UTILIZATION OF ROUTINE HEALTH DATA IN DECISION MAKING BY MANAGEMENT TEAMS IN SELECTED LEVEL 4 HOSPITALS IN NAKURU COUNTY, KENYA

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DECLARATION

This thesis is my original work with no prior presentation for a degree in any other university.

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DEDICATION

This research thesis is dedicated to the hospital managers, my dear husband, my children, and my parents for being my source of inspiration and strength.

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ABBREVIATIONS AND ACRONYMS

DDIU	-	Data demand and information use
DHIS	-	District Health Information System
GOK	-	Government of Kenya
HIS	-	Health Information System
HMIS	-	Health Management Information System
HMT	-	Hospital Management Team
ICT	-	Information and Communication Technology
KEPH	-	Kenya Essential Package for Health
KHSSP	-	Kenya Health Sector Strategic Plan
KQAMH	-	Kenya quality assurance model for health
MEASURE	-	Monitoring and Evaluation to Assess and Use Results
NL5H	-	Nakuru Level 5 Hospital
PRISM	-	Performance of routine information system
RHD	-	Routine Health Data
RDQA	-	Routine Data Quality Assessment
PHC	-	Primary Health Care
RHIS	-	Routine Health Information System
SPSS	-	Statistical Package for the Social Sciences
UHC	-	Universal Health Coverage
WHO	-	World Health Organization

DEFINITION OF OPERATIONAL TERMS

Data management - This is the ability to collect, analyze, interpret, disseminate, and use them in decision-making

Decision making - This is the thought process of selecting a logical/evidence-based choice from available options by use of available quality data

Evidence-based decision-making - This is a proactive, interactive and inquisitive process that considers data during decision-making

Quality data - Data that has been checked for timeliness, correctness, accuracy, consistency, and for completeness and found to be adequate

Utilization of data - This is the retrieval of data either manually or by use of a computer, in order to analyze, interpret, disseminate and use the information in decision making

Routine health data - Data collected on a daily basis by health workers as they go about their duties

Data Demand - The importance of information to decision-makers and stakeholders

Health worker - Any licensed personnel who is in contact with patients as they offer services

Hospital management team - This is a group of people responsible for the functioning and progress of a hospital. Any manager of a unit, department or project and is required to make managerial decisions in their line of work

ABSTRACT

Health data are the relevant information routinely collected in health institutions by health workers. The health population needs can only be identified through data collection, collation and analysis as this provides information that should be used by the hospital management teams (HMT), in prioritizing resource allocation for service delivery, health work force, essential medicines, and governance. In most hospitals, these crucial managerial responsibilities seem to be lacking the support of data use for evidenced decisions, leading to poor service delivery and unnecessary referral of patients, yet the same hospitals, task their health workers with data collection and monthly submission of reports. In light of this, this cross-sectional study, assessed the utilization of routine health data for decision-making by HMTs of the selected level 4 hospitals in Nakuru County; Molo, Subukia, Olenguruone, and Naivasha sub-county hospital. This was achieved by determining the extent of use of the data collected for decision-making, examining data quality and identifying organizational factors influencing the utilization of routine health data in decision-making. The study population was 146 Hospital management team members, selected by use of the census sampling method. The study used three data collection tools; the questionnaire and the interview schedule. An observation checklist was used to identify the presence or absence of list of items representing quality data and evidence of data. A pre-test was conducted on a group of 15 hospital management team members (10% of the sample size) from the Langa-Langa sub-county hospital. A Cronbach reliability coefficient of 0.72 was achieved for each of the constructs and thus considered reliable. Analysis for Descriptive and inferential statistics was done by utilizing Statistical Package for the Social Sciences (SPSS) version 25. The study found that Nakuru county had an average data utilization index of 62.9%, good use and that the accuracy of data collected, as well as the use of registers as a data collection tool were significantly associated with the use of Health data at a p-value of 0.025 and 0.043 respectively. The study recommended that the CHMT and HMT train, mentor, and empower health managers and all health workers on data management, data integration in policy development, standardize data collecting tools and data use through SOPs for all health facilities, develop a data quality assessment tool and provide support towards evidence-based interventions.

CHAPTER ONE: INTRODUCTION

1.1 Background of the study

Decision-making depends on data, which also serves as the foundation for accountability. Health data are the relevant information routinely collected in health institutions in an ongoing manner. In Kenya, data is managed by the District Health Information System 2 (DHIS 2) a web-based software development project by the Health Information System (HIS) program. The health information system is divided into five phases i.e. Information generation which is the type of data collected, tools for data collection and storage; Information validation, the process of improving accuracy and representativeness; and The information analysis which requires one to understand the information one collects; Information broadcasting, the process of its sharing and the last and most important is information utilization in decision making.(Dehnavieh et al,2019)

According to Goodarzi et al,2021, Providing the right information at the right time about the right things becomes nearly impossible in the absence of high-quality data, making it difficult to design, monitor, and evaluate effective policies. The disparities in access to and utilization of data and information were seen to be enormous and continued to grow. Too frequently, data that could be used for decision-making was not made available because they were not well-documented and harmonized, were released too late, or were missing the level of details required. The fact of decision-making is that routine health data is indispensable in assessing the performance and impact of various health programs and interventions in health care.

