECTIVE STAFF PERFORMANCE IN IMPROVING DATA MANAGEMENT IN SELECTED FACILITIES IN MOMBASA COUNTY, KENYA

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DECLARATION AND APPROVAL

Declaration by the student

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

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DEDICATION

I bestow this thesis to my family- my Late husband Macharia Njuguna, Daughter Njeri Macharia; Son Njuguna Macharia, and my Late Mama Drisilla Kayanda for their support and abundance of prayer.

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ABSTRACT

Preceding studies in upcoming nations have shown a diversity of reasons that may endanger data value in HIS. Some of these issues are related to the facility's setup and the technical knowledge of the healthcare providers. Conferring to study, many upcoming nation's well-being info systems are unable to offer essential support info. The lack of preferment of info culture harms the enactment of Health Info Systems (HIS). This research aimed at assessing reasons influencing effective staff actions in improving data management in designated amenities in Mombasa County, Kenya. The aspects to be explored were divided into three categories: organizational reasons, individual/team reasons, and external environmental reasons. The study was conducted in Mombasa County and used a cross-sectional research strategy with a mixed methods tactic. The 2080 healthcare workers formed the study's target population. In addition, the researcher targeted source documents, Ministry of Health (MOH) 711 reporting tools, and the Kenya Health Info System (KHIS) in 53 public health facilities, 172 private health facilities, and 17 FBO/NGO health facilities. The sample size for the study was 242 healthcare workers, 57 source documents, 24 MOH 711 reporting forms, and 24 KHIS in 24 levels 5, 4, and 3 private, Public, and FBO/NGO health facilities in Mombasa County. Both stratified and purposive sampling methods were employed in this research. Questionnaires, interviews, focus group debates, and data verification tools were employed to obtain quantitative and qualitative data for this research. Quantitative data were examined using incidences, proportions, mean, std, variation of coefficient, cross-tabulations, coefficient Phi correlation, and binary logistic regression (at 0.05 significance level). Qualitative data were analyzed using content analysis. The results indicated that organizational aspects ($\phi = 0.268$, $OR = 0.284$, $p > 0.05$), staff effectiveness ($\phi = 0.408$, $OR = 0.056$, $p > 0.05$), and individual attributes ($\phi = 0.141$, $OR = 0.424$, $p > 0.05$) did not have a significant impact on improvement in data administration, while knowledge and skills ($\phi = 0.535$, $OR = 0.031$, $p < 0.05$) was found to have a significant effect on improvement in data organization. The study concluded that the awareness and skills of healthcare employees are substantial predictors of enhancement in data management at the well-being amenities in Mombasa County. The study recommends that the Ministry of Healthiness at the nationwide level and the department of Healthiness in Mombasa County should ensure that(Human Resources for Health) HRH norms on Healthiness Management Info System (HMIS) officers are adhered to and ensure that all health employees are adequately competent in data management which will improve their competency.

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LIST OF ABBREVIATIONS AND ACRONYMS

DDIU	Data Demand and Information Use
DOHs	Department of Health Services
HCWs	Healthiness Care Workers
HIS	Healthiness Info System
HMIS	Healthiness Management Info System
HMN	Health Metrics Network
HRM	Human Resources for Health
KHIS	Kenya Healthiness Info Systems
LMICs	Low- and Middle-Income Nations
LSCH	Likoni Sub County Hospital
M&E	Monitoring and Evaluation
MOH	Ministry of Health
OJT	On job training
PRSCH	Port Reitz Sub County Hospital
RDQA	Routine Data Quality Audit
SDGs	Sustainable Development Goals
TSCH	Tudor Sub County Hospital
WHO	World Health Organization

CHAPTER ONE: OUTLINE

1.0 Introduction

This research was to explore factors of operative staff routine in cultivating data quality management in selected fitness amenities in public, private, and FBO/NGO sectors in Mombasa County. This section covers the following: study background, problem statement, justification, purpose and study objectives, research query, scope, limitation, and delimitation.

1.1 Background

Healthiness info is the basis of healthiness system building pillars that strengthens access to information, allowing health professionals to apply the same principles in improving policy, forecasting, executing, observing, and evaluating well-being systems(Karuri et al., 2014). Worldwide, momentous human and financial capital are capitalized in data collection at well-being facilities and the community. Well-being workers collect information from patients and health facilities and report on health facility activities regularly. As a result, it facilitates communication between health workers and patients and allows for continuous patient management(WHO, 2016).

The roots of a quality improvement organization go back to the work of people like Ignaz Semmelweis, a 19th-century obstetrician who promoted the importance of hand washing in medicine. In addition, Florence Nightingale, a nurse in England, pointed to a link between poor living conditions and high mortality among soldiers treated in military hospitals(Chelagat et al., 2013). In the US, the reporting of data began with the passing of the Human Rights Act of 1964 and the Medicare Act of 1965(Reynolds, 1997). This has been the result of a growing focus on the physician's response to motivation and encouragement. This has resulted in the development of a Medical Quality Reporting System (PQRS) under Tax Reduction since 2011. According to a Botswana study, nurses have a negative attitude toward data assortment and recording(Ledikwe et al., 2014). The application of well-being data is an essential component of well-being departments' capacity, and the effectiveness of public health is dependent on the effectiveness of effective knowledge(Turnock et al., 2010). The primary objective of suggestion-based decision-making is to expand wellcare quality by swelling the capability of the healthcare system to respond to the needs of the population it serves. Limited resources, as well as the necessity for accountability, continue to support a strategic approach to improving health systems. However, key stakeholders are not effectively utilizing the most common health data in informing policy, public health practices, and actions(Braa et al., 2012).

Well-being management info system (HMIS) is an area of ongoing and important investment by governments, donors, and organizations. Such investments compel evidence of accountability and decision-making. HIS was not one of hard study and testing. The lack of structured evidence has its limitations in learning, sharing, and investing in HIS-led state-of-the-art practices. The Sustainable Development Goals (SDGs) necessitate high-quality data to track development and accomplishment(United Nations, 2017), assuming that relevant information is readily available and accurate. However, because of its limited completeness, timeliness, representation, and correctness, this valuable data source is frequently ignored in upcoming nations. Program managers and other decision-makers use general health information less when they have low trust in its quality(United Nations, 2017).

Recognizing the inaccuracy of conventional well-being data and the desire for accurate well-being data from funders and administrations, the presidents of eight international and commercial organizations issued a plea in 2010 to states and key stakeholders to invest in effective and efficient information systems. The World Bank, USAID, WHO, and other partner governments dispensed a "Five-Point Demand to Achievement" at the 2015 Outcomes Health Measurement and Accountability Conference, calling for satisfactory speculation in well-being informatics and arithmetical programs in all nations by 2030, among other things(World Bank, 2015).

According to studies, data collectors and local health managers in health facilities or counties use very little of this vast amount of information(Nsanzimana et al., 2012). Given the volume of data collected, it is rarely regarded as adequate consideration. A catastrophe to contemplate all relevant indications before making choices impairs the well-being system's capability to react to the most pressing desires(Gimbel et al., 2017).

Inefficiencies in info-based verdict-making are discovered because the individuals who assemble and examine data are not always the same people who make decisions in the healthcare system. An extensive information system research steered in Atlantis, South Africa revealed that the amount of statistics collected was very large, but the amount of useful data extracted from it was small. Health information is worthless if it is not utilized to inform practice and attempts to enhance the quality of data will be misused unless it includes interventions to enhance demand and utilization of information within the organizations(Braa et al., 2012).

Traditional info systems in developing nations do not offer the required info to support decision-making for a variety of motives. Some of the reasons given in the books include lack of detail, poor data analysis, inadequate knowledge culture, shortage of qualified staff, and HIS staff being considered an encumbrance owing to heavy workloads, particularly at the health facility level (Ehsani-Moghaddam et al., 2021). Aside from the rapid expansion of data capturing and recording requirements within the fitness info system, there is little suggestion that data is utilized(Hotchkiss et al., 2010). According to the studies, data users have various info needs, require info at various levels of data, and play various roles in the decision-making practice(Kihuba et al., 2014). Studies have indicated challenges regarding data usage in Kenya among healthcare providers in counties that do not use this information for planning purposes. For example, representatives of the National Public Health Laboratory Services reported that they believe that many labs think that information is collected for reporting purposes at the national level, rather than for local decision-making. Some regions may not even know that certain data is available.

According to a study performed in Kenya, researchers should begin a conversation with regional MOHs to promote a data agenda at the County level to enhance data demand and information usage. (MOH, 2014)According to several top investigators, governments do not verify the data supplied by institutions. APHIA Plus, for example, claimed that information is used by institutions but not regions: "About 90% of locations submit reports worldwide." However, the report now only lasts a few days at the CHRIO offices before you check-in. Key informants also stated that data utilization at the institutional level was inconsistent at times and that many locations did not examine their reports. According to the National AIDS and Sexually Transmitted Infectious Diseases Program, institutions will disseminate material without first vetting it: Service delivery centers will only disseminate reports on their initiative. It can't be both ways(Handley et al., 2015). They should search through the details and consider what this information means to us. They do so now to meet reporting requirements rather than to improve the system. APHIA Plus and the National AIDS and STI Controller Platform have revealed that they are attempting to teach regions how to use information through meetings, capacity development, and other means(Ehsani-Moghaddam et al., 2021).

1.2 Problem Statement

The Well-being Info System is critical to the planning and management of well-being services, and it can play a noteworthy role in platform development and broadcasting at all levels. Regrettably, many upcoming nations' HISs are incapable to offer the essential sustenance info. The data generated is of poor quality, and it is not being used effectively to apprise making of decisions (Lippeveld, 2013).

Lack of cultural awareness promotion affects the performance of HIS. Insufficient information about the usefulness of the data is connected to inadequate need and use for statistics in many countries. Laws, procedures, prices, and systems govern many organizations. They can reverse or prevent health staff's capacity to use data to inform policy(Aqil et al., 2009). Time and again, information is collected from shelves, information, or reports and is not disseminated on time, and is used extensively in advocacy, strategic planning, program growth, and policy growth. Quality data alone is insufficient to ensure data usage because decision-makers' information needs are frequently overlooked in data collection efforts, and data usage is often overlooked in decision-making processes(Aqil et al., 2009).

Thaer & Alrubaey (2023)conducted research on staff results which showed that data quality testing, computations, and data classification were between 66.77% and 74.6%, with the data interpretation very low at 64.55%. Respondents also generally believed that performing HIS tasks had negative consequences, (the average motivation rate was 43.4%)(Thaer & Alrubaey, 2023). The Malawian research found both strengths and shortcomings in HMIS functioning, with notable deficiencies including atypical data quality tests and untrustworthy instructions. A similar study should be used to teach efforts to improve health management information systems in developing countries(O'Hagan et al., 2016).

Another research conducted in Malawi and its collaborators found that the facilities performed well in selected data quality categories, such as consistency across registers, reports, and DHIS-2 on women completing fourth ANC visits throughout the campaign. However, in some service areas such as ARI, data quality is low(Nisingizwe et al., 2014). While well-being offices and hospitals are more likely to have a competent HMIS workforce, there is inadequate workforce teaching at the well-being amenity level, which contributes to inadequate data level and low data usage at an official level(Getachew et al., 2022). Other gaps identified in the same study are limited training for HMIS staff - especially at the health facility level. Quality research found that there was limited at all stages of data reporting; pre-operative training of data collection and reporting staff (statistical secretaries of institutions and HMIS staff in counties) and refresher courses after the introduction of new tools and methods(Hazel et al., 2017).

Lower Eastern had all three of these borders with more than 80% and Nyanza and Western was available and 90% complete although the time was 80% in the West and 78% in Nyanza. The best-performing region is the Northeast with 79% availability, 65% completeness, and 69% punctuality. Data verification may be excessively reported or reported under multiple audited indicators. There was an over-reporting of women receiving FP (105%), IPT2 (103%), Pregnant Women with low birth weight (115%), and PMTCT / ART at 122%. This assertion has produced little reporting of ANC visits and service delivery by skilled healthcare providers in health facilities (99%) and complete reporting of maternal mortality in health facilities (90%)(GOK, 2019).

According to the KHIS policy objective, there has been significant improvement in HIS over the years, however, some gaps still exist; there are insufficient guidelines and skills of HIS staff, data management of unskilled staff, lack of integration, and poor cooperation, among others. In addition, the culture of information use is not fully accepted in the health sector due to a weak legal framework to coordinate and manage the production of health-related information across all sectors, and various actors(GOK, 2019).

An analysis of the Mombasa County Data Verification Report presented under the Transforming Universal Care Project Health Systems revealed that family planning services provided and reported on DHIS2 suggested that IUCD was not properly recorded at 221.8 percent followed by emergency pills with over-reporting mean points. -50 percent compared to FP inclusion and integration(MOH, 2014). In the same report, a comparison of the source document and DHIS2 in the ANC's fourth visit data showed the accuracy of the April-June 2018 review period was reported to be over 86%5(MOH, 2014).

1.3 Justification

Mombasa County Health Facilities comprise over 80% private, while 16 % are public facilities, this has contributed to issues of poor data quality as a result of high staff turnover in facilities owned by private (CHSIP 2014-2018). The tenacity of this investigation was to provide testimonial data that would assist the County in strengthening the health information system affecting staff performance in selected Mombasa health facilities. The study is beneficial to the academic community by adding to the existing body of awareness and understanding of the critical issues persuading staff performance in data management. The study's findings could be utilized by both national and county stakeholders to develop county health information policies that are responsive to staff productivity. Overall, the goal of this investigation was to offer comprehension into facility experience, drawing lessons to help DOHS -County Government, MOH, and other partners develop effective mechanisms to build a long-term facility well-being info system that is receptive to the requirements of the community and the whole populace Useful recommendations and measures to aid in the realization of Kenya's vision 2030 under universal health coverage. The study helps other researchers to carry out further studies on interventions on factors in staff performance in data management in the public health sector.

1.4 General objective:

Assessment of factors influencing effective staff performance in improving data management in selected facilities in Mombasa County, Kenya.

1.5 Specific objectives

1. To establish organizational factors affecting data management in selected facilities in Mombasa County, Kenya.
2. To assess staff effectiveness in improving data management in selected facilities in Mombasa County, Kenya.
3. To determine levels of knowledge and skills associated with data quality management among staff in selected facilities in Mombasa County, Kenya.
4. To identify individual attributes associated with data quality management among staff in selected facilities in Mombasa County, Kenya.

1.6 Research Questions

1. What is the level of staff effectiveness in data quality management in selected facilities in Mombasa County, Kenya?
2. What are the organizational factors associated with data quality management in selected facilities in Mombasa County, Kenya?
3. What are the levels of knowledge and skills associated with data quality management among staff in selected facilities in Mombasa County, Kenya?
4. What are individual attributes that are associated with data quality management among staff in selected facilities in Mombasa County, Kenya?

1.7 Study Scope

The research focused on aspects persuading actual staff routine in enlightening data management in designated amenities in Mombasa, Kenya. It targeted healthcare providers in public, private, and faith-based facilities in the six sub-counties. The study was steered between July and September 2021.

The research subjects consisted of licensed health professionals educated from medical schools/colleges drawn from 24 (levels 5, 4, and 3) high-volume health facilities in Mombasa County. Using Yamane's model, the research sample size was 372 healthcare workers/providers spread proportionately throughout the county(Yamane, 1973).

1.8 Study Limitations

This study had two major limitations. The first is the corona 19 pandemic which disrupted most service delivery in Mombasa County due to most attention shifting to prevention, disease management, and control, for instance, some facilities closed down once they identified staff infected with the disease. This was handled through callbacks (going back to the facilities which were closed during the data collection period or selecting another facility that had similar characteristics). The second was the geographical nature of Mombasa County's public, private, and FBO facilities in accessing facilities due to protocols. To minimize the challenge, the researcher scheduled appointments with facility management before the data collection period.

1.8.1 Study Delimitations

This research focus was facility-based and did not account for the community level. The researcher interviewed only the health care providers that regularly interacted and provided procedures to patients and clients in a heavy workload section of the facilities and were tasked with collecting health data and making most decisions on matters of service delivery or management. The researcher interviewed only staff who were on duty during the data-gathering era.