Hospital Management teams, which comprise medical superintendents, Hospital administrators, hospital accounts, procurement, and all departmental heads are

mandated to expeditiously utilize the Hospital management services funds as per the Facilities Improvement Financing Bill, 2023; and are expected to use statistical information to evaluate the efficacy of existing healthcare initiatives, ensuring that resources are directed towards interventions with proven positive outcomes (Kuyo, 2019). By tracking patient outcomes, adherence to treatment protocols, and preventive measures, hospitals refined their strategies for better patient care and community health. In addition to internal decision-making, routine health data was crucial for reporting and compliance with regulatory requirements. This not only ensured transparency but also fostered trust among the community and regulatory bodies. Financial planning and budget allocation also benefited significantly from routine health data. By analyzing cost, data associated with different healthcare services and interventions, management teams were able to make informed decisions on budget priorities (Tulu et al, 2021).

On a global scale, data was seen to aid in containing new risks to global health, it quantified the burden of illness and tracked health improvement. According to the SCORE global report (2020),133 countries with HIS were assessed for data use and management,43% had a moderately developed HMIS, while only 5% showed a capacity to sustain. On data use, only 60% of the countries had a well-developed capacity to use data and evidence for policy and planning.75% of those were the high-income countries, leaving out the low-income countries. In the same report published under World Banks' Development Data(2022), Sub-Saharan Africa was noted to rate lowest at 51% in the world banks' statistical performance indicators, which measured data use, data services data sources, and data infrastructure. North America was the highest at 88% followed by Europe and Central Asia at 79%. This was below the recommended 95%.

According to Kawakyu et al, (2023), The efficacy and effectiveness of any hospital were attributed to a good management system while the opposite was true. The management and organization of hospitals were found to be critical components in ensuring the effective delivery of healthcare services. Hospital administrators oversaw various aspects of hospital operations, from financial management and resource allocation to quality improvement and patient safety, and thus were required to make decisions that held consequences for the health outcomes of individuals and communities.

Health data has a unique role in strengthening the other five building blocks of health systems. In this regard, the PRISM analytical framework of health information system performance identified three main determinants of the use of health information: the technical aspects of data processes and tools, the behavior of individuals who produce and/or use data, and the system/organizational context that supports data collection, availability, and use. (Measure Evaluation,2019). This study focused on the demographic data of the data users, the data processes and tools used for data collection, as well as the organizational factors that influenced data use in decision-making.

According to WHO,2022, although data collected in health facilities was not a complete representation of the entire community it served, where reporting rates were high, facility utilization rates should be higher than 95%, which was rarely the case. In concurrence with the above information, several studies showed a very low rate of RHD use e.g. in Uganda (59%), Tanzania (58%), South Africa, (65%), and Cote D'Ivoire, (38%). (Mekonnen,2021), or lack of data use in decision-making. A similar study by Otieno et al, (2020) indicated that decision-making was done by the higher

bodies which didn't involve the health management information system. Therefore, the first objective of this study sought to determine the extent to which routine health data was used for decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

The second objective of the study was to examine data quality factors. A study done in Myanmar; Asia, by Hlaing and Myint (2022) on factors affecting data quality revealed that the HMIS did not deliver accurate and reliable data and was often questioned regarding its accuracy, consistency, representativeness, and completeness. Sebsie,(2021) also asserted that sufficiently complete and accurate data from all dataset reports was very crucial and useful for decision-making and lack of it thereof affected the quality of decisions made. These findings informed the need to examine the factors that influenced data use for decision-making by hospital managers.

In a study done in Ethiopia on Routine health information utilization and associated factors among health care workers, Mekonnen (2021) asserted that organizational characteristics, specifically the variables of resources, leadership, and organizational structure, had a statistically significant effect on data use and performance. For example, strong leadership, regular feedback. availability of standard guidelines on data management and training on health information had an association with the utilization of routine health information. In addition to these organizational characteristics, this study sought to identify organizational factors influencing the utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

The WHO and the Institute for Health Metrics and Evaluation stated that to improve the accuracy and utility of health information for decision-making, the commitment

levels of healthcare providers and managers were the basis and steps towards improving the quality of health service which was but a mandatory step on the path to reaching the sustainable development goals and universal health coverage. (Gisemba et al, 2022).

1.2 Problem statement

With the introduction of UHC (Universal health coverage) and its target for 2022-2030, the need to have an efficient healthcare service delivery at different levels of service provision was heightened. More pressure and attention was directed toward institutions that offer primary health care such as level 4 hospitals. The Hospital management teams responsible for running these hospitals, were then expected to deliver high quality and affordable services for a rising sum of patients by use of data, since the current and future health care requires evidence in order to justify action. Since the inception of devolution, no evaluation had been done to assess the success or shortcomings of the HMIS initiative to consolidate data for easy access and use.

A Nakuru health taskforce report (2017-2018), on four level 4 hospitals showed that clients often bypassed available services or were referred to seek similar services at higher levels of service care. This was due to perceived or existing low-quality services offered at lower levels of health care. The inability of the level 4 hospitals to manage health concerns, led to an influx of patients in higher levels of health care and caused an increase in preventable mortalities and morbidities. The county referral hospital also called Nakuru level 5 hospital (NL5H) had a bed capacity of 784 with an average total occupancy of 87%. Hospital records showed some overwhelmed departments such as surgical ward at 111% occupancy, Orthopedic wards at 95% and Medical wards at 108% occupancy. Referrals were at an average of 55 patients per

month and mortalities at an average of 35 deaths per month. The most common cause of deaths as of 2021 analysis was pneumonia, which could have been managed at level 4 on early detection. (PGH,2021)

With all the resources invested on data management, (Approximately 9 million as of 2018-2019 and 11 million estimated for 2023-2024 HMIS budget) it was not known how and whether the Hospital management teams utilized their facility data in decision making. According to WHO 2022 general principles of RHD use, the facilities data utilization rates should be higher than 95%, however this was noted to be a very rare occurrence. Failure to assess and evaluate information use, RHIS cannot be said to improve evidenced decision-making. This study, therefore, sought to assess the utilization of routine health data in decision-making by hospital management teams in selected level 4 hospitals in Nakuru County, Kenya.

1.3 Justification

The HMTs are responsible in the running of the facilities, ensuring quality health services and collecting revenue to guide in resource allocation. Through accurate data use, the workforce is equipped with the necessary materials, supplies, infrastructure, resources, and policies to deliver services (Kuyo,2019).

In 2015, Nakuru County was affected by the Cholera outbreak which killed 11 people out of 65 countrywide, while in April 2016, it was hit by the Influenza outbreak which claimed the lives of 39 children together with the neighboring counties. Most of these cases were referred to NL5H because the sub-county hospitals could not contain the epidemic causing overstretching of the services and resources in the referral hospital, which eventually affected the quality of care offered. Early detection of these crises at the community level would have been crucial in mitigating the losses if routinely

collected data were properly utilized by the stakeholders at their respective levels for planning and management.

In 2017, the CeC Health Nakuru County, appointed a health infrastructure committee to assess seven hospitals on their capacity to deliver services, amongst them were the four level 4 hospitals, picked for the study, namely Naivasha sub-county hospital, Molo sub-county, Olenguruone sub-county and Subukia sub-county hospital. Their recommendations touched on poor health indicators, lack of basic infrastructure and equipment that led to unnecessary referrals, and dysfunctional HMIS systems amongst others. The selected facilities also covered the highest workload serving a large population. Molo- 236,786, Naivasha- 385,864, Subukia- 170,191, and Olenguruone- 259,286 people.

This incapacitation of health facilities led to increased mortalities in the last five years. According to a Nakuru County Statistical Abstract, 2022, in the year 2017 there were 8,966 reported deaths 4,259 of which occurred in health facilities, in 2018 there were 9761 deaths, with 5,750 occurring in health facilities,2019 had 9,009 deaths with 4919 occurring in health facilities, in 2020, 9696 deaths were registered,5378 of which occurred in health facilities and 2021 12,476 deaths were registered with 6,054 deaths occurring in health facilities. This showed an annual mortality rate increment of 6.8% of deaths occurring in health facilities in Nakuru County between the years 2017 to 2021. This trend was similar to a study done by Bastani et al,2022, that showed Poor data management practices were the reasons for recurrent errors and associated injuries or death in health facilities.

Despite the efforts directed at the improvement of health management and information systems, the peripheral health systems still suffered from inadequate data

quality and use causing a lack of evaluation for health targets, a major failure in linking evidence to decisions which evidently led to irreversible consequences.

1.4 Research Questions

1. To what extent is routine health data utilized for decision-making by management teams in selected level 4 hospitals Nakuru County, Kenya?
2. What are the socio-demographic factors influencing utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya?
3. What are the data quality factors influencing utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya?
4. What organizational factors influence utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya?

1.5 Objectives

1.5.1 Broad Objective

To evaluate the utilization of routine health data in decision-making by Hospital management teams in selected level 4 hospitals in Nakuru County.