1.9 Definition of Key Operational Terms

1. **Assessment:** In this study refers to validating the quality of the described data processes and management processes, evaluating the basic data management and commentary systems, and the application of the findings of the test to identify and implement a data quality improvement solution.
2. **Data quality:** refers to data completeness, accuracy, and timeliness reported by facilities/sub counties using the standardized ministry of health tools to Kenya health information system (KHIS)
3. **Factors:** Data is a resource that is translated into information evidence for informed decision-making. For example; Patient care/indexing persons designing and monitoring public health interventions, health planning, and budgeting resource mobilization and management informed Policies formulation among others. Therefore, to have effective practice for ensuring data quality, we need to understand what causes poor-quality data. Understand the effects/consequences of poor data and how to strengthen data quality.
4. **Effective staff performance**: this study is a collective responsibility across selected cadres in health data management. This involves timely and correct data collection for patients' interventions and staff can use data to inform solutions. Having a common understanding and joint commitments in identifying performance gaps and aligning actions to priorities. Also carrying out route cause analysis to identify priorities for planning actions and resource mobilization and finally give feedback to all stakeholders

5. **Improving data management:** This includes increased capacity in data management processes, as well as monitoring and evaluating functions and capabilities at all levels of service delivery. And, if possible, create data management improvement plans for all levels of care. This should also include forums for support supervision, periodic performance reviews, and data reviews.
6. **Facilities:** Refers to all health care service delivery institutions by ownership and levels of care this includes public, private for-profit/private, FBO/NGO from level two to five., for example, hospitals, health centers, clinics, and dispensaries.
7. **Staff**: is a health care worker who is trained and allowed by the organizational body (licensed) to provide health care service as per the law. He or she mostly interact and documents patients/clients' encounters using health management information system tools and also makes a summary of patient/client encounter in aggregated format for onward reporting on either daily, weekly, or monthly to the next level of service delivery
8. **Organization system:** how well does the system support health care providers to achieve the most desired performance through accountability, support supervision, and giving prompt feedback among others
9. **External environment:** in this study support or hinder the ability of well-being care workers to perform and achieve their strategic performance, for instance, if policies/guidelines are not well disseminated then HCWs will have gaps in implementing some interventions in service delivery and in return it will affect data quality for decision making
10. **Physical environment** is a well-functioning workplace with required functioning equipment, commodities, Job aids, protocols, HMIS tools, connectivity, working

space, power and water among others contribute to good staff performance or the opposite.

11. **Individual/Team attributes:** this is the extent to which individual personal attributes affect individual or team performance. Example -how does gender, moral values, work experience, or internal motivation contributes to poor or good performance.

CHAPTER TWO: REVIEW OF THE LITERATURE

2.0 Introduction

The theoretical outline for health info systems is the emphasis of this chapter, which includes the following sections: health information system theories, conceptual frameworks, empirical and critical literature review concerning, factors persuading active staff concert in refining data management in designated amenities in Mombasa, Kenya.

2.1 Empirical Literature Review

According to the literature review several investigations in emerging nations have been shown to make data quality measurements in standard HIS at local and regional levels(Ledikwe et al., 2014). Rumisha et al.,(2020) conducted standardized research in Tanzania that inspected the implementation of nationwide data collection approaches and data quality at a single local infirmary in Tanzania as a case of research that focuses on institutional-level data. The researchers used a variety of quality approaches, such as interviews, direct observations, and retrospective clinic reports. Among the findings is a comprehensive catastrophe to ensure the absoluteness and precision of foundation booklets used for documenting the exterior of the well-being institution(Chanyalew et al., 2021).

An investigation discovered that hospital data was not being employed efficiently for decision-making. The Measure Assessment monotonous data quality audit tool has been utilized in a diversity of nations and for a variety of purposes, demonstrating its use in quality data assessments. The audit tool was used in Nigeria to analyze the quality of HIV data to improve Grant Submissions by combining both methods: data confirmation and system testing(Abah, 2012). The study discovered insufficient quality information in Nigerian ART clinics, which was due to late data transmission from health facilities and a high level of health facility employees. Furthermore, human resources in the general well-being info system continue to be an essential element in evaluating data quality since a robust reporting system is built on crucial efficient, and operational structures operated by health professionals(S.O et al., 2012).

2.1.1 Organization Factors Associated with Data Quality Management

The notion of leadership is complex and hard to define, and each research represents it slightly differently. There was significant evidence of leadership role in both Rwandan and Ugandan health systems in research done by Inberg and Holvoet, which examined the Rwandan and Ugandan well-being systems. When evidence was used to solve a problem in Rwanda, strong management was cited as an issue(AA Bhattacharya, 2020).

In Uganda, a bi-annual meeting with full-time ministers and secretaries to assess and debate health sector performance has been found to increase interest in quality and data utilization. In another study in Uganda, Khananura et al discovered that including local-level managers in the procedure of development, implementation, monitoring, and evaluation of programs increased management's capacity to exploit accessible change-promoting data(Kananura et al., 2017).

A close relationship was found between the support monitoring and the incidence of sustenance with chi-square $X2 = (1) = 37.913$, $n = 81$, $p < .05$. Lastly, official documents were infrequently obtainable, especially in the standard operational procedure, data quality process, strategic plan, operational strategies, and strategy to improve data superiority by coordinating organizational management, efficiency, efficiency and speed of health facilities. The documents have indicated challenges regarding data usage in Kenya among healthcare providers in districts that do not use this information for planning purposes (Cheburet & Odhiambo-Otieno, 2016).

Representatives of the National Public Health Laboratory Services, for example, stated that they believe many laboratories assume information is gathered for national reporting purposes rather than for local decision-making. Some areas may be unaware that certain data is available. According to a CRD spokeswoman, while their current report contained data from the district and district levels, the provincial government was unaware that the data was separated into those categories: Our director was invited to give a data role paper at a government conference in Mombasa around three months ago(Cheburet & Odhiambo-Otieno, 2016).

He took advantage of the occasion to release the [Annual Vital Statistics Report], and the regional government teams were astounded that the researcher had the type of data they desperately required for planning purposes. Respondents stated that researchers should begin conversations with the regions-MOH to promote a data agenda at the County level to increase data searching and information usage(MOH, 2014). APHIA Plus, for example, claimed that information is used by institutions but not regions: "About 90% of locations submit reports worldwide." However, the report currently only lasts a few days in the CHRIO offices before you log in"(Cheburet & Odhiambo-Otieno, 2016).

Significant informants also stated that data utilization at the institutional level was inconsistent at times and that many locations did not examine their reports. According to the National AIDS and Sexually Transmitted Infectious Diseases Program, institutions will disseminate material without first vetting it: Service delivery centers will only disseminate reports on their initiative. It can't possibly be the other way around(Rumisha et al., 2020). They should be looking into the specifics and asking themselves what this data means to us. Currently, they do so to meet reporting requirements rather than to enhance the system. APHIA Plus and the Nationwide AIDS and STI Control Platform have disclosed that they are attempting to teach regions the use of information through meetings, field practicum, and quality of data training (Frieden, 2014).

In a randomized controlled trial conducted in one of Kenya's leading healthcare institutions (Muthee et al., 2018), the subsequent remarks were made; Separate and inadequate data on patient care, Lack of proper access to nursing records, Inadequate credentials due to severe staff shortages, inadequate nursing training on the importance of nursing informatics, no audit conducted by nursing literature. According to a study conducted at Mombasa County referral Hospital, Coast General, the researcher found that more than half (69.5%) of healthcare workers used general health information to make a decision, while only 30% reported receiving little training in data management. Inadequate support management by the instant manager was reported to be 52.5% while, less than half (45.4%) reported an unreasonable burden as disrupting the management and use of information(Nzomo, 2017).

Research conducted by healthcare managers in Mombasa County, Kenya, to evaluate the organization's exploitation of well-being info in decision-making. The findings revealed that organizational features (2 = 0.233; $t = 4.552$; p 0.01) were momentous predictors of healthcare managers' use of health info in decision-making in Mombasa County. These findings imply that changes in these characteristics (responses, supporting support, and availability of information system resources) will enhance data use in policy directions. In terms of the accessibility of possessions for HIS services, 57 percent of well-being care managers in Mombasa County disagree that there are enough possessions for HIS services.

A study was done by Otieno et al., (2020) in Mombasa County reported that very little funds are allocated to implement HIS activities. In all of these studies conducted in Kenya, none of them have researched, factors influencing staff performance in data management, prompting the researcher to research the topic to add to the body of information and inform policymakers at the National and Regional levels.

2.1.2 Technical Factors(Staff Effectiveness) Associated with Data Quality Management

Disparities between genuine skills and health professionals' assumptions have a direct influence on the output and operations of the Routine Well-being Info System, such as data gathering, data acquisition, retention, delivery, dispensation, investigation, presentation, and reaction. In most nations, the role of RHIS in data validation, review, and utilization is limited. Higher-level managers have little awareness of data quality review procedures.

Some of the most frequent difficulties that health personnel face in many nations are a lack of problem-solving abilities(Chen et al., 2014). 37 percent of health workers in ten countries, including Côte d'Ivoire and Uganda, demonstrated knowledge and problem-solving abilities. Furthermore, in many countries, a lack of data awareness contributes to poor quality data and information utilization. Respondents from ten countries indicated that there was a need for more or fewer data to be produced, and that data was not being analyzed regularly. According to the survey, there is a need to improve the ability to utilize data to inform decision-making(Teixeira et al., 2017).

Surveys conducted on performance indicators show that data quality testing, computations, and data classification were between 66.77% and 74.6%, with data interpretation being significantly lower by 64.55%. Respondents also generally believed that performing HIS tasks had negative consequences, (the average motivation rate was 43.4%) (Mustansiriy, 2015). Studies have shown that capacity gaps are a hindrance to the functioning of the well-being system, and how effectively people are involved. Thus, in the developed world, HISs are often viewed as barriers relative to a management tool. This is because of inconsistencies in the data collected, poor data quality, duplication, and waste among similar health information systems (Mustansiriya, 2015).

As HISs continues to change, energy-building strategies are a way to keep health workers up to date with change. For example, the Republic of Bangladesh aligned the power-building strategies with the changes made to HIS. The Bangladesh Department of Health and Family Research Researcher has unveiled a capacity-building program in line with changes to data collection systems as part of the health sector's M&E strategy(Ward et al., 2017). The assumption here is that increased data and analytics capabilities will be required to track progress toward Supportable Growth Goals, which is one of the M&E strategy's key objectives. Despite on-the-job training, Ahsan and his colleagues concluded that it remains a challenge for Bangladesh to ensure staff with evidence-based monitoring skills(Ahsan et al., 2017).

The Malawi study revealed both fortes and faintness in HMIS operation, with significant dimness being inconsistent monitoring and data quality checking. A similar study should be used to teach efforts to improve HMIS in developing countries(O'Hagan et al., 2017). Another research conducted in Malawi and its patterns showed that Resources performed well in certain data quality aspects, such as consistency across indexes, reports, and DHIS-2 on the number of females who went to the ANC four times during the campaign (Musenze & Thomas, 2020). However, in several service areas, such as ARI, data quality is poor.

Other gaps identified in the same study are limited training for HMIS staff - especially at the health facility level. According to quality research, there is a lack of training at all stages of data reporting, including pre-operative training of staff involved in data collection and reporting (statistical secretaries of institutions and HMIS staff in districts) and refresher courses after the introduction of new tools and methods(Hazel et al., 2017).

A Tanzanian study found mixed results in terms of healthcare practitioners' ability to evaluate and apply family planning data in decision-making. Some research participants stated that they used the data collected at two health facilities in the counties of Lindi and Geita to appraise the periodic services they provided, which helped them appraise what was required and what goods(Talib et al., 2013). Many data analysis findings have been put on walls and bulletin boards in these institutions, demonstrating that people are studying aggregated data and sharing the results with others. However, one of the most difficult issues for all health institutions visited has been data quality assurance, particularly accuracy. This is due to congestion as a result of a personnel shortage and healthcare professionals who do not have enough time for data input. The bulk of health personnel (more than 73%) cannot evaluate data and use computers. Most healthcare institutions have a poor culture of data demand and info use.

The research uncovered several issues that limit healthcare professionals' ability to comprehend and apply data in planning. These include an absence of training in data assembly, analysis, and presentation, among other things. and usage; a poor or non-existent Internet connection; and a lack of data collecting, investigation, and distribution technology, such as PCs. Healthcare professionals, particularly those in low-income health institutions, may not have an Internet connection, which makes it difficult for them to use DHIS 2. Due to a lack of data ownership, healthcare professionals believe that data cannot be used and that their primary concern should be data gathering. They believe that data created at well-being facilities belong to the council's well-being management team (CHMT), not the institutions, which elucidates why regional data investigation and decision-making are rare(Anasel et al., 2019).

2.1.3 Individual Attributes Associated with Data Management

According to a Tanzanian national implementation information system study, all staff accepted data assortment as a necessary part of their occupation. However, there were several reservations about the accuracy of the MTUHA data. Admittance to teaching was restricted, mathematics abilities were typically low, MTUHA information transmission within the infirmary was inadequate, and a better knowledge of HIS full competencies was required(Sadikoglu & Olcay, 2014). Although normal data-collecting services are effective, finishing the second data tool was insufficient. Internal inconsistency between several sorts of data tools was discovered. Duplicates and data gathering that has not been used continually are examples of this. Sixteen of the 72 forms (22.2%) comprising one of the most significant secondary information papers (Infirmary Data / MTUHA 2) might not be accomplished using the info gathered in the primary statistics books. Furthermore, the infirmary made no usage of secondary data. The development plan was the infirmary's primary scheduling file. Only three of the 22 indicators in this program were comparable to the MTUHA indicators(Hedt-Gauthier et al., 2012).

According to research conducted in the public well-being sector in Thararaka Nithi County, Kenya, just one (4.8%) information producer has received training at an urban hospital. The remaining 20 responses (95.2 percent) were all temporary and untrained data and information management personnel. 20 (95.2%) of respondents did not have computers and did not comply with IT, whereas 1 (4.8%) had a computer and did comply with IT(Asemahagn, 2017).

All 21 responders (100%) agreed that HIS tools were difficult to utilize. The study's findings indicated an absence of technical competence in data collecting, investigation, and processing, as well as a shortage of computers to handle data as technological variables. In terms of organizational aspects persuading info usage, 38 (92.7%) of info producers and well-being managers reported a lack of sustenance for workforce training in factual decision-making skills, while 3 (7.3%) reported organizational support for staff training in factual decision-making skills(Karyotakis & Moustakis, 2014).

The requirement to fill out numerous reporting forms leads to data shortages and reduces staff motivation to evaluate and use health data. Workers must fill out reporting forms due to a lack of computers, which upsurges the likelihood of errors and adds to poor data excellence. Understanding and applying health information necessitates the development of previously unheard-of abilities in the training of health professionals(Dagnew et al., 2018).

Aptitude building in data examination and the application generates the conditions for the suggestion-based making of decisions. Furthermore, organizational variables that influence knowledge include a lack of support for staff decision-making skill training, a lack of support for the use of well-being info, and a lack of a culture that encourages the use of knowledge(Asemahagn, 2017).

2.1.4 Behavioral Factors(Staff Knowledge And Skills) Associated with Data Quality Management

According to a study conducted in Iraq using system theories on behavioral factors such as key indicators of HIS success, demand, trust, motivation, and ability of HIS users to perform HIS functions directly affect HIS processes and data Understanding why certain data/data is collected, indicated the required data level for his details(Wandera et al., 2019). Problem-solving is another much-needed skill to use data to describe and solve a problem (results show that the overall confidence of HIS operations is 69.41 percent; very low in comprehension (64.55 percent) and very high in data quality control (74.6 percent), the study reported. many existing reasons for this gap. The study concluded that the overall confidence in HIS activities is often higher compared to the low level of HIS activities. The visible promotion of knowledge culture has often been high which is inconsistent with perceptions(Kihuba et al., 2014).

Ledikwe et al., (2014) used interviews based on a conventional data quality research method to perform a qualitative study in Botswana. The study discovered that in Botswana, there are frequently strong monitoring and evaluation mechanisms in place with regional and national staff members to assure the provision of quality health information. During the research period, there were documented issues with electronic data systems in the nation. Among these problems include the availability of numerous applications that cannot combine various fitness systems, rendering the systems unstable for many workers in the system(Ledikwe et al., 2014). The absence of Motivation or motivation has been highlighted in the literature as a feature in healthcare workers' decisions, and it lingers to be the primary factor of staff presentation.

According to the study, behavior, infrastructural, and system-based variables were identified as influencing data worth in general fitness info systems. Behavioral variables include health professionals' motivation and the presence of stimulants or mitigators. Focus groups cited factors found in the research for poor data quality, such as a significant amount of information required for tools, data collection form forms, and insufficient abilities(Ahanhanzo et al., 2015).

According to research, specialized technologies and techniques for the creation, management, and enhancement of RHIS procedures, directly and indirectly, contribute to the outflow of RHIS. It also examines the accessibility and usability of forms and data-collecting procedures. The review emphasized technical difficulties connected with a lack of information technology, as well as data management obstacles, inadequate diagnosis and categorization, excessive data collecting, a lack of validated indicators, and procedures linked with low technical expertise(Dickson et al., 2014). In Liberia, for example, the Ministry of Well-being and Social Benefit (MOHSW) has deployed District Wellbeing Info System (DHIS) software, which can generate raw data, pivot tables, dashboards, and maps to offer an inclusive view of the well-being system's efficacy. However, due to a lack of technical competence, it is rarely used by top management in regional health offices(Sharma et al., 2015).

Surveys performed in Ethiopia's Southern National, Nationalities, and Peoples Region (SNNPR) revealed that, although being meant to assist data collection and analysis, the textbooks are not generally available at well-being institutions and district well-being offices. Dickson and colleagues discovered that inefficiency in several sectors hampered the adoption of evidence-based treatments. Dickson et al., (2014) discovered particular impediments to the development of key treatments to enhance the health of mothers and babies in eight of the 13 countries with the highest maternal and neonatal mortality rates in this research. Leadership and management, health workers, health service delivery, and HIS all revealed a lack of capacity as a bottleneck(Ndabarora et al., 2013). Some of the energy-related issues studied include "researched staff ability for data managing and custom;" "lack of or research management, counseling, and observing systems in well-being amenities;" and "staff shortages, poor disposition, and the distribution of equality between urban and rural areas"(Sharma et al., 2015).

Table 1:Critical Literature Review

Name & Year Of Researcher	Research Title	Results	Gaps In Organization, Physical Environment, Individual Attribute
Nzomo (2017)	Use of monotonous well-being info for decision-making among healthcare employees at Coast General hospice, Mombasa County	The research showed that more than half (69.5%) reported user data to inform decisions. However, 30% reported partaking in minimal drill in data management	The study did not show an association of individual attributes to health information performance management
Mucee et al. (2016)	Routine fitness management info utilization in the public well-being sector in Tharaka Nthi County	The study revealed a mere five percent (4.8%) of info creator was trained in a sub-county hospital. The rest of the 20 (95.2%) had inadequate skills in data collection analysis and processing. Issues with numerous HIS tools that consume time in filling. The absence of computers to handle data is a technical factor influencing the use of well-being info	The study did not show an association of individual attributes to health information performance management
Teklegiorgis et al. (2016)	Level of data quality from well-being management info systems in resource-	Overall data quality was found to be 75.3% in units and/or sections. Trained staff to fill	

	limited and settings its linked aspects in Eastern Ethiopia	format, decisions based on supervisor dictates and section heads seek response were significantly linked with info utilization	
Richeal et al. (2017)	National Valuation of Data Quality and Linked systems-level Aspect in Malawi	The study revealed Weakness in infrequent data quality checks. Unreliable supervision by managers Lack of trained facility staff in health information management	Individual attributes linked with the value of data were not assessed
Wilms et al. (2014)	An in-depth, probing valuation of the execution of the National Well-being Info System at a district-level hospital in Tanzania	Access to training was limited. Poor record keeping. In some hospitals, planning documents were not aligned with MTUHA indicators	The study did not show the association of the physical environment with staff performance in data management
Cheburet and Otieno (2016)	Organizational aspects upsetting data quality of predictable healthiness management info system quality: Case of Uasin Gishu County Referral Hospital, Kenya	The study showed almost forty percent(39.5%) of the defendants described the convenience of typical functional measures while none of the participants specified an absence of data superiority procedure	The study did not show an association between individual attributes with staff performance in data management
Mackfallen et al. (2019)	Measuring Well-being Suppliers' Capacity to Examine	Of most healthcare providers 73% have	The study did not show an association with organization

	and use family forecasting data	insufficient skills for data analysis. Staff Lack of data ownership	systems such as leadership and governance in data management
Otieno et al. (2020)	Organizational factors of health info use in deciding on well-being care managers in Mombasa County Kenya.	Research findings showed that 63% of healthcare managers in the Mombasa region agreed (Mention of 3.52 and standard deviation of 0.991) that there are response processes HIS. Feedback is provided in the method of accounts from low-level to high-level managers managers and vice versa In the source availability in his duties, 5 7% of healthcare managers in the Mombasa region he did not acknowledge that there were sufficient assets allotted to HIS activities. Little, if any, Funds allocated to HIS services and not all fitness amenities in Mombasa County have HRIOs.	The study did not show an association of physical environment with staff performance in data management

2.2 Theoretical Framework

This study defines a theoretical framework as a pre-existing assembly of ideas in the review, a convenient map for analysis (Liehr, 2000). It provides the structure for analyzing a problem and serves as a guide for examining the relationships between variables(Liehr, 2000).

2.2.1. Health Information Systems

The HIS is distributed into 2 parts: clinical and secretarial. The distinction between the two is in how they employ information. In clinical practice, they are allied to a genuine individual name or sole identification. Decisions about this patient are centered on this info, which highlights the rank of data superiority and precision. The data is isolated from the patient in the managerial component of the organization and is no longer utilized to make choices regarding individual patients(Kihuba et al., 2016). As a result, the demand for precision in each situation isn't as significant. Instead, the value of data at this close is heavily reliant on descriptions, similar code use, and so on. This technology is also critical to the security of HIS data. The clinical component of the HIS consists of two parts (Figure 1): scientific catalogs that keep clinical information system and are always connected to the appropriate patient, evidence-based judgement sustenance, and a technical system that offers doctors the most up-to-date scientific information(Kjellberg & Murto, 2021).

A system of market information that offers information about the development and use of resources for local, regional, and national marking and management - historically called "health care statistics," a system of information about the disease, which captures diseases and disease prevalence, lifestyle and health risks, as well as disease surveys(Kjellberg & Murto, 2021).

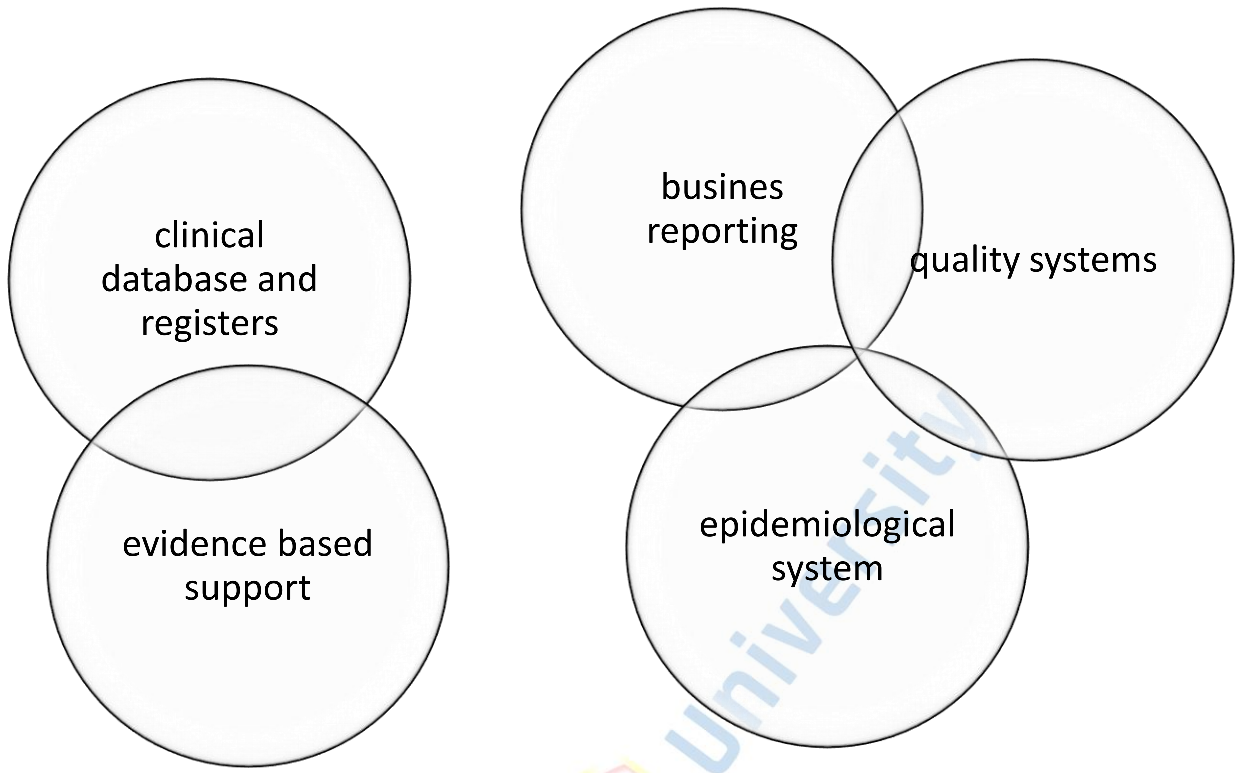

Figure 1: Components of HIS

Source: Theoretical framework for a health information system (Nenonen & Nylander, 2002).

These five main components are made up of several subsystems and are also complexly connected (Figure 1). The clinical databases are the basis for feeding knowledge to those subsystems. The data obtained was generated at the service points, clinics, etc. of doctors or nurses. Stored in these archives, they are used in clinical practice. Any manager and this clinical information are collected for use in the area. This information, as well as clinical data that has been coded (e.g., ICD-10, etc.), is transmitted to administrative/statistical systems. Traditionally, business reporting systems and national health data are based on the cause of death information. For hospital discharge data, an increasing number of nations have created registry or survey-based systems. In Kenya, we have KHIS –which is hosted at the national level and one requires a password to access both administrative, program, and clinical statistics all over the world(Nenonen & Nylander, 2002).

2.2.2 The Organizational Levels of the System

Data usage on today's HISs starts with the service provider. In addition, health professionals working in clinics use data continuously in their clinical knowledge to determine their effectiveness, cost, efficiency, and effectiveness. This becomes ideal when a specialist is called to account for his or her patients' responsibilities in the community(ELLIS, 2006). This necessitates procedures for efficient chronic illness follow-up, the utilization of epidemiological background data, and so on. The data is still connected to specific individuals and has been used to identify and facilitate services utilized by 'expensive patients' or patient groups, for example. Much management information is utilized, for example, for branding (evaluating doctor's grades and marking at public and private clinics)(Kiberu et al., 2014).

At the regional level, the usage is mostly administrative, and data cannot be lawfully directed to individual patients, for example, in Finland. The emphasis here is on service systems and the introduction of the idea of intensive care. The demands for fairness, efficiency, safety, and quality at the nationwide level, as well as the formation of a nationwide well-being policy, impose great demands on the info system. The importance of global organizations will expand in the future. For example, the European Union is currently taking on a growing number of activities and duties that were previously exclusively stated in the context of each country(Bernal-Delgado & Estupiñán-Romero, 2021).

2.2.3 Theories on Meta-Data

For decades, there has been awareness in statistical efforts of the restricted existence of data and knowledge in supplying fundamentals for making the decision. To compensate for this restriction, a plethora of systems have been created that offer the context knowledge required to comprehend the data or info. These systems, in general, give information on the data-collecting process.

2.2.4 Organization Management Theories:

In contrast to the metadata ideas that are rarely discussed, organizations and managers have developed different theoretical approaches. These four are described in the book Integrrer Organisationslära, Berzelius, and Skärvad. Science administration (Frederick W. Taylor), management conservatory (Henri Fayol), governing school (Max Weber), and human affairs are some organizational ideas (Elton Mayo). These principles can be used in conjunction with Jreisat's four leadership ideas while developing the HIS theoretical framework. Trait philosophy (1940-1950) emphasizes on the qualities of a leader-in-the-making.

The Action-Behavior leadership method is centered on how a leader acts. It distinguishes three styles: dictatorship, laissez-faire, and democracy. The emergency approach looks at how a leader responds to a variety of situations and aims to empower, empower others, and promote and build a new corporate culture in the leadership of change. In national health care, the term 'managers' is not commonly used. Instead, we are talking about procedural direction, resource allocation guidance, and information management (Nenonen & Nylander, 2002).

2.2.5 Amalgamation of Knowledge Hierarchy and Metadata Theories

The integration model of the technical sequences and metadata concepts discussed below provides a clear analysis of this relationship to simplify the systematic development of arithmetic knowledge in social services and well-being care. The data here is interpreted as basic data elements, as a single discharge record with diagnostic data from patient data(Kihuba et al., 2014). When this data is linked to descriptions of data objects, ICD-10 codes, etc., data can be generated, such as the span of stay in the diagnostic phase in question.

As a result, in this context, the information and reference are the same. When particular facts, such as the average duration of stay, are connected to specific contextual information, such as local plan information and national clinical recommendations, awareness is created, which implies that these patients understand how they are handled in that region(Maokola et al., 2011). When this information is re-linked to appropriate contextual information, such as a responsible public servant or personal physician information, it may be used to identify the entire health system, worldwide awareness, insights, concepts, and so on. It may be important to gain an idea, a real understanding of this(Braun et al., 2013).

This wisdom can also encourage good deeds, finding new and different ways to solve some of the problems of the old way. Therefore, in this model, the four levels of information management correspond to the two metadata levels used by Sundgren. Local metadata is similar to a very low metadata level(Agarwal et al., 2015). The global metadata for the remaining levels of the list of information managers is divided into two parts: Sequence of information: 'meta facts' and 'meta-awareness.' It is often referred to as 'meta intelligence,' but as the number of transmissions and communication objectives decreases as one ascends to this position of management, so the meta-element is subordinate, not passive to anyone(Nenonen & Nylander, 2002).

Research has shown that information management (KM) receives relevant information from the right user, and this information is used to improve the performance of the organization and/or the individual(Jennex et al., 2014). KM does what it takes to get the most out of information resources (Becerra-fernandez & Sabherwal, 2015). Information management (KM) to obtain relevant information from the relevant user, and to use this information to advance the presentation of the organization and/or the individual(Jennex et al., 2014). KM does what it takes to get the most out of information resources(Becerra-fernandez & Sabherwal, 2015).

The relationship between information and metadata creates an initial explosion from the data and generates intelligence when data objects are related to the conforming context info (metadata)

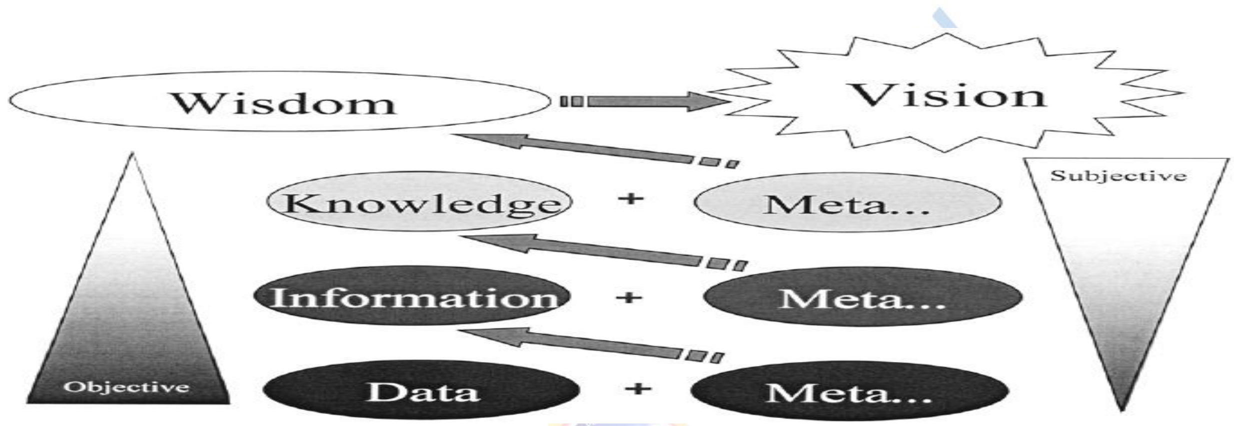

Figure 2: Subsystems of the main components of a HIS

Source: Theoretical outline for a healthiness info system(Nenonen & Nylander, 2002).