1.5.2 Specific objectives

1. To determine the extent of routine health data use for decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

2. To identify Socio-demographic factors influencing the use of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

3. To examine data quality factors influencing the use of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

4. To identify organizational factors influencing the use of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

1.6 Significance and Anticipated Output

The Kenyan government decentralized the decision-making process to the point of data collection. Nevertheless, it had not been evaluated whether this initiative by the government had succeeded. This study was therefore significant in that, it assessed the intensity of data use for decision-making by Hospital management teams in Nakuru county and thus could act as a reference for informing the county government, through the CHMT on the status of the national government's initiative in data management and the capacity of the hospital managers in sub-county hospitals in data management for appropriate intervention. The findings could also act as a spring of literature for researchers to do auxiliary studies about routine data consumption for decision-making at points of data collection.

1.7 Delimitation and Limitation

1.7.1 Delimitation

The study evaluated routine health data utilization by Hospital management teams only in Naivasha, Molo, Olenguruone and Subukia level 4 hospitals. The findings of the study were therefore limited to Nakuru County. Nevertheless, since the endeavor of the study was to assess the use of data at a devolved point, lack of representativeness did not interfere with the intended goal of the study.

1.7.2 Limitation

The researcher did not have control over prevarication by the Hospital management team members. Nevertheless, efforts were made to link information provided by study participants with available documented evidence.