2.3 The Conceptual Outline.

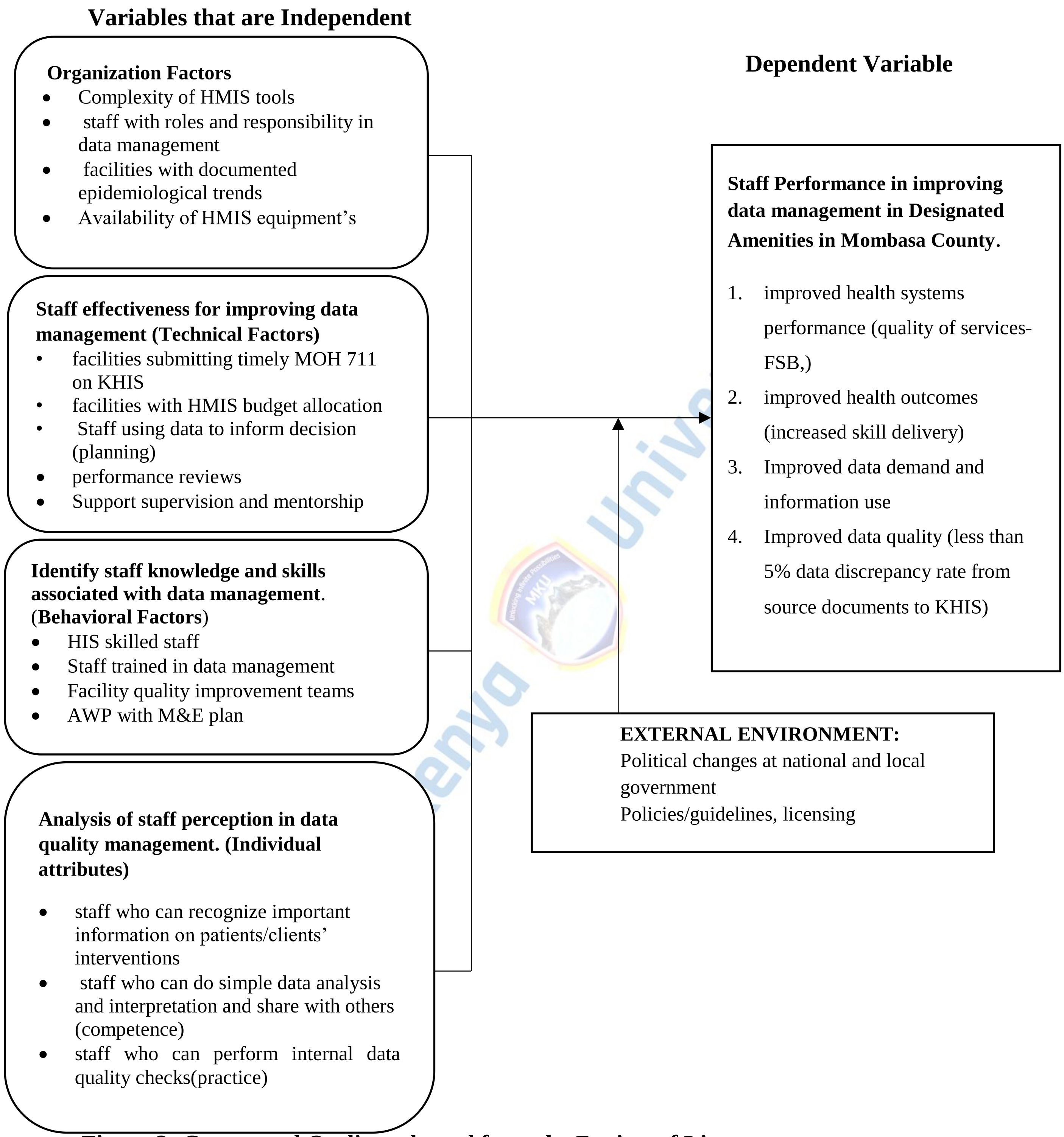

Figure 3: Conceptual Outline adapted from the Review of Literature

2.4 Summary of the Conceptual Outline

The indication-based decision-making framework is created as a consequence of the high demand for health information, which is met by collecting, organizing, and analyzing data, making info available to decision-makers, and, ultimately, simplifying the use of information to advance the well-being system activity and health outcomes. Ministers and governing bodies are among the goals of the organization. Health institutional managers and leaders must thus ask how well organizational programs promote desired performance. Clear organizational goals, planning techniques, and structures, as well as good leadership, are all important considerations. Clear operational expectations and mandates, supporting management systems, clear operating rules and procedures, and effective job duties are all essential. Incentives are effective management systems such as finance, labor, and employees who must be able to answer the question "What will I receive" to meet quality standards, particularly when operational circumstances are harsh, salaries are poor, and there is a lack of well-being employees or staff. With a clear set of goals, feedback, and rewards for greater performance, incentives may drive people to perform better. Employees are incentivized to contribute positively to the organization's goals and achievements in successful firms. The overarching concern is whether employees and groups have a purpose to do what is expected of them. Clear expectations about accountability, accountability, and autonomy are among the factors to examine. Positive performance evaluations, Appropriate reward and compensation systems, Recognized good performance; repercussions of bad performance Participation, meaningful work, professional growth and employment possibilities, open employee recruiting, management methods, and assessment, Channels of communication and access that are clear, and Sufficient financial resources.

Organizational systems such as leadership, governance, and individual/team factors such as knowledge, skills, and values will influence each other as shown in the figure above. - For example, staff shortage, inadequate budget allocation and complexity of HMIS tools will influence support supervision/ mentorship, performance reviews, and budget allocation to the HMIS unit which will result in an increased number of skilled HMIS staff with well-defined characters and tasks resulting in data demand and info utilization and improved health outcomes. All this relationship, however, is controlled by the external environment- such as policies and guidelines on health information systems.

CHAPTER THREE: METHODS AND MATERIALS

3.1 Outline

This section describes the procedures that were utilized in this investigation, which include the following: research strategy, study populace, selection method, data collecting tools, procedure, and statistical computation.

3.2 Research Design

A cross-sectional research strategy was utilized in this investigation. Lauren 2020 defines a cross-sectional design as a research design that collects data from a large number of individuals at one time. The argument for using this technique is based on the design's capacity to collect data from many distinct persons at a single moment in time, as well as its cost-effectiveness in terms of time and other properties. Furthermore, according to Kothari,(2014), a cross-sectional study strategy allows data to be gathered at a single moment in time, as opposed to a longitudinal strategy, which collects data across time. The design allows the identification of relations between variables that are not manipulated.

3.3 Research Approach

A mixed methods approach was used for this project, which included a questionnaire survey of Health Care Workers (HCWs), in-depth interviews and Focus Group Debates (FGDs) with key informants, and data verification by document review. A mixed methods approach combines data collection and analysis methods from both qualitative and quantitative methodologies in a single thesis(Adamson, 2004). That is, the investigators gather or examines both quantitative and qualitative data to answer the study queries that have been developed for a specific thesis. The researcher was able to employ data collecting and analytic techniques that answer questions regarding both the complex nature of the spectacles from the partaker's point of view and the relationship between the study variables, which justifies the use of mixed approaches for this research(Adamson, 2004).

3.4 Study Location

This research was carried out in Mombasa County at various public, private, and FBO health institutions. Mombasa County is located in Kenya's southeastern coastal area. It is bounded to the north by Kilifi County, to the south by Kwale County, and to the east by the Indian Ocean. The county's population is expected to be 1,208,333 people, with 610257 men and 598046 women (KNBS, 2019).

In the Mombasa County well-being system, health amenities are mainly delivered by the public segment, private health sector, and the FBO/NGO sector. In total, the public sector controls 53 health facilities, the FBOs/NGOs sector 17, and the private sector 172. The County's well-being delivery system is systematized into 5 levels of care as per the standards and values - Community (Level 1 community units), primary (Level 2 & 3 primary care facilities), and Secondary (Level 4 county referral facilities & level 5 regional referral facility). The county hosts one (1) Level 5 Hospital, 25 level 4 hospitals, 331 level 3 health facilities (health centers, maternities, and nursing homes), 27 level 2 facilities (dispensaries and medical clinics), and 1 level 1 facility (community unit). The county has a total of 2080 health care professionals of which 1347 are from Public facilities, 532 are from Private for-profit while FBO/NGO has 201(Report, 2021).

3.5 Variables of the Study

3.5.1 Variable that was Dependent

The independent variable for this investigation was Staff Performance in improving data management. The following indicators were assessed to assess staff performance in improving data management; improved health systems performance (quality of services-FSB,), improved health outcomes (increased skill delivery)Improved data demand and information use, and Improved data quality (less than 5% data discrepancy rate from source documents to KHIS)

3.5.2 The Independent Variable

The independent variable for this study was

- Identify staff knowledge and skills associated with data management(Behavioral Factors); the following indicators were assessed; HIS skilled staff, Staff trained in data management, Facility quality improvement teams, and AWP with an M&E plan.
- Analysis of staff perception in data quality management(Individual attributes); the following indicators were assessed; staff who can recognize important information on patients/clients' interventions, staff who can do simple data analysis and interpretation and share with others (competence), and staff who can perform internal data quality checks(practice)
- Organization Factors, the following factors were assessed; Complexity of HMIS tools, staff with roles and responsibilities in data management facilities with documented epidemiological trends, and Availability of HMIS equipment's
- Staff effectiveness for improving data management (Technical Factors); the following indicators were assessed; facilities submitting timely MOH 711 on KHIS, facilities with HMIS budget allocation, Staff using data to inform decision (planning)performance reviews, and Support supervision and mentorship.

3.6 Target Populace

The target populace for this investigation was the 2080 healthcare workers distributed across 53 public, 172 private for-profit, and 17 FBO/NGO health facilities in Mombasa County. Table 2 below shows an instantaneous of the target populace per category.

Table 2: Target Populace

Ownership	No. of Health Facilities	No. of Health Professionals
Public	53	1347
Private for-profit	172	532
FBO/NGO	17	201
Total	**242**	**2080**

Source: Mombasa County Health Sector Performance Report 2021

The study population comprised healthcare workers from levels 5, 4 3 health facilities in Mombasa County drawn from public, private, and FBO/NGO sectors (Report, 2021). This is because levels, 5, 4, and 3 health facilities account for the largest facility-based patient workload in the health delivery system. These facilities are distributed across all the six sub-districts in Mombasa County. The study focused on the well-being of employees who were accountable for daily documenting in-patient source documents and used routine data to improve quality, including In-charges of the facilities, Health Facility Data Managers, Clinicians, Nurses, Health Records Information Officers (HRIOs), Medical Laboratory Officers (MLOs) and Pharmacists/technologist. In addition, source documents at the selected facilities, MOH 711 reporting tools, and the KHIS were part of the study population.

3.7 Criteria for Inclusion And Exclusion

3.7.1 Criteria for Inclusion.

i. Had to be an approved level 5 or 4 or 3 health facility in public, private, or FBO/NGO sectors.
ii. Had to be an in-charge, data manager, or an HCW (clinician, nurse, HRIO, MLO, pharmacist/tech) of the selected facilities.
iii. Had to be a registered employee of the study facility.
iv. Had to be tasked with collecting health data and making most decisions on matters of service delivery or management.
v. Had to consent to participate in the study.
vi. Selected facilities' source documents, MOH 711 reporting tools, and the KHIS

3.7.2 Exclusion Criteria:

i. Level 2 private facilities and community units.
ii. Health care workers from level 2 private facilities and community level.
iii. Healthcare workers from the selected amenities will be absent from duty during the data-gathering period.
iv. Healthcare workers were employed six months before the study.
v. Level 4 and 3, 2 public facilities and HCWs involved in the pre-test study.

3.8 Selection and Sampling Methods

3.8.1 Sampling Size Determination

Due to the vastness of the research area, the high number of health facilities, and the consequent impact on cost and time constraints, the Gays formula was employed to enhance representativeness, the researcher sampled 10 % of the 242 well-being amenities in the public, and private, and FBO/NGO sectors in Mombasa County. Therefore, 24 health facilities were nominated for this study. Purposive sampling was used to recruit the various type of health facilities based on ownership (public, private, and FBO/NGO). The amount of workload in these health facilities was used as a factor for the distribution. Table 3 presents the distribution.

Table 3: Distribution of Sample Facilities

Type of Ownership	Population	Sample
Public	53	6
Private	172	17
FBO/NGO	17	3
Total	**242**	**24**

The number of HCWs to be encompassed in the investigation sample was executed using Yamane's (1967) method at the level of significance of 0.05.

$$n = \frac{N}{1 + N(e)^2}$$

Where n = Sample size; N = Population size; and e = Significance level

Therefore, the calculated HCWs sample size was;

$$n = \frac{2080}{1 + 2080(0.05)^2} \cong 335$$

A modification was made to upsurge the calculated section size to excuse an estimated 10% drawing. This alteration was made by distributing the intended illustration size n by (1-w) where w is the estimated percentage of removal

$$n^{**} = \frac{n}{1 - w}$$

Thus, the attuned size of the sample was;

$$n^{**} = \frac{335}{1 - 0.1} = 372$$

The sample was distributed into two categories of participants; 38 key informants (facility in-charges and health facility data managers from the 24 selected facilities) were involved in the in-depth conferences and FGDs; and 334 HCWs (clinicians, nurses, Health Record Information Officers (HRIOs), Medical Lab Observes (MLOs), Health Management, and Information System (HMIS) officers and Pharmacists) were involved in the questionnaire survey as indicated in table 4 below. The distribution of the 334 participants across the 24 selected facilities was determined using proportionate sampling (appendix, 11), based on the populace of healthcare employees, excluding in-charges of facilities and health facility data managers, in each of the facilities. The population data were attained from the human resource department of the respective amenities.

$$\text{Proportionate sample size} = \frac{\text{Sample size}}{\text{Population size}} \times \text{Sub} - \text{group size}$$

In conducting data verification, 3 source documents in each of the 24 selected facilities, the MOH 711 reporting tool at the respective facilities, and the KHIS were reviewed.

Table 4: Distribution of Sample Health Care Workers

Category	**Sample Size**
Facility In-Charges and Health Facility Data Managers	38
HCWs (Clinicians, nurses, HRIOs, MLOs & Pharmacists/Technologists)	334
Total	372

3.8.2 Sampling Procedures

The 24 health facilities were selected from levels 5, 4, and 3 facilities using the non-probability selection technique of purposive sampling method based on patient workload. Therefore, health facilities with the highest patient workload were selected to constitute the 24 facilities. Consequently, the 24 in-charges and 24 health facility data managers from the selected facilities were encompassed in the trial of the study.

The selection of the 334 HCWs (clinicians, nurses, Health Record Information Officers (HRIOs), Medical Lab Observes (MLOs), & Pharmacists) in the 24 selected fitness amenities was done using the possibility sampling method of the stratified selection method. The study adopted this sampling procedure to ensure that the HCWs from each of the designated health amenities are sufficiently embodied in the sample of the investigation (Kothari and Gaurav, 2014). Therefore, the selected 24 health facilities formed the strata in the study. The investigation then apportioned the sample size to a proportional stratum to their sizes (number of HCWs) using a proportionate distribution technique (Sample Size/Populace Size) x Sub-group Size). After apportioning the size of the sample to each section, the research utilized a simple random selection procedure to select the health workers who were encompassed in the study. This process was executed distinctly for each stratum to obtain the prerequisite size of the stratum.

The 3 source documents to be reviewed, for the period April 2021 to June 2021, per study facility were selected purposively to include ANC/PNC register, immunization register, and family planning register. All MOH 711 reporting tools for the selected period at the selected facilities and the KHIS were also reviewed.

3.9 Data Collection.

A questionnaire survey, 2 sets of KIIs, 6 FGDs, and data verification were steered to assemble data for this research. The study surveyed 334 HCWs (clinicians, nurses, HRIOs, MLOs, HMIS officers, and Pharmacists) from the 24 selected health facilities using a designed survey (appendix 2). The research survey form was used to obtain data on socio-demographic characteristics, factors affecting data management, staff effectiveness in improving data management, knowledge and skills associated with data quality management, and individual attributes associated with data quality management at the selected facilities. The research form was self-administered through drop and pick technique within a single day per well-being capability.

Two (2) sets of KIIs were conducted with 24 in-charges of the selected facilities and 24 health facility data managers respectively. Interview guides (appendices 3 and 4) were used to collect comprehensive, systematic, and in-depth. Four (4) FGD sessions, comprising between 9–10 participants, were directed by the in-charges and well-being facility data managers from the selected health facilities. All KII and FGD sessions were chronicled using a digital voice plotter and later transliterated verbatim by the investigator. On run-of-the-mill, each KII session took roughly 30 minutes and the FGD session took approximately 60 minutes.

3.10 Pre-testing

The questionnaire and conference guides for both FGD and KIIs were pre-tested among eligible partakers, and the data verification checklist was pre-tested with eligible documents. Pre-testing of the data collection tools was done in three (3) health facilities randomly selected from levels 4 or 3 health facilities in Mombasa County. The random selection was done independently for the public sector, private sector, and FBO/NGO sector facilities to select one facility each from the respective sectors. The pre-test was conducted among 37 (10% of the study sample) HCWs including 3 in-charges, 3 facility data managers, and 31 HCWs (clinicians, nurses, HRIOs, MLOs, HMIS officers, and Pharmacists) of the selected facilities. The 31 HCWs were recruited using stratified random sampling in proportion to the number of HCWs per facility. The facilities and the participants of this pre-test study were not encompassed in the main study and the data gathered were not used in the analysis. However, the process and output of the pre-test were useful in informing applicable alterations in the content of the tools, and data gathering methods and events to improve the eminence of the procedure and output of the main study.

3.11 Reliability and Validity

3.11.1 Validity

Accuracy is achieved when investigation tools degree what they are designed to portion (Kothari and Gaurav, 2014). The researcher engaged the expert advice of supervisors to review the questionnaire, KII, FGD guides, and data verification checklist to ensure that the instruments measured the underlying concepts of the study and were adequate to resolve research queries.

3.11.2 Reliability

Reliability is the degree to which an apparatus steadily measures similar findings(Kothari, 2014). Using the results from the pre-test, the Cronbach test, with the help of IBM SPSS Statistics for Windows, version 25, was conducted to measure the internal consistency of the questionnaire. Cronbach alpha values of over 0.7 were considered to depict that the instruments were reliable(Taber, 2018).

Reliability of the KIIs and FGD guides was directed using an inter-coder consistency test, To compute inter-coder consistency, the investigator calculated all the codes from collective duo of analyzed two codes using encoding frames. From the total codes provided in the script, it was possible to find the number of identical codes included in the written content (including agreed codes). The proportion of the agreement was calculated, with the number of codes approved upon as a numerator and the total number of codes provided as a denominator. Inter-coder consistency ratings of 80% and above were measured as suitable in this study.

3.11.3 Reliability of Results

The questionnaire was made of Likert scales containing four-point Likert-type items which were used to quantify the sentiments of the partakers towards the fundamental constructs in the research. The investigation employed Cronbach's alpha to quantity the inner reliability of the Likert scale data sets. Organizational factors were assessed using 7 Likert-type items which produced a Cronbach's alpha of 0.734; staff effectiveness was evaluated using 8 Likert-type objects which generated a Cronbach's alpha of 0.908; knowledge and skills were assessed using 5 Likert-type items which yielded a Cronbach's alpha of 0.926; individual attributes were assessed using 4 Likert-type objects which produced a Cronbach's alpha of 0.829; while data demand and use was evaluated using 7 Likert-type items which produced a Cronbach's alpha of 0.747. All the Cronbach's alpha test scores were >0.7 signifying that the Likert scales were consistent in demonstrating the fundamental constructs in the investigation. Table 6 presents the consistency results.

Table 5: Consistency Results

Scale	N of Items	Cronbach's Alpha
Data demand and use of data	7	.747
Organizational Factors	7	.734
Staff Effectiveness	8	.908
Knowledge and Skills	5	.829
Individual Attributes	4	.838

3.12 Data Processing

Primary data was gathered using an opinion poll containing four-point Likert scale data sets which were utilized to amount the sentiments of the partakers towards the underlying constructs in the investigation. The respondents were required to designate their level of contract or difference towards various statements in the data sets. Expressive statistics were designed to rate their opinions. The width of every argument in the Likert measure is 0.75 [(4-1) ÷ 4], therefore, 1 to 1.75 depicted strongly disagree, 1.751 to 2.5 disagree, 2.51 to 3.25 approve, and 3.251 to 4 sturdily agree.

Additional data was obtained through a data verification checklist to measure upgrading in data organization across the selected 24 well-being amenities in Mombasa County to augment data on the dependent variable collected using questionnaires. The data collected included improvement in health system performance (measured based on FSBR), improvement in health outcomes (measured based on 4^{th} ANC attendance, number of skilled deliveries, and live births), and improvement in data quality (measured based on data discrepancy rate from source documents to KHIS). Data for the period July to September 2021 was compared with data from the same period in 2020 to measure improvement. The results obtained were then categorized using a two-point Likert scale as either (1) not improved or (2) improved. Expressive statistics using frequencies and proportions were used to summarize the findings.

To assess the associations between the variables that were independent and the variable that was dependent, the four-point Likert gauge data sets from the survey were combined into single amalgamated variables by figuring the mean marks of the Likert-type items for each Likert gauge data set.

To improve the validity of the model, the four-category response data set, strongly upset, upset, approve, and strongly approve, was merged into a two-category response data set, disagree and agree, using the following formula;

Max = Uppermost Score (HS) = 4

Min = Bottom Score (LS) = 1

Assortment = HS - LS = 3

No. of Groups = Two = 2

Interval = Range ÷ No. of Categories = 3 ÷ 2 = 1.5

Disagree (Group_1) = Min to (Min + Interval) = 1.00 – 2.50

Agree (Group_2) = (Max - Interval) to Max = 2.51 – 4.00

The amalgamated scores acquired by merging the Likert-type items were then recoded based on the two-group reply data set. All mean totals dwindling between 1.00 through 2.50 were recoded to 1 (disagree), while all mean scores dwindling between 2.51 to 4.00 were denoted to 2 (agree).

The merged data were further aggregated using mean scores to obtain facility-based aggregate scores for the selected 24 health facilities. Data on the dependent variable (data demand and use) from the questionnaire was further combined with data from the verification checklist to obtain a composite score (improvement in data management). Phi correlation coefficient and binary logistic regression were then conducted to define the relationship between the independent variables (organizational factors, staff effectiveness, knowledge and skills, and individual attributes) and the dependent variable (improvement in data management).

3.13 Analysis of Data

Quantitative data from the questionnaire survey and data verification were patterned for inaccurate entries, imperfect data, outliers, and copies before the actual examination. The data were eviscerated, implicit, and administered using IBM SPSS Statistics Version 25. In every research objective, a Descriptive examination of specific incidences, magnitudes, mean, standard deviance, and measurement of disparity was conducted to summarize the findings. Cross tabulation and Phi coefficient were done during the bivariate analysis. Variables significant in the bivariate examination were then included in the binary logistic regression to produce a model. The statistical implication was set at $p<= 0.05$) The information generated was shown in tables and figures. Qualitative data from KIIs and FGDs were examined using the content examination.

3.14 Ethical Consideration

All stakeholders were requested to grant the necessary management permissions. This includes ethical approvals from the Mount Kenya University Institutional Research and Ethics Committee, the National Commission for Science and Technology Innovation (NACOSTI), and the Mombasa Department of Health Services, among others. These approvals were sought through formal applications from local authorities and awaiting responses to the letters of approval. A clear and instructive stakeholder info sheet provided a detailed description and was provided to all staff members who were interviewed at health facilities. This was conveyed by an agreement form (Annexure 6) which was consented to by the participants once they give permission. Data collection only took place when institutional staff (participants) fully accepted the investigation terms by ratification of the agreement form.

Clarifications were provided to clear any doubts and misunderstandings. Partakers were also up-to-date of their right to pull out from the investigation at any time devoid of results. Contributors were also guaranteed that the info they shared would be kept unidentified to protect partakers' identities. Participants' logs, the only link between the participants' names and code numbers, all questions, and KII / FGD scripts were stored in a locked file cabinet. Only the investigator and investigation subordinate was able to access these files. Code books linking participants' names with codes, and audio recordings of KII / FGD were damaged once they had been interpreted and tested for accuracy. The investigator and subordinate did not take a copy or delete documents from selected facilities.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Outline

This section presents the outcomes and deliberations on features persuading effective staff concert in refining data management in designated conveniences in Mombasa County, Kenya. The study respondents were healthcare workers from 24 (levels 5, 4 3) health facilities in Mombasa County drawn from public, private, and FBO/NGO sectors, distributed across all the six sub-counties in Mombasa County. The research was effectively carried out and the data composed were examined using IBM SPSS version 25. The findings are presented in figures and tables, charted by an explanation of the same. The results are organized concerning the study's goals.

4.1.1 Rate of Response

Data was collected from 299 (89.5%) HCWs and 36 (94.7%) health facility in-charges/data managers using questionnaires and KIIs/FGDs respectively. Table 7 presents the supply of questionnaire respondents conferring to the health facility level.

Table 6: Distribution of Respondents

Respondents	Sample	Actual	%
Facility in-charges/data managers	38	36	94.7
HCWs	334	299	89.5
Total	**372**	**335**	**90.0**

Additional info on the dependent variable was also gained through data verification conducted by the researcher in all the selected 24 (100%) health facilities. Table 8 presents the distribution of the well-being amenities.

Table 7: Distribution of Health Facilities

Category		F	%
	Level 3	11	57.9
Facility Level	Level 4	7	36.8
	Level 5	1	5.3
	Public	15	78.9
Facility Type	Private	3	15.8
	FBO/NGO	1	5.3

4.2 Demographic Characteristics

The researcher collected some background information about the survey partakers to understand their conformation, credentials, and understanding of data management. The info composed included the partaker's age, gender, cadre, education level, employment duration, duration of service in the current facility, and section of work. The results indicated that 222 (74%) were below 40 years, 193 (65%) of the respondents were female, 103 (34%) were nurses, 193 (65%) were diploma holders, 197 (66%) had been employed for less than 10 years, 198 (66%) had operated in the current facility for less than 5 years, while 113 (38%) were working in the OPD section. Table 10 presents demographic results.

Table 8: Demographic Information

Characteristic		F	%
	20-29	100	33.4
	30-39	122	40.8
Respondents' Age	40-49	43	14.4
	50-59	32	10.7
	60 and above	2	0.7
Respondents' Gender	Female	193	64.5
	Male	106	35.5
	CLINICIANS	94	31.4
	HRIO	53	17.7
Respondents' Cadre	MLO	23	7.7
	NURSE	103	34.5
	Pharm/Tech	26	8.7
	Cert	15	5.0
	Dip	193	64.5
Respondents' Education Level	HND	14	4.7
	Degree	65	21.7
	Masters	12	4.0
	6-12 Months	35	11.7
	1-4 Years	93	31.1
Respondents' Employment Duration	5-9 Years	69	23.1
	10-15 Years	45	15.1
	15-19 Years	13	4.3
	20+ Years	44	14.7
	6-12 Months	58	19.4
	1-4 Years	140	46.8
Respondents' Duration of Service in the Facility	5-9 Years	51	17.1
	10-15 Years	30	10.0
	15-19 Years	10	3.3
	20+ Years	10	3.3

Respondents' Section of Work	OPD GENERAL	113	37.8
	MCH	63	21.1
	SPECIAL CLINIC	52	17.4
	LAB	27	9.0
	HMIS	44	14.7

4.3 Improvement in Data Management

Improvement in data management was assessed using four indicators including improvement in healthiness system enactment, improvement in well-being outcomes, data quality, and data demand and use. Data on the first three indicators were obtained from the facility source documents and KHIS using verification checklists, while data on the last indicator was obtained from the respondents using a questionnaire.

4.3.1 Improvement in Health System Performance

Improvement in health system performance was measured by comparing data on the quality of services through Fresh Still Birth Rate (FSBR) for the periods July to September 2021 and July to September 2020. The FSBR was calculated by separating the number of FSB by the corresponding number of live births for the respective periods, and the resulting figure was multiplied by 1000. The results indicated an FSBR of 11% for 2021 which was an increase from an FSBR of 9% for 2020. Thus, the increase in FSBR indicated a decline in health system performance across the selected 24 health facilities. Figure 4 presents the findings.

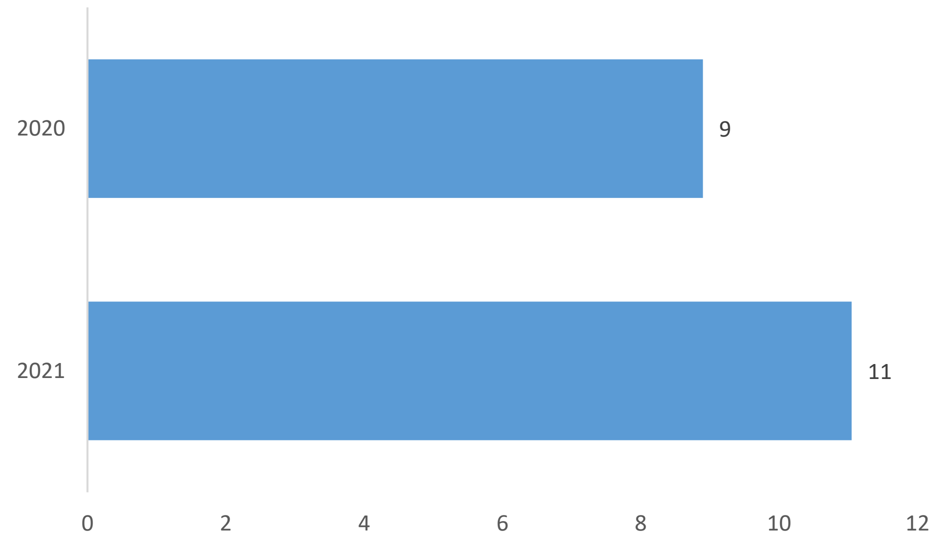

Figure 4: Health System Performance

4.3.2 Improvement in Health Outcomes

The researcher compared data on the number of 4th ANC attendance, number of skilled deliveries, and number of live births for July to September 2021 with corresponding data from a similar period in 2020. The results indicated that, in the year 2021, the number of 4th ANC attendance increased by 1,071, the number of skilled deliveries increased by 924, and the number of live births increased by 49, as compared to the year 2020. Figure 5 presents the findings.

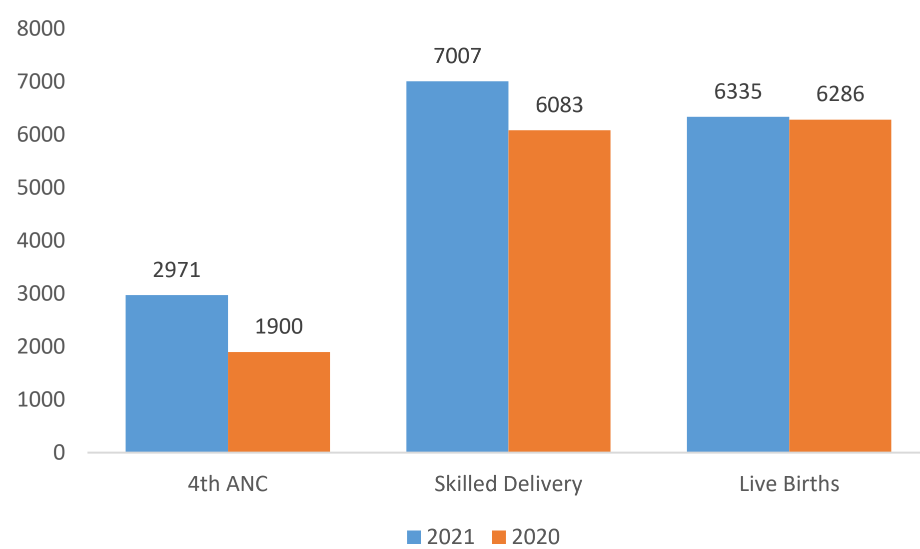

Figure 5: Health Outcomes

4.3.3 Quality of Data

Data quality was evaluated by verifying the data reported on KHIS with the data recorded in the facility source documents. The researcher verified the availability, completeness, and accuracy of data on 4th ANC, skilled deliveries, FSB, PENTA 1, PENTA 3, COCs, POPs, Injectables, IUCDs, and Implants. The researcher was able to observe that, in all 24 facilities, data on the various parameters were 100% available and 100% completely recorded. Data accuracy for the various parameters was calculated by dividing the figure reported in KHIS by the figure recorded in source documents, and the resulting figure was multiplied by 100 to get the percentage. A discrepancy rate (from 100%) of more than $^{+}/_{-}5\%$ was considered to indicate inaccuracy in data reporting. The results indicated that, when all facilities are aggregated, the discrepancy rate for all the parameters was less than 5%. Thus, the reporting of data from the source booklets to the KHIS was considered accurate. The results further indicated that there was under-reporting of skilled deliveries, COCs, IUCDs, and Implants, while 4th ANC, FSB, PENTA 1, PENTA 3, and Injectables were over-reported. Only data on POPs had a discrepancy rate of 0% (was reported 100% accurately). Figure 6 presents the findings.