1.8 Conceptual framework

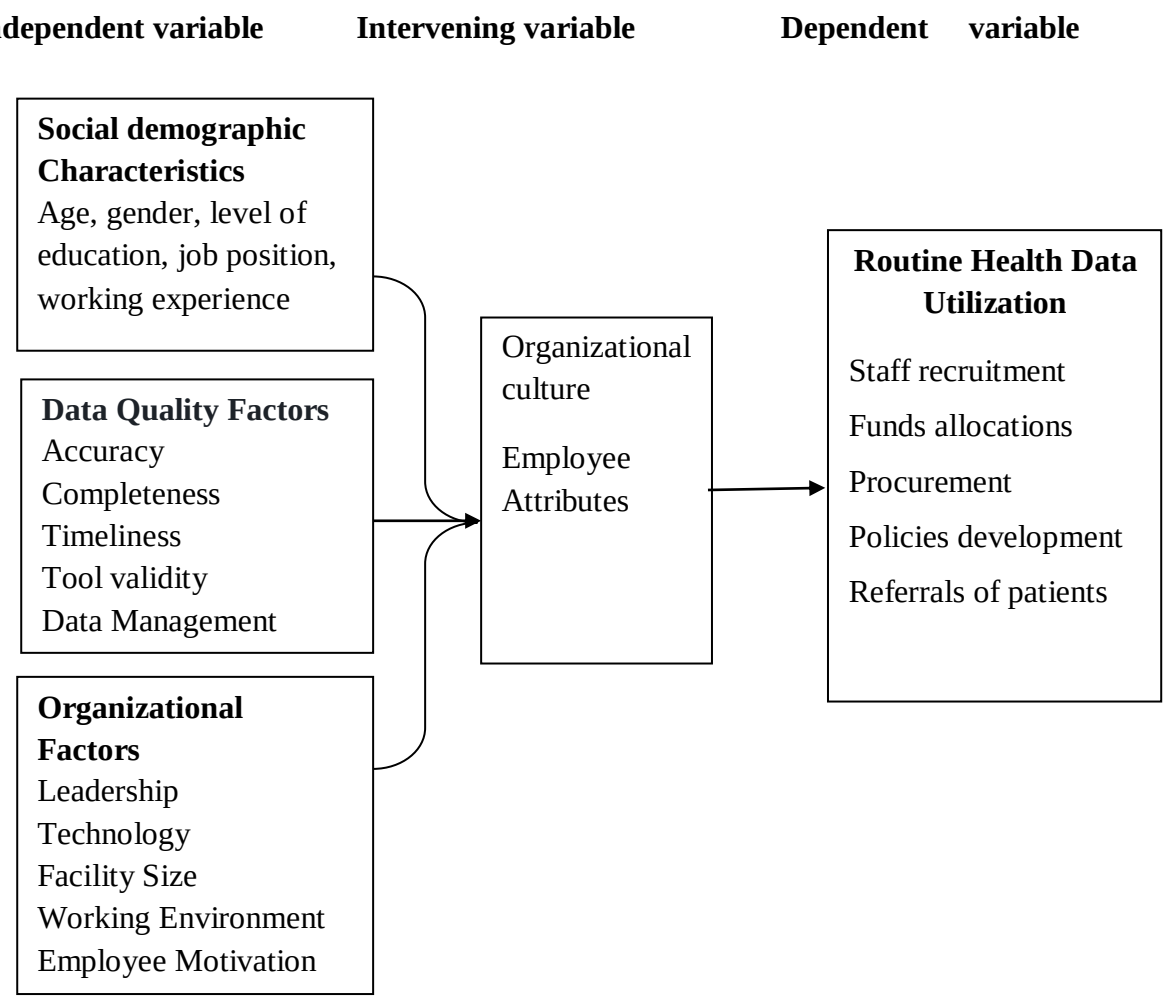

Figure 1.1: Conceptual Framework of the Study

Source: Adapted from measure evaluation, 2010

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents reviewed literature for variables conceptualized in the research study. The sections began by describing the routine data management system and the discussion was derived from the study objectives i.e. Extent of RHD use among the HMT members in Level 4 hospitals and Socio-demographic factors, data quality factors, and organization factors that influenced RHD use in the decision-making. Further, the section was concluded by a summary of the literature review.

2.2 Routine Information Management System

The world health organization refers to health information management system (HMIS) as a continuous integrated effort in gathering, processing, reporting and using health information to persuade policy making, programmed action and research. An effectual and integrated HMIS was described as a fundamental approach in upgrading the quality of health service delivery and improving health outcomes as it was considered the principal source of timely data and a channel for information exchange for evidence-based planning and decision-making.

2.3 Extent of Routine Health Data Use

In a bid to advance accessibility and affordability of health care to local communities, the government of Kenya through KEPH organized public hospital service provision in levels with specific type of services and referral systems as stated by the MOH. (KHSSP III). In this study, the level of interest was level 4 hospitals, previously known as district hospitals and currently referred to as sub-county facilities which are the primary health care facilities, as they are meant, and are equipped to deal with preventive, promotive, curative and rehabilitative services. The question of the study

was; do the decision makers in these PHC facilities utilize data in deciding on the management of the service delivery and various activities performed in a hospital?

The challenge of data use is not only confined in Kenya, according to WHO Development Data Document 2022, Sub-Saharan Africa was noted to rate the lowest at 51% in the world banks' statistical performance indicators. Health systems managers in developing countries including Kenya were seen to shy away from data use due to various challenges. A study done by Ayele et al,2024 rated Kenyan data use at an average of 48.1%. while another study done by Zenebe et al., 2023, showed Ethiopia to have performed relatively well with 78% rate of data utilization as compared to other poorly performing countries i.e. 42% data use in Tanzania, 59% in Uganda, Liberia at 58% and 65% in South Africa. This was below the recommended 95% (WHO,2022). On the specific areas of data use in health facilities, a study done in North Gondor zone, Ethiopia, with sample size of 720 was used, 90.1% of the respondents reported using data for disease monitoring, 85% on pharmaceutical procurement, 89.6% on monitoring health activities, 92.6% on scrutinizing data quality, 86.7% in allotment, on planning 89%, on department performance evaluation 88%, 86.5% on personnel performance appraisal and 87.1% for community mobilization (Dagnew et al., 2018).

In the Kenyan context, several studies had been done in different counties. A study done by Karijo,(2021) in Kitui County, showed 34% of the health managers used data to guide decisions while 66% (73/110) health care managers did not. On various areas of decision-making, 46% used data on daily program management, 37% for medical supply and drug management, 51% in the formulation of patient care, 31% of the participants reported use of data on financial statements, 35% for budget allocation,

33% in management of human resource, 40% in key health objectives monitoring and policies and 70% for identifying emerging epidemics.

A similar study done in Coast General Hospital, Kenya by Mboro (2017) indicated the use of data by the hospital managers as slightly above average at 69.6%. In the areas of the study, those who used data in the management of supply and drugs were 74%, gaps identification with the aim of training at 72%, Resource mobilization was 66%, Staffing decisions at 60%, and service delivery improvement at 67%. At Gucha Sub-county in Kisii county, a study done by Obwocha et al 2016, indicated data/information utilization rate at only 30% leading to inadequate resource distribution. In Nairobi County, the estimated data use in making decisions was at 60% with Kenyatta National Hospital reporting that only 53.6% of nurses utilized research findings in practice while 70.5% based their decision-making on knowledge achieved during nursing school training (Gathua,2016).

Contemporary healthcare practices require evidence to justify action in meeting the varying needs of health. Health managers, therefore, need to shift from conventional practices to evidenced decision-making.

2.4 Socio-demographic factors influencing data use

As the use of technology in health care increases, it is essential to identify socio-demographic characteristics such as age, gender, level of education, and position in health care management members, that may hinder one from utilizing data for decision-making. Some studies showed that the introduction of HMIS web-based software may scare elderly managers and favor young managers in health care. In line with this, this study sought to identify socio-demographic factors that had potential to

influence RHD use for decision-making among the managers of level 4 hospitals in Nakuru county.