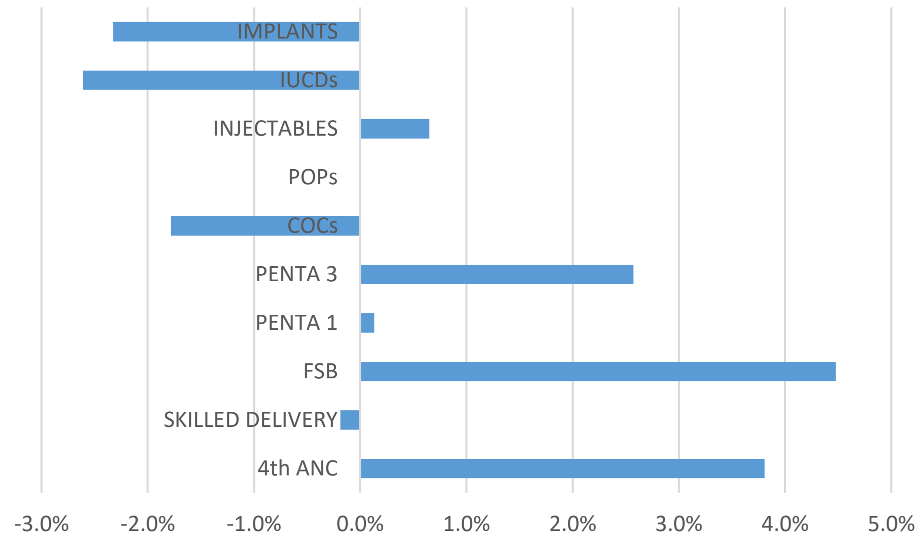

Figure 6: Data Discrepancy Rate

Results from the interviews and FGDs with facility in-charges and facility data managers revealed that (63.2%) of the facilities received data quality updates monthly during the data review meeting. Some (21.1%) of the facilities received quality updates quarterly, others (10.5%) weekly, and one indicated that they received them when the need arises. Below are some of the responses;

We get data quality updates every month during data review meetings (KII 5).

We get quality updates whenever the need arises (KII 23).

Additionally, the in-charges and facility data managers indicated that their role in facility data quality verification included collecting, compiling, and feeding data into the DHIS, organizing monthly data reviews before submission to sub-county, chairing/coordinating data review meetings, and ensuring data generated represents the actual facility performance.

The facility data managers further noted that they work with other health workers to ensure the availability, completeness, and accuracy of facility health information reports. Below are some of their responses;

I work with all departments to maintain the quality and ownership of data (KII 16).

During the reporting period, each department participates in compiling reports which improve the data verification exercise (KII 9).

4.3.4 Data Demand and Use

Data ultimatum and use were evaluated based on respondents' opinions using a four-point Likert scale containing 7 items. The partakers were required to indicate their level of demand for data and use of info for various purposes using a rating scale from (1) never, (2) rarely, (3) sometimes, through to (4) always. The results indicate that the data was demanded and used 'sometimes' for staff training (mean = 3.20, std. dev. = 0.855, coefficient of variation < 30%), and 'always' for planning and budgeting (mean = 3.74, std. dev. = 0.492, coefficient of variation < 30%), priority setting (mean = 3.64, std. dev. = 0.633, coefficient of variation < 30%), disease monitoring (mean = 3.63, std. dev. = 0.670, coefficient of variation < 30%), resource mobilization (mean = 3.33, std. dev. = 0.867, coefficient of variation < 30%), staff distribution (mean = 3.35, std. dev. = 0.819, coefficient of variation < 30%), and quality improvement (mean = 3.39, std. dev. = 0.784, coefficient of variation < 30%). All the coefficient of variation values is less than 30% indicating that the mean scores characterized the communal thoughts of the partakers. Table 11 presents the findings.

Table 9: Data Demand and Use

	N	Min	Max	Mean	Std. Deviation	Coefficient of Variation (%)
Planning and budgeting	299	2	4	3.74	.492	13.2
Priority setting	299	1	4	3.64	.633	17.4
Disease monitoring	299	1	4	3.63	.670	18.5
Resource mobilization	299	1	4	3.33	.867	26.0
Staff distribution	299	1	4	3.35	.819	24.4
Staff training	299	1	4	3.20	.855	26.7
Quality improvement	299	1	4	3.39	.784	23.1

Results from the interviews and FDGs with facility in-charges and facility data managers revealed that (68.4%) of the facilities used data daily scheduling activities and allocation of resources. Other facilities indicated to use of data quarterly, or monthly basis during data review meetings or whenever needed for planning and decision-making. Below are some of the responses.

> *We use data daily to schedule activities and allocate resources to the various service delivery points in the facility (KII 3).*

> *Monthly during data review meetings (KII 17).*

> *We use it quarterly for target setting and an indication of achievement to identify performance (KII 21).*

> *Whenever needed for decision-making (KII 33).*

Additionally, (89.5%) of the in-charges indicated that they had evidence to show previous data demand and information use. The evidence listed included dashboards, reports, presentations for data reviews, and trends/talking walls (chats) for interventions.

4.3.5 Facilities' Rating on Improvement in Data Management

The researcher rated each facility using a 2-point rating scale, (1) not improved and (2) improved, based on the four indicators to determine whether there was an improvement in data management or not. Facilities were rated as improved if their; - FSBR for 2021 had declined compared to 2020; health outcomes for 2021 had improved compared to 2020; aggregate discrepancy rate was less than $^{+}/_{-}5\%$; and the combined average rating on data demand and information use was above 2.5. The ratings for the four indicators were aggregated using mean whereby facilities with mean values between 1 to 1.5 were categorized as not improved while facilities with mean values between 1.51 to 2 were categorized as improved. Thus, when data on the four indicators (health system performance, health outcomes, data quality, and data demand and information use) were aggregated, the results indicated that data management improved in 12 (63%) of the health facilities. Figure 7 presents the findings.

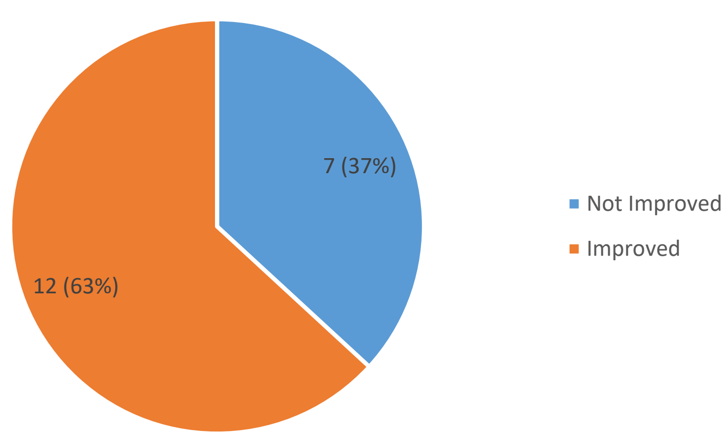

Figure 7: Improvement in Data Management

Findings from the interviews and FGDs with facility in-charges and facility data managers indicated that most facilities had experienced changes in health information management for the previous six months preceding the study. Some of the changes included monthly data reviews, timely report submission with data reviews, verification of data before submitting, increased workload due to new service delivery points, improved documentation, training of staff on HMIS tools, etc. Below are some of the responses;

> *We conduct monthly data review meetings, something that was not regularly conducted in the past (KII 11).*

> *There is improved documentation because the staff has been trained on HMIS tools (KII1 18).*

However, there were mixed feelings among in-charges and facility data managers concerning their experience in data management. While some indicated that they were comfortable in handling data management, some described their experience as challenging because they lacked knowledge and skills in data management. Below are some of the responses;

> *It has not been easy given that I have not been trained (KII 12).*

> *It is easy, to collect and summarize monthly reports (KII 4).*

> *Teamwork and timely reporting are issues of concern, departments bring their data late (KII 7).*

> *There is a lack of space to keep our data, it is difficult to maintain and get patient files and do data entry (KII 25).*

The health workers, in-charges, and facility data managers further indicated that their recommendations for the future in strengthening HIS in their respective facilities included; - introducing EMR data management at all service delivery points; capacity building on data demand and info use at all stages, strengthening data reviews and feedback, employing qualified HMIS staff, training of staff on data management, ensuring adequate budget allocation for HMIS, purchase of office equipment including computers, utilization of data in decision making, etc. Below are some of the responses;

We intend to ensure that besides CCC, all other service delivery points are paperless. This will enhance timeliness in reporting and data capture (KII 20).

Lobby for the employment of more staff who are trained in data management (KII 34).

Each facility should have a data office with adequate HMIS staff (KII 2).

4.4 Organizational Factors Associated with Data Management

Organizational factors associated with data management were assessed based on respondents' opinions using a four-point Likert gage encompassing 7 items. The partakers were prerequisite to indicate their level of settlement with certain statements using a rating scale extending from (1) strongly upset, (2) upset, (3) approve, through to (4) strongly approve. The results indicated that the respondents agreed with most of the statements, although their opinions were widely varied (coefficient of variation = 30% and above) on certain statements. For instance, the respondents agreed that staff received support from seniors (mean = 2.86, std. dev. = 0.857, coefficient of variation > 30%), facilities had HMIS budget allocation (mean = 2.68, std. dev. = 0.911, coefficient of variation > 30%), and HMIS staff had access to office space/equipment's and tools (mean = 2.81, std. dev. = 0.909, coefficient of variation > 30%). Additionally, the respondents disagreed that routine MOH registers and summaries were complicated (mean = 2.13, std. dev. = 1.105, coefficient of variation > 30%). Table 12 presents the findings.

Table 10: Organizational Factors Associated with Data Management

	N	Min	Max	Mean	Std. Deviation	Coefficient of Variation (%)
Staff use standard HMIS tools comfortably	299	1	4	2.81	.796	28.3
Staff have clear roles and responsibilities in data management	299	1	4	2.90	.835	28.8
Facility documents epidemiological trends	299	1	4	2.85	.811	28.5
Routine MOH registers and summaries are complicated	299	1	4	2.13	1.105	51.9
HMIS staff have access to office space/equipment and tools	299	1	4	2.81	.909	32.3
The facility has an HMIS budget allocation	299	1	4	2.68	.911	34.0
Staff get regular support from seniors	299	1	4	2.86	.857	30.0

Results from the interviews and FGDs with facility in-charges also revealed that (63.2%) of the facilities had a budget for data management. The results showed that the budget was mainly allocated for DQA training, data reviews, purchasing HMIS tools, employment of HMIS staff, transport, and logistics for data transfer. Below are some of the responses;

Yes, the budget is offered for DQA training to support EMR supervision and DQA assessments (KII 1).

No, but it is very important to have a budget allocation for data management (KII 8).

No, we need to factor (KII 37).

These verdicts are steady with the outcomes of (Ahanhanzo et al., 2014). In a study steered in Benin, Ahanhanzo et al., (2014) established that infrastructural and system-based reasons that impact data quality in general well-being info systems include the availability of suitable data gathering tools, amount and quality of human capital in and use of well-being info systems, well-being management principles for openness, homogenous data quality control and robust info on well-being data.

However, the findings differ from the findings of several other studies. Cheburet and Odhiambo-Otieno (2016), in research, steered in Uasin Gishu County Referral Hospital, Kenya, found that the popular of the partakers indicated that the hospital lacked standard operating procedures and institutional documents were rarely available, especially in the typical operational procedure, data superiority process, tactical plan, operational strategies, and policy to improve data quality. Nzomo, (2017) in a study conducted at the Coast General Teaching and Referral Hospital, Mombasa County, found that inadequate management support by the immediate manager was reported by the respondents. In another study conducted in Mombasa County, Otieno et al., (2020)found that limited funds were allocated to HIS services and that not all well-being amenities in the county had HRIOs.

4.5 Staff Effectiveness (Technical Factors) Associated with Data Management

Staff effectiveness associated with data management was assessed based on respondents' opinions using a four-point Likert scale containing 8 items. The partakers were obligated to designate their level of pact with certain statements using a rating scale ranging. The outcomes indicated that the partakers agreed with all the statements, although their responses on certain statements widely varied (coefficient of variation > 30%). For instance, the respondents agreed that staff could use all HMIS tools contentedly with the least sustenance (mean = 2.68, std. dev. = 0.881, coefficient of variation > 30%), staff could demonstrate beyond numbers (mean = 2.75, std. dev. = 0.841, coefficient of variation > 30%), staff could distinguished illness patterns and get significant info about patient/client care (mean = 2.82, std. dev. = 0.852, coefficient of variation > 30%), and that decisions were based on evidence on data (mean = 2.85, std. dev. = 0.882, coefficient of variation > 30%). Table 13 presents the findings.

Table 11: Staff Effectiveness Associated with Data Management

	N	Min	Max	Mean	Std. Deviation	Coefficient of Variation (%)
Staff can use all HMIS tools (documentation) comfortably with minimum support.	299	1	4	2.68	.881	32.9
Staff cross-check monthly reports (MOH 711) before acquiescing them to the next level	299	1	4	2.99	.877	29.3
Staff can make a simple investigation of the data	299	1	4	2.87	.797	27.8
Staff can demonstrate beyond-numbers - interventions	299	1	4	2.75	.841	30.6
Staff can provide complete and accurate reports which are used for decision making	299	1	4	2.95	.850	28.8
Staff can share information with seniors and peers during review meetings	299	1	4	2.98	.837	28.1
Staff can recognize disease patterns and get important information about patient/client care.	299	1	4	2.82	.851	30.2
Decisions are based on the confirmation on data	299	1	4	2.85	.880	30.9

Results from the interviews and FGDs with facility in-charges and facility data managers revealed that all the facilities interrogated their facility data monthly during data review meetings. Additionally, some (10.5%) indicated that they also interrogate the data quarterly for target setting and performance review, and one integrated the data weekly for IDSR. Below are some of the responses;

> *We interrogate facility data every month during data review meetings (KII 29).*
>
> *Data interrogation is done monthly during review meetings and quarterly during targeting setting and review of facility performance (KII 10).*
>
> *We interrogate facility data every week for IDSR (KII 24).*

All the in-charges further noted that the last time they had analyzed their respective facility data was one month before the study. Additionally, the in-charges indicated that their contributions to HIS in their respective facilities included data entry monthly, data analysis, DQA validation, coordination of data reviews, verification of monthly reports before submissions, using data to make decisions, and budgeting and technical support in facilitation of HIS, among others.

The findings differ from the results from different studies. Anasel et al., (2019), in research, steered in fitness amenities in Lindi and Geita, Tanzania, established mixed findings on healthcare practitioners' capacity to evaluate and apply data in decision-making. Some research partakers stated they utilized the data they obtained to assess the once-a-month services they offered, which helped them guess what was required. The researchers also established that data analysis findings had been displayed on walls and bulletin boards, demonstrating that healthcare workers were studying aggregated data and sharing the results with others. However, the majority of the health personnel could not evaluate data and use computers. Most health facilities had a poor ethos of data examination and use in decision-making.

4.6 Knowledge and Skills (Behavioral factors)Linked with Data Management

Awareness and skills associated with data management were assessed based on respondents' opinions using a four-point Likert scale containing 5 items. The partakers were required to indicate their level of covenant with certain declarations using a rating scale. The results specified that the partakers agreed that facility/section decisions were based on proof preference (mean = 2.51, std. dev. = 1.060, coefficient of variation > 30%), and that facility/section staff were involved in planning/implementation and monitoring of service delivery/programs indicators (mean = 2.57, std. dev. = 1.089, coefficient of variation > 30%)). On the other hand, the partakers disagreed that the capability /section had adequate HMIS skilled staff responsible for routine health information tasks (mean = 2.47, std. dev. = 1.085, coefficient of variation > 30%), facility/section staff were trained in data management (mean = 2.50, std. dev. = 1.091, coefficient of variation > 30%), and that facility/section staff were involved in quality improvement teams (mean = 2.46, std. dev. = 1.066, coefficient of variation > 30%). However, all the coefficient of variation values were greater than 30%, indicating that the opinions of the respondents on the various statements were widely varied. Table 14 presents the findings.

Table 12: Knowledge and Skills Associated with Data Management

	N	Min	Max	Mean	Std. Deviation	Coefficient of Variation (%)
Facility/section decisions are based on evidence preference	299	1	4	2.51	1.060	42.2
The facility/section has adequate HMIS-skilled staff responsible for routine health information tasks	299	1	4	2.47	1.085	43.9
Facility/section staff are trained in data management	299	1	4	2.50	1.091	43.6
Facility/Section staff are involved in planning/implementation and monitoring of service delivery/programs indicators	299	1	4	2.57	1.089	42.4
Facility/section staff are involved in quality improvement teams	299	1	4	2.46	1.066	43.3

Results from the interviews and FGDs with facility in-charges revealed that the majority (68.4%) of the in-charges knew data quality. This is shown by their ability to describe data completeness and accuracy. However, a few in-charges indicated that they had no idea. Below are some of the responses;

Completeness means all variables in a data set or tool are filled & accuracy means that what has been collected in the registers and summaries is actually what is reported (KII 8).

I have no idea what data completeness and accuracy entail (KII 16).

Most of the facility data managers were also aware of the tools used for data quality checks and described them to include MOH reporting tools, MOH registers, and KHIS.