In a study done in Kitui county, Kenya by Karijo 2021, some of the sociodemographic data assessed were profession or the cadre and level of education where both were found to have a statistical significance to data use at a p-value of 0.002, and Gender at a p-value of 0.007 agreeing with a study by Lancet Global Health 2021 where the female gender was seen to be pro-active in data use as compared to male gender as according to research. A similar study was done by Dagne & Melaku 2020 on factors affecting research data utilization among nurses and midwives indicated that nurses' level of education had no clear relation on the utilization of research on health data as the major barriers on data utilization were attitude, insufficient time and inability to understand statistical terms used in research articles.

Several other studies concurred with consideration of the socio-demographic factors in the influence of data use for decision-making. According to Morike et al.(2023), a study done in Kisumu County showed a statistically significant association between level of education p=0.0001 and routine data use for decision-making since the majority of the participants with a postgraduate level of education reported using routine data for decision-making more often compared to undergraduates. However, the study differed from the previous study in that the gender of the health worker (p= 0.056) and job experience (p=0.703) were found to have no statistical relationship to the use of routine data for decision-making

On age as a social demographic factor, Negera, et al. (2023) in a study done in LLu Abar Bor Zone, Oromia region, Ethiopia'' stated that, Health workers under the age of 30 were approximately 60% less likely to use routine health data for decision

making than those over the age of 30 years. The researcher further explained that the variation was because health workers under 30 years old were typically beginners who lacked adequate skills, training, support supervision, and feedback related to the use of routine data in health matters decision-making.

2.5 Data quality factors influencing data use

The quality of data is a varied paradigm, which includes numerous dimensions, such as: accuracy, consistency, totality, timeliness and integrity. Ibrahim and Satar (2021) discussed data quality in four ways: aptness or relevance entirety, timely and accuracy where relevance is the comparison of data collected against its capacity in managing information needs and entirety is evaluated not simply by completing all of the data fields on the report form used in data collection, but also as the number of facilities reporting in a region and the type of data reported. Realizing quality data therefore is not a simple task and it was exacerbated by lack of well-trained personnel and lack of clear rules and standards to guide creation of information for decision-making.

According to SCORE,2020, a global report on health data systems and capacity, the finding indicated that, out of the 133 global countries evaluated,42% had no documentation on quality checks for the health facility data,39% had partial documentation and only 19% had comprehensive documentation on the quality of data. Indeed, in many countries in sub-Saharan Africa, data quality monitoring remained a challenge in ensuring data quality for meaningful interpretation (Shama et al., 2021).

A complete data set provided a comprehensive view of patient health, facilitating thorough analysis and enabling healthcare practitioners to consider all relevant factors when making diagnoses or treatment plans. A study done in Ethiopia, by Getachew et

al. (2022) on data quality and associated factors at health centers revealed that the district's data quality scores fell short of 90% in all categories, including timeliness, content completeness, and accuracy. It was discovered that factors affecting data quality included lack of supportive supervision, inaccuracy incomplete, registrations, and lack of confidence. Therefore, in achieving high-quality data for the decision-making process, all stakeholders were expected to provide the necessary support to improve data quality in routine health information systems.

In most hospitals in Kenya, the nurses were tasked with the responsibility of entering clinical data into prefabricated tally sheets. More often, they were overwhelmed by their demanding clinical duties and disregarded the tally sheet which then went unfilled, and this contributed to incompleteness. The data collected by untrained and busy individuals is usually poor and deficient, making it inaccurate thus affecting the decision maker’s confidence in the use of data and consequently the data management. A study done in Uasin Gichu County referral hospital by Cheburet, (2016), indicated 70% (57/82) of the data collectors were nurses and 30% (25/82) were accounts staff. 51 respondents of the same study (63%) said that the data producers were not trained while 37% said the data producers were trained. In Tharaka-Nithi County, the trend was similar with 95.2% of the respondents, who reported that casual laborers were the major data collectors in the hospitals and that they lacked computers, and were also untrained on data collection (Mucee, 2016).

According to WHO, (2022), weaknesses to data quality were distinctive to systems that depended on paper transmission, manual aggregation, and analysis of data. Wamae,(2015) stated that Kenya had 66% of its health data tools being paper-based, most of which had been developed by specific programs for their project

management, and yet they were used in other sectors without customization. Paper based data management technique is fraught with storage and retrieval problems which eventually led to inaccurate and incomplete data. In Tharaka-Nithi County, in a study done on data use determinants, the respondents complained that they collected data on paper first and then transferred it to an electronic system while 34% of the data was captured only on paper. (Mucee,2016). Paper-based data collection posed another challenge due to the proliferation of inadequate data collection. In Coast General Hospital, the respondents rated the quality of data as; 48.7% poor on timeliness, 47% poor on accuracy, and 42.8% poor on completeness (Mboro, 2017).