The findings are steady with research directed in Malawi which revealed that while well-being offices and infirmaries were more probable to have a competent HMIS workforce, there was an inadequate qualified HMIS workforce at the well-being capacity level, which was backed by inadequate data level and low data usage at the facility level. The study also revealed limited training of HMIS staff, especially at the well-being facility level(Regeru et al., 2020).In another study (Mucee, 2016) the Public Well-being Sector in Thararaka Nithi County, Kenya, also revealed insufficient data and information management personnel and a lack of training in data management. Most of the data and information management personnel were employed temporarily and were highly untrained.

4.7 Individual Attributes Associated with Data Management

Individual attributes associated with data management were assessed based on respondents' opinions using a four-point Likert gage comprising 4 items.. The results indicated that the respondents agreed that staff routinely performed data quality checks before submitting to the next level (mean = 2.77, std. dev. = 0.848, coefficient of variation > 30%), staff used data to inform patients/clients interventions (mean = 2.75, std. dev. = 0.883, coefficient of variation > 30%), staff routinely displayed data to monitor performance (mean = 2.76, std. dev. = 0.885, coefficient of variation > 30%), and that the facility/section had a data demand and information use champion (mean = 2.71, std. dev. = 0.930, coefficient of variation > 30%). However, all the coefficient of variation values were greater than 30%, indicating that the opinions of the respondents on the various statements were widely varied. Table 15 presents the findings.

Table 13: Individual Attributes Associated with Data Management

	N	Min	Max	Mean	Std. Deviation	Coefficient of Variation (%)
Staff routinely perform data quality checks before submitting them to the next level	299	1	4	2.77	.848	30.6
Staff use data to inform patients/clients of interventions	299	1	4	2.75	.883	32.1
Staff routinely display data to monitor performance	299	1	4	2.76	.885	32.1
The facility/section has a data demand and information use champion	299	1	4	2.71	.930	34.3

Results from the interviews and FGDs with the facility in-charges also confirmed that the majority (73.7%) of the facilities had a HIS champion, while those facilities that did not have recommended to have one. Below are some of the responses from the interviews;

Yes, she is very helpful (KII 31).

No, we need one because he/she plays a very important role (KII 26).

In addition, 200 (67%) of the respondents indicated that they were encouraged by the senior management to learn data management from outside sources including online training, CME, desk reviews, M&E forums, conferences, etc., out of which 123 (61%) had attended the training less than 6 months before the study. Results also indicated that 287 (96%) were willing to play a role in HMIS, and 262 (88%) indicated that staff ideas and recommendations regarding HIS are considered by the senior management team. Table 16 presents the findings.

Table 14: Individual Attributes Associated with Data Management

		F	%
Does senior management encourage other health providers to learn data management from outside sources?	Yes	200	66.9
	No	99	33.1
When was the last time you attended the above training?	<6 Months	123	61.5
	6-12 Months	41	20.5
	More the 12 Months	24	12.0
	None	12	6.0
Would you like to play any role in HMIS	Yes	287	96.0
	No	12	4.0
Are staff ideas and recommendations regarding HIS considered by the senior management team?	Yes	262	87.6
	No	37	12.4

The verdicts are supported by investigations conducted by Ledik (2014) and Glèlè et al. (2014) who confirmed that human resources play an important role in defining data quality in the general well-being info system, which is primarily recognized by the well-being of employees' skills. Ledikwe et al.,(2014), in an investigation, steered in Botswana, noted that motivation or lack of incentive was an aspect of healthcare employees' conclusions, and it lingers to be the primary element of staff enactment. Ahanhanzo et al., (2015) indicated that well-being amenities with a well-trained workforce and organization capacity have better well-being data. They also noted that health professionals' motivation and the presence of stimulants or mitigators influence data quality in general well-being info systems.

4.8 Phi Correlation Coefficient

The investigator conducted a Phi Coefficient test, at an implication level of 0.05, to define the degree of relationship between the variables that were independent and the variable that was dependent. The outcomes showed that knowledge and skills ($\phi = 0.535$, $p = 0.020$) had a strong positive relationship with upgrading in data management. This means that an increase in knowledge and skills would be accompanied by an improvement in data management. However, organizational aspects ($\phi = 0.268$, $p > 0.05$), staff efficiency ($\phi = 0.408$, $p > 0.05$) and individual traits ($\phi = 0.141$, $p > 0.05$) had no significant relationship with improvement in data management. Table 17 presents the findings.

Table 15: Phi Correlation Coefficient

		Data Management		**Phi Coefficient**		
		Not Improved	Improved	Value	N	Sig.
Organizational Factors	Disagree	2	1	.268	19	.243
	Agree	5	11			
Staff Effectiveness	Disagree	3	1	.408	19	.075
	Agree	4	11			
Knowledge and Skills	Disagree	4	1	.535	19	.020
	Agree	3	11			
Individual Attributes	Disagree	2	2	.141	19	.539
	Agree	5	10			

4.9 Logistic Regression Analysis

A binary logistic regression was performed to assess the effects of organizational factors, staff effectiveness, knowledge and skills, and individual attributes on data management in selected 24 well-being amenities in Mombasa County.

4.9.1 Goodness-of-fit Test

A goodness-of-fit test was conducted using the Hosmer-Lemeshow test, at a significance level of 0.05, to define whether the predicted likelihoods deviate from the observed likelihoods in a way that the binomial dispersal does not predict. The calculated p-value was greater than the significance level ($p > 0.05$), which indicates that the model fits the data. The findings are provided in Table 18.

Table 16: Goodness-of-fit Test

Step	Chi-square	df	Sig.
1	7.685	4	.104

4.9.2 Classification of Cases into the Specified Categories

The study also evaluated whether the binomial logistic regression model appropriately forecast cases from the self-governing variables. This was conducted by evaluating the efficiency of the predicted cataloging against the real organization. The results showed that the model correctly categorized 94.7% of cases. Findings are offered in Table 19.

Table 17: Classification of Cases

	Observed		Predicted		
			DV		Percentage Correct
			Not Improved	Improved	
Step 1	DV	Disagree	7	0	100.0
		Agree	1	11	91.7
	Overall Percentage				94.7

a. The cut value is .500

4.9.3 Variation in the Dependent Variable Explained by the Model

To comprehend how much variation in the dependent variable was elucidated by the model, the research used Nagelkerke R2. The findings designated that the model elucidated 59.9% of the variance in improvement in data management. The results are presented in Table 20.

Table 18:Summary of the Model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	14.056[a]	.438	.599

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

4.9.4 Contribution of the Independent Variables to the Model

The Wald test was used to define the statistical implication for each of the variables that were independent at a substantial level of 0.05. From the results, organizational factors ($p > 0.05$), staff effectiveness ($p > 0.05$), and individual attributes ($p > 0.05$) had no significant contribution to the model/prediction, while knowledge and skills ($p < 0.05$) added significantly to the model. This means that knowledge and skills had a significant influence on improvement in data management at the selected well-being amenities in Mombasa County. Table 21 presents the results.

Table 19: Contribution of Independent Variables in the Model

							95% C.I. for Exp(B)	
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
Organizational Factors(1)	-1.258	1.646	.584	1	.445	.284	.011	7.161
Staff Effectiveness(1)	-2.880	1.633	3.109	1	.078	.056	.002	1.379
Knowledge and Skills(1)	-3.489	1.614	4.670	1	.031	.031	.001	.723
Individual Attributes(1)	-.857	1.507	.323	1	.570	.424	.022	8.138
Constant	2.805	1.305	4.618	1	.032	16.524		

a. Variable(s) entered on step 1: Organizational Factors, Staff Effectiveness, Knowledge and Skills, Individual Attributes

When the odds ratio [Exp(B)] in Table 19 is converted into a percentage, using the formula {[1 – Exp(B)]*100}, the results indicate that a facility was 97% less likely to experience improvement in data management if the facility staff lacked adequate knowledge and skills. This means that the lack of adequate HMIS skilled staff responsible for routine health information tasks, lack of staff that was adequately trained in data management, and lack of involvement of staff in quality improvement teams hindered the improvement in data management in some health facilities. This was steady with the discoveries of research conducted in ten countries, including Côte d'Ivoire and Uganda. The study established that a lack of awareness and skills in data management has played a significant role in the lack of data quality and information use(Admon et al., 2013). Another study (Thaer & Alrubaey, 2023) also revealed that capacity gaps were a barrier to the functioning of the well-being system, and how effective people are involved.

CHAPTER FIVE: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.0 Outline

This section offers a precipitate of the results of the research, conclusions drawn, endorsements for practice, and areas for additional research.

5.1 Summary of the Findings

The main objective of the research was to measure, aspects coaxing actual workforce presentation in refining data management in chosen amenities in Mombasa County, Kenya. Data was collected from healthcare workers across 24 (levels 5, 4 3) health facilities (public, private, and FBO/NGO) in Mombasa County and analyzed using IBM SPSS for Windows, version 25. Descriptive analysis was conducted using mean, standard deviation, and coefficient of variation to summarize the results of the individual variables. Additionally, inferential analysis was conducted using Phi Correlation Coefficient and Binary Logistic Regression, at a connotation level of 0.05, to decide the association between the independent variables (organizational factors, staff effectiveness, knowledge and skills, and individual attributes) and the dependent variable (improvement in data management).

Improvement in data management was assessed using four indicators including improvement in well-being system performance, improvement in well-being outcomes, data quality, and data demand and info use. Improvement in well-being system performance and health outcomes was assessed by comparing data for the quarter of July-September 2021 with data for a similar period in 2020. Data quality was assessed by verifying the rate of discrepancy in data reporting from facility source documents to KHIS (a discrepancy rate of less than 5% was deemed acceptable), while data demand and information use was assessed based on respondents' opinions using a likert scale rating. The results indicated that health system performance declined, health outcomes improved, data reporting was accurate, and data demand and information use were at high levels. Therefore, in general, the results indicated an improvement in data management in most health facilities.

The first specific objective of the study was to establish organizational factors affecting data administration in designated amenities in Mombasa County, Kenya. Descriptive statistics results indicated that in the selected facilities; - staff had clear roles and responsibilities in data management, and facilities documented epidemiological trends. Additionally, respondents widely differed on whether staff was able to use standard HMIS tools; whether the facilities had HMIS budget allocation; whether staff had access to office space/equipment/tools; and whether staff received managerial support. However, the Phi coefficient and binary logistic regression results indicated that organizational factors had no significant influence on improvement in data management in the designated well-being amenities.

The second specific objective of the research was to evaluate staff efficiency in refining data management in designated amenities in Mombasa County, Kenya. Descriptive statistics results indicated that well-being providers in the selected facilities were able to; - cross-check monthly reports (MOH 711) before acquiescing them to the next stage; make a simple examination of the data; provide comprehensive and precise reports; and share info with seniors and peers during the review meeting. Moreover, respondents widely differed on whether; - staff could use all HMIS tools contentedly with the least sustenance; whether staff could validate beyond numbers; whether staff could identify illness outlines and get vital info about patient/client care; and whether results were based on suggestion. However, the Phi coefficient and binary logistic regression results indicated that staff effectiveness had no significant influence on improvement in data management in the designated well-being amenities.

The third specific objective of the study was to determine levels of knowledge and skills associated with data quality management among staff in selected facilities in Mombasa County, Kenya. Descriptive statistics results indicated that there were wide differences of opinion on whether; - facility/section decisions were based on evidence preference; that facility/section staff were involved in planning/implementation and monitoring of service delivery/programs indicators; the facility /section had adequate HMIS skilled staff responsible for routine health information tasks, facility/section staff were trained in data management; and whether facility/section staff were adequately involved in quality improvement teams. The Phi coefficient and binary logistic regression results indicated a significant relationship between knowledge and skills and improvement in data management in the selected health amenities. The results indicated that a facility was less likely to experience improvement in data management if the facility staff lacked adequate knowledge and skills.

The fourth goal of the research was to ascertain individual attributes linked with data quality management among staff in selected facilities in Mombasa County, Kenya. Descriptive statistics results indicated that respondents had divergent views on whether in the selected facilities;- staff routinely performed data quality checks before submitting to the next level; staff used data to inform patients/clients interventions; staff routinely displayed data to monitor performance; and there were data demand and information use champions. However, the Phi coefficient and binary logistic regression results indicated that individual attributes had no significant influence on improvement in data management in the selected health facilities.

5.2 Conclusions

Based on the research results the following are the Conclusions; -

Health facilities in Mombasa County experienced a decline in health system performance (increased FSBR) and an improvement in health outcomes for the year 2021 compared to 2020, accuracy in data reporting, and high levels of data demand and information use. Thus, in general, there was an upgrade in data management in most well-being amenities.

Health providers in Mombasa County had clear roles and responsibilities in data management and documented epidemiological trends. Additionally, respondents widely differed on whether they were able to use standard HMIS tools, had access to office space/equipment/tools, received adequate managerial support, and whether they had adequate HMIS budget allocation. However, organizational factors had no significant influence on improvement in data management in well-being amenities in Mombasa County.

Healthiness providers in Mombasa County were able to cross-check once-a-month reports (MOH 711) before acquiescing them to the next stage, make a simple examination of the data, provide comprehensive and precise reports, and share info with seniors and peers during review conferences. However, staff effectiveness had no significant influence on the enhancement in data management in well-being amenities in Mombasa County.

Health providers in Mombasa County had divergent opinions on whether their decisions were based on evidence preference, whether they were adequately involved in planning/implementation and monitoring of service delivery/programs indicators, whether health facilities had adequate HMIS skilled staff responsible for routine health information tasks, whether facility/section staff were trained in data management, and whether facility/section staff were adequately involved in quality improvement teams. However, there was a momentous association between knowledge and skills and enhancement in data management in health amenities in Mombasa County. A facility was less likely to experience improvement in data management if the facility staff lacked adequate knowledge and skills.

Health providers in Mombasa County held divergent views on whether data quality checks were routinely performed before submitting to the next level, whether data was used to inform patients/clients interventions, whether data was routinely displayed to monitor performance, and whether there were data demand and info use champions in the well-being facilities. However, individual attributes had no significant influence on improvement in data management in well-being amenities in Mombasa County.

5.3 Recommendations for Practice

(i). The Ministry of Well-being at the national level and the division of health in Mombasa County should ensure that HRH norms on HMIS officers are adhered to by ensuring that all health facilities have adequate HMIS skilled staff responsible for routine health information tasks.

(ii). The Ministry of Health and the division of health in Mombasa County should ensure that all health providers are adequately trained in data management to improve their knowledge and skills rates in this field.

(iii). The department of health in Mombasa County and the health facility managers should ensure that all health providers are adequately involved in quality data management which will in turn improve their competency in terms of knowledge and skills.

(iv). Health workers should ensure that they perform quality data checks through adequate utilization of skills and knowledge before acquiescing reports to the next level and adequately using well-being info in decision-making.

5.5 Recommendations for Additional Research

The results have discovered that the factors under consideration in this study did not exhaustively explain the upgrading in data management in well-being amenities in Mombasa County. Therefore, the research suggests that further rsearch should be steered focusing on other aspects persuading improvement in data management.

The study should also be replicated in other regions to compare findings to produce more awareness on factors related with improvement in data management and thus assist health departments in the counties to adopt effective strategies to improve data management across well-being amenities.