Relevant and timely data, births accurate decisions, and in the same breath, irrelevant data delivers irrelevant information, which adds to a confused decision-making process. Therefore, it is vital that managers are attentive to what they require, how to attain it and to capitalize on quality of data generated in their facilities to boost user confidence, in order to make informed decisions.

2.6 Organizational factors influencing use of data

According to the Kenya Health Information System (HIS) policy, a decentralized system introduced by the Ministry of Health (MOH) was to be used by all health institutions and emphasized on consumption of data at the point of collection. Such decentralization increased freedom of decision and responsibility of actions taken at each point of care, consequently, demand for more skills was heightened for the decision makers and hospital managers concerning data handling and use to support decisions taken at all levels of a health care system (Nilashi, 2019).

Otieno and Kawila (2020) described decision-making as having three elements, i.e. Data, questions, and stakeholders, whereby without all these components one would

fail to make evidence-based decisions. The organization/institution was the stakeholder as it had an interest in the decisions being made by its managers. However, there existed a conflict between data users (considered as the decision makers) and data producers (considered as the data collectors). For instance, the data users felt that data producers lacked responsiveness to health priorities and data producers felt that data users were unprepared to measure or evaluate the consequences of their decisions. In the presence of these disagreements, the information fails to reach decision-makers in time.

According to SCORE, 2020, only 50% of the countries had a well-developed institutional capacity for data management and only 42% of the countries had a strong national Health management system. Similar factors were noted in a study done in Bangladesh by Hossain et al. (2019) which revealed that the organizational, technical, and behavioral traits of healthcare providers influenced how often they used health information. Some of the factors seen to frequently influence routine health information utilization were analysis abilities, a lack of data demand and use culture, oversight and frequent feedback, organizational structure and HMIS training, knowledge, workload, computer proficiency, computer access, availability of HMIS guidelines, formats and human resource availability. A study in Ethiopia conquered with the factors mentioned and emphasized on the organization factor as the most common in influencing data use. (Tulu et al., 2021)

Organizational challenges noted in different health facilities in Kenya were, lack of feedback on data use as seen in a study done by Mumo (2023) in Makueni County where the county feedback on data use was at 94%, lack of support from the management, for instance in Tharaka-Nithi County, Mucee (2016) reported of 38/41

respondents in a study to have indicated lack of support of staff training, 39 (95.1%) stated lack of supportive supervision and 40 (97.6%) indicated low information culture with no attempts to improve it. In Malindi sub-County hospital, the respondents appreciated the provision of policies and guidelines on data use at 96% with only 55% acknowledging feedback from their managers regarding quality of data collected and its consumption. The availability of tools for data collection was at 58.8%, supportive supervision was seen to be low at 44.4% and even lower was the hospital funding of the HMIS activities which was at 7.2% (Chorongo, 2016).

This was similar to a study done by WHO, (2022) that indicated HMIS received just a little amount of funding. Yet, according to The Abuja declaration, it was agreed that HMIS was to be allocated 15%. Lack of funds led to task shifting where hospitals address the deficits by using nurses and other health care workers instead of records officers to take the initiative in collecting and arranging data. On the level of motivation, in Coast general hospital, 129 (55.1%) of the respondents said the motivation was moderate with 12 (5.1%) reporting it as high and 32 (13.7%) as low. In a focused discussion, one of the respondents pointed out that they (data producers and users) were frustrated with a lot of paper work yet there was no feedback and appreciation from the authority (Mboro, 2017). In a similar study done by Dagnew et al. (2018), in North West Ethiopia, the health workers and managers of the public health facilities that participated in the study demonstrated positive belief in RHIS use at 337 of the 720 respondents and 228 had negative belief towards RHIS use. On custom or culture of data use, 135 respondents said it was good while 430 respondents felt the culture of data use was poor, on value placed on RHIS use, 90 respondents said it was good while 475 respondents said it was poor.

Some of the possible interventions by institutional management to improve data use as mentioned by the respondents in the Coast General Hospital through a study by Mboro (2017), were training and mentorship of the data producers and users to enhance the confidence of use (33.2%), regular feedback and information sharing to encourage assessment of progress for improvement or reward (20.7%), systems automation to move from paper based which was time-consuming to computer-based for ease in analysis and retrieval after storage (13.3%), availing equipment and data collecting tools (9.4%) and hiring of HRIO for data management.

2.7 Summary of literature review

The utilization of data to inform decisions in our facilities was seen to be essential because it guided the management and evaluation of health programs. However, findings showed that on average only 37% of healthcare managers used data while 66% failed to use data in decision-making. Some of the reasons highlighted as influencing data use were poor data quality and various organizational challenges in supporting data management. With the above challenges compromising the use of data, there was the need for prompt and timely assessment of the level of data usage and the factors that hindered data use for appropriate intervention.

CHAPTER THREE: MATERIALS AND METHODS

3.1 Introduction

This chapter presents the methodology which is the blueprint that was utilized in undertaking the study. The sub-sections include research design, location of the study, study variables, study population, sample size and sampling techniques, research instruments, pre-test, validity and reliability, data collection techniques, data analysis, logistical and ethical considerations.

3.2 Research Design

This study employed cross-sectional study design as it could be used in both Analytical and Descriptive studies. The cross-sectional study design was appropriate since it enabled the researcher to capture both quantitative data as collected by the use of a questionnaire and qualitative data as collected by the use of a key informant interview, at one given point in time.

3.3 Variables

The independent variables of the study were Socio-demographic factors, data quality factors, and organizational factors. Demographic factors were measured by age, gender, level of education, job position, and working experience. The data quality factors were measured in terms of data accuracy, its completeness and timeliness among others. Organizational factors were measured in terms of human resource support (training, supervision, motivation), resource allocation, infrastructural support, services offered, data collection tools available, number of patients attended, years of existence and leadership style among others. The dependent variable was the extent of routine health data use in decision-making for patient care, staff recruitment, revenue appropriation, ordering commodities and supplies, monthly planning, policy and projects, patient referrals, and performance monitoring.

3.4 Location of the Study

The study was undertaken in Nakuru county one of the 47 counties in Kenya and the fourth largest cities. Nakuru County lies within the central parts of Kenya's Great Rift Valley and covers an area of approximately 7,504.9 Km². Its coordinates are latitude**:** 0° 29' 59.99" N and Longitude**:** 36° 00' 0.00" E. Nakuru County borders eight Counties, namely; Laikipia to the North-East, Kericho to the West, Narok to the South-West, Kajiado and Kiambu to the South-East, Baringo to the North, Nyandarua to the East and Bomet to the West.

The cosmopolitan County covererd an area of 7,504.9 Km² and an estimated population of 2.35 million people as of 2023. The County was divided into 11 Sub-counties/constituencies and 55 Wards and is headquartered in Nakuru City. The major economic activities in the County included Agriculture, forestry, and fishing. The county had 221 health facilities 15 of which were level 4 hospitals most of which were named after their respective constituency. These hospitals offered primary health care services to patients and coordinated referrals from level three and two health facilities to Nakuru level five hospital situated a few meters from Nakuru town.

The four-level 4 hospitals targeted by the study were Olenguruone Hospital in Kuresoi North sub-county located 83km North of Nakuru town Subukia Hospital in Subukia sub county located 38km East of Nakuru town, Molo Hospital in Molo Sub-county located 43 km west of Nakuru town and Naivasha hospital in Naivasha sub-county located in North West of Nakuru town. (Nakuru County Integrated Development Plan 2023-2027)

3.5 Study Population

The target population of the study was 156 hospital management team members in Subukia, Molo, Naivasha and Olenguruone sub-county (Level 4) hospitals. The hospital management team members comprised of 4 medical superintendents and deputies, 4 hospital administrators, 4 nursing officer in-charges, 4 hospital accountants, 4 health records department in-charges, 4 procurement department in-charges, 4 human resource officers, 4 Laboratory department in-charges, 4 radiology department in-charges, 4 pharmacy department in-charges, 4 physiotherapy department in-charges, 56 head clinical departments and 56 ward in-charges. Out of the 156t target population, 146 of the hospital management team members were respondents of the study while among them 10 of the hospital management team members were key informants (Medical Superintendents, Hospital Administrators and Health Records Department In-charges).

3.6 Sample Size and Sampling Technique.

A purposive sampling technique was used to select the hospitals in the study. This was guided by the fact that the seven hospitals were the major health facilities in Nakuru County and had been earmarked for upgrade. The seven hospitals were clustered according to their level of service delivery i.e. tertiary (level VI) referral services units, Secondary (level V) referral service units, Primary (level IV) referral service units, primary care service units (Health centers, level- III), (Dispensaries-level II) and community units (level I). The recommendations in the county health infrastructure report were considered in picking the hospital for progress evaluation.

Table 3.1: Nakuru Health Task Force Report 2017-2018

Hospitals earmarked for upgrading	Hospital level	Recommendations given
Nakuru County Referral Hospital	Level V	Upgrade to level 6
Naivasha sub-county referral hospital	Level IV	Upgrade to level 5
Molo sub-county hospital	Level IV	Improve the quality of services
Olenguruone sub-county hospital	Level IV	Improve the quality of services
Gilgil sub-county hospital	Level III	Improve on infrastructure to be considered for level 4
Subukia sub-county hospital	Level IV