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APPENDICES

Appendix 1: Data Verification Checklist

Health Facility: Facility code:

Month: year:

MOH 711 MONTHLY SUMMARY FORM

Identification of MOH tools source document:

ANC, DELIVERY, FP, FCDRR, LAB, IMMUNIZATION TALLY SHEET, POST NATAL REGISTERS

ANC/PNC									
	MONTH:			MONTH:			MONTH:		
	REGISTER	MOH 711	KHIS	REGISTER	MOH 711	KHIS	REGISTER	MOH 711	KHIS
1ST ANC VISIT									
COMPLETED 4TH ANC									
Number of skilled delivery									
Live Birth									
Fresh Still Births									
Maternal Deaths									

IMMUNIZATION SERVICES									
	TALLY SHEETS	MOH 710	KHIS	TALLY SHEETS	MOH 710	KHIS	TALLY SHEETS	MOH 710	KHIS
PENTA 1									
PENTA 3									

FAMILY PLANNING									
	REGISTER	MOH 711	KHIS	REGISTER	MOH 711	KHIS	REGISTER	MOH 711	KH

									I S
COCs									
POPs									
INJECTABLES									
IUCDS									
IMPLANTS									

Availability, Completeness, and Accuracy of Data Elements

	QUESTIONNAIRE						
	PART 1:SOCIO DEMOGRAPHIC						
	FACILITY NAME		**LEVEL**		**OWNERSHIP**		
	Category(Select)	**Nurse**	**HRIO**	**CLINICIAN**	**Pharm/Tech**	MLO	
1	AGE						
2	GENDER						
3	CADRE						
4		**SELECT WHERE APPROPRIATE**					
5	EDUCATION	Certificate	Diploma	HND	Degree	Masters	PHD
		SELECT WHERE APPROPRIATE					
6	How long have you been employed since college/campus graduation?	6-12 months	1-4 years	5-9 yrs	10---15 years	15--19 years	20+
7	How long have you been working in this facility?	6-12 months	1-4 years	5-9 yrs	10---15 years	15--19 years	20+
8	Which section / unit you currently work in	OPD GENERAL	MCH	SPECIAL CLINIC	LAB	HMIS	PHYSIO/OT

PART 2: Practice (Evidence Based Decision Making)
SELECT(TICK) WHERE APPROPRIATE TO THE SCALE OF 1--4

1	Please state the level of demand for data and the use of info	**Rarely used**	**sometimes**	**always**	**None**
a.	planning and budgeting				
b	priority setting				
c	disease monitoring				
d	resource mobilization (proposal writing)				
e	staff distribution				
f	staff training				
g	quality improvement teams				

PART 3: Organization factors affecting data management: in your opinion, rate to a scale 1-4

	kindly rate the extent to which you approve (scale 1-4)	**Disagree**	**Neither agree**	**agree**	**Strongly agree**
a.	Staff use standard HMIS tools comfortably?				
b	Staff have clear roles and responsibilities in data management?				

c	The facility documents epidemiological trends?				
d	Routine MOH registers and summaries are complicated				
e	HMIS staff have access to office space/equipment's and tools				

Appendix 2: Questionnaire

PART 4: staff effectiveness in improving data management

	Please rate staff effectiveness in improving data management	**disagree**	**Neither agree**	**agree**	**Strongly agree**
a.	Staff can use all HMIS tools (documentation) securely with the tiniest sustenance.				
b	Staff cross-check monthly reports (MOH 711) before submitting it to the next level				
c	Staff can make a simple analysis of the data				
d	staff can demonstrate beyond numbers -interventions				
e	Staff can provide complete and accurate reports which are used for decision making				
f	Staff can share information with seniors and peers during evaluation summits				
g	The facility has HMIS budget allocation				
h	Staff can recognize illness outlines and get important info about patient/client care.				
j	Staff get regular support from seniors				
k	Decisions are based on evidence on data				

PART 5: knowledge and skills associated with data quality management select(tick) where appropriate to the scale of 1- 5

	To what extent do you agree with the following,	**strongly disagree**	**partly disagree**	**disagree**	**agree**	**strongly agree**

a	Facility/section decisions are based on evidence preference					
b	Facility /section has adequate HMIS skilled staff responsible for routine health information tasks					
c	Facility/section staff are trained in data management					
d	Facility /Section staff are involved in planning/implementation and monitoring of service delivery/programs indicators					
e	Facility/section staff are involved in quality improvement teams					

PART 6: individual attributes associated with data quality management select(tick) where appropriate to the scale of 1- 5

	To what extent do you agree with the following	strongly disagree	partly disagree	disagree	agree	strongly agree
a	Does your section staff routinely perform data quality checks before submitting to the next level					
b	Does your section staff use data to inform patients/clients interventions					
c	Does section staff routinely display data to monitor performance					
d	Does your section have a data demand and information use champion					

e. Does your seniors encourage health providers to learn data management from outside sources (online training, CME, desk reviews, M&E forums, conferences, etc.) Yes or No?

f. Given a chance, will you want to play HMIS roles? Yes or no

g. If no, what is the reason?..

h. Are your ideas and recommendations regarding the health information system considered by the senior management team? Yes or No

i. In your view, what do you think can be done to boost the demand for and use of data at the facility level? ---

We have come to the end of the questionnaire.

Thank you much for your time

Appendix 3: Well-being Facility Data Manager Discussion Guide

1. Facility Code: ______________________

2. Facility Type:

3. Facility Location:

Urban or Rural

4. Ownership:

Age of participant

Cadre

Questions

1. How long have you worked in this section (<1yr, 1-3years; 4-9Years; 10+)
2. What is your position in handling data in this health facility?
3. What are the process of routine data gathering and reporting in this facility?
4. What difficulties do you face in managing facility data?
5. Do you work with anyone to ensure the completeness and accuracy of your Health Information report?
6. Please describe………………………………………………………………………...
7. Have you attended training on data management and specifically DDIU in the last six months?
8. How often in a year?
9. What is your perception of the quality of the data?
10. Please explain the use of any data quality mechanisms.

11. Does this facility check on the data completeness report before submission to the next level?

12. If yes please explain how it is performed

13. What are the bottlenecks in improving the health information system in your facilities?

- Given the bottlenecks What do you think should be done to enhance the facility's health information system?

Appendix 4: Facility In-Charge Interview Guide

KEY INFORMANT GUIDE

- Does this facility have a HIS champion and is he/she helpful? If not, what is your take?
- How often do we get data quality updates?
- Can you describe data completeness and accuracy?
- What is your role in facility data quality?
- Can you describe your experience in data management?
- How often do you interrogate your facility data?
- When was the last time you analyzed your facility data?
- How often do you use data?
- Do you have evidence to show previous data demand and information use?
- Does this facility have a kit on data management if yes describe it and if no what do think?
- What has changed in terms of health information management for the last six months?
- What is your contribution to the health information system in this facility?
- What are your plans for strengthening HIS in this facility?

Appendix 5: Individual Interview and Focus Group Discussion Protocols

Protocols for Key Informer Conferences and Focus Group Discussions with Staff

Protocol for One-on-One Interviews

CONSENT

I'd want to express my gratitude for agreeing to chat with us today. Sarah is my name, and I am a student at the University of Mount Kenya.

My research assistant's name is XX. [Let XX introduce herself.]

I'll interview you. XX will primarily listen and take notes, but she will have opportunities to contribute info and ask follow-up queries at key times.

The recording has not yet begun. Once I've done presenting the topic and you agree to proceed, I'll turn it one.

You were invited to today's interview because you work as a healthcare professional in this facility.

We'd want to learn more about your position and experience with health information strengthening, as well as what might be done to enhance it.

Because the facility health information system is the central focus of the well-being care system, it is critical to truly understand the most significant aspects for data completeness and accuracy in evidence-based decision-making and to be present at the table in aiding to shape research in driving policy and guidelines as far as the universal health coverage agenda is concerned. (Improving performance)

We want to know how we can combine your and other [“staff'] opinions and experiences into Public Health Research and the enhancement of well-being info systems. We'd want to hear about your experiences with the facility's HIS/data management, as well as your views on what has and hasn't worked for you.

The Information Sheet that we supplied you contains all of the information that I have presented to you. Please read it again if you haven't already.

Do you have any questions concerning the interview or the focus group?

Appendix 6: Consent Form

Title of Research: Assessment of, reasons persuading operative workforce performance in data quality management in designated amenities in Mombasa County, Kenya

Principle Investigator: My name is Sarah and my study number is REG. NO: MPH/2017/74534

Master's Degree in Public Health from Mount Kenya University

Purpose of the Study: This study aims to provide evidence-based information which will help the County strengthen the health information system affecting staff performance in selected well-being amenities in Mombasa. The study will benefit the academic arena as it will add to the existing body of knowledge and understanding of the factors of staff performance in data management. The result of the study can be utilized by both National and County stakeholders to formulate a county health information policy that will be responsive to staff performance. The general determination of this research proposal is to give insight into facility experience, drawing lessons to help DOHS -County Government, MOH, and other partners develop effective mechanisms to strengthen sustainable facility health information system which is responsive to the needs of the community and entire population. Useful recommendations and measures to aid in the realization of Kenya's vision 2030 under universal health coverage. The study will help other researchers to carry out further studies on interventions on, factors in staff performance in data management in the public health sector. The response to these questions will be treated with confidentiality and only used to inform the research study. We will not take your name and /or any of the details that identify you during this interview. The interview may take approximately 25 minutes of your time. You are free to respond/ not to respond to any question you are not willing to respond to and you are free to opt out of the survey at any point you want to. Please note that there are no direct benefits to participating but the information you will provide will help strengthen a sustainable facility well-being info system that is responsive to the needs of the community and the entire population. Useful recommendations and measures to aid in the realization of Kenya's vision 2030 under universal health coverage.

Voluntary Participation and Authorization Participant: Your decision to participate in this study is entirely volunteer. If you decide to not partake in this research, it will not affect the care, services, or benefits to which you are entitled.

Cost: There is no cost for participating in this study. The only cost involved is your time.

I voluntarily agree to participate in this □ Yes □ No

I understand that I will be given a copy of this signed Consent Form.

Name of Participant (print):

Signature: Date:

Name of Witness (print): Signature: Date:

Person Obtaining Agreement: Signature: Date:

Note: A copy of the signed, dated agreement form must be kept by the Major Investigator(s) and a copy must be given to the partaker.

Appendix 7: MKU-ERC Approval

Mount Kenya University

REF: **MKU/ERC/1948**

Date: 21 October 2021

TO: **SARAH MAJALA KAYANDA**

REG: **MPH/2017/74534**

Dear Sir/Madam,

RE: ASSESSMENT OF MAJOR FACTORS INFLUENCING EFFECTIVE STAFF PERFORMANCE IN IMPROVING DATA MANAGEMENT IN SELECTED FACILITIES IN MOMBASA COUNTY, KENYA

This is to inform you that **Mount Kenya University** has reviewed and approved your above research proposal. Your application approval number is **1021.** The approval period is **21/10/2021 - 20/10/2022.**

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 **Mount Kenya University**
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 **Mount Kenya University** within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to **Mount Kenya University** within 72 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal
vii. Submission of an executive summary report within 90 days upon completion of the study to **Mount Kenya University**

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://research-portal.nacosti.go.ke and also obtain other clearances needed.

The Chairman
Mount Kenya University
Ethics Review Committee
P. O. Box 342 - 0100, Thika

Yours sincerely,

Dr. Peter G. Kirira
Chairman, Mount Kenya University IERC

Main Campus, General Kago Road, P.O. Box 342-01000 Thika. Tel: +254 67 2820 000, Cell: +254 720 790 796, 0709 153 000

Appendix 8: NACOSTI Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 115327

Date of Issue: 29/October/2021

RESEARCH LICENSE

This is to Certify that Ms.. SARAH MAJALA KAYANDA of Mount Kenya University, has been licensed to conduct research in Mombasa on the topic: RE: REQUEST FOR APPROVAL FOR ASSESSMENT OF MAJOR FACTORS INFLUENCING EFFECTIVE STAFF PERFORMANCE IN IMPROVING DATA MANAGEMENT IN SELECTED FACILITIES IN MOMBASA COUNTY, KENYA for the period ending : 29/October/2022.

License No: NACOSTI/P/21/13993

115327

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.

Appendix 9: Authorization to Conduct Research in Mombasa County

OFFICE OF THE COUNTY CHIEF OFFICER
MEDICAL SERVICES

Email : cohealthmsa@gmail.com
When replying please quote

P O Box 90441 – 80100
Mzanifu Kombo Street,
MOMBASA

Ref: COH/MSA/RSC/2021/(8)

15th November, 2021

Sarah Kayanda
PPHIM&E
MOMBASA

RE: AUTHORIZATION TO CONDUCT RESEARCH IN MOMBASA COUNTY

We refer to your application letter dated 27th October, 2021 on request for authorization to undertake research project titled ***'Major Factors Influencing Effective Staff Performance in Improving Data Management '*** in Mombasa County.

The proposed study will take place at the following Health Facilities namely:

- Coast General Training and Referral Hospital
- Tudor Sub County Hospital
- Jomvu Model
- Port Reitz Sub County Hospital
- Bokole Health Centre
- Mlaleo Health Centre
- Mrima Maternity Hospital
- Likoni Sub County Hospital
- CGTRH Chaani
- CGTRH Vikwatani
- Shimo Main
- Mvita Health Centre
- Mewa Hospital
- Jocham Hospital
- Bomu Hospital
- KPA
- Mikindani Medical
- Miritini CDF
- Shelly Beach

This office has no objection to your request and hereby approves the study to be done at the mentioned facilities. By a copy of this letter the CEO, Coast General Training & Referral Hospital, all the Medical Superintendents, Sub County Medical Officers of Health are requested to accord you the necessary assistance.

On completion of the study, you are required to disseminate the findings to the County Health Management Team for the recommendations to be considered.

Thank you

DR KHADIJA JOOD SHIKELY, HSC
COUNTY CHIEF OFFICER, MEDICAL SERVICES
COUNTY GOVERNMENT OF MOMBASA.

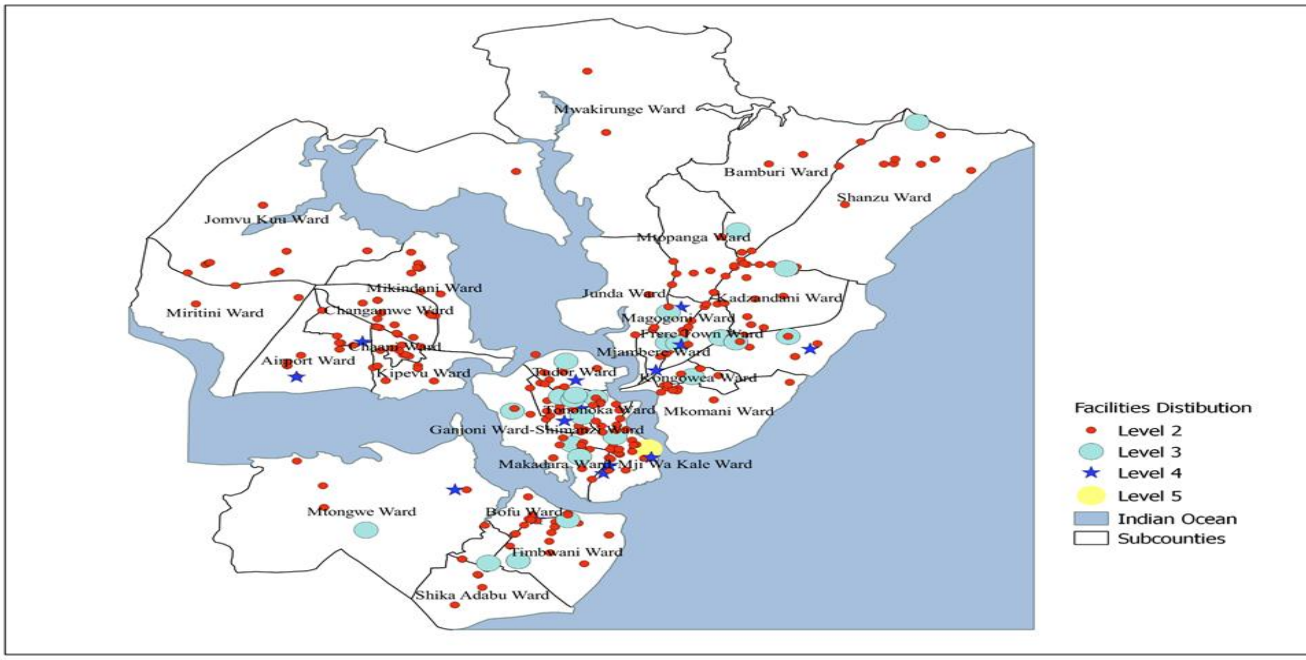
Cc: The CEO – Coast General Teaching & Referral Hospital
All Sub County Medical Officers of Health
All Medical Superintendents

- Port Reitz Sub County Hospital
- Likoni Sub County Hospital
- Mrima Maternity Hospital
- Tudor Sub County Hospital

Hospital Administrators

- Bomu Hospital
- KPA
- Mewa Hospital
- Bomu Hospital
- Mikindani Medical
- Jocham Hospital

Appendix 10: Distribution of Health Facilities in Mombasa County



Appendix 11: Proportionate Distribution of Study Sample

Health Facility	Population	Sample
Bokole Health Center	79	13
Coast General Teaching and Referral Hospital	135	22
Jomvu	104	17
Kaderbhoy Medical Clinic	67	11
Kisauni Health Center	55	9
Likoni Sub-County Hospital	165	27
Mbuta Model Health Center	49	8
Mewa Hospital	61	10
Mikindani Medical Center	73	12
Miritini CDF Dispensary	55	9
Mlaleo Health Center	122	20
Mrima Hospital	226	37
Mvita Clinic	61	10
Portreitz Sub-County Hospital	355	58
Shika Adabu (MCM) Dispensary	92	15
Shelly Beach Hospital	24	4
Shimo la Tewa Health Center	153	25
Tudor Sub-County Hospital	154	25
Ziwa la Ng'ombe Medical Clinic	12	2
Total	**2042**	**334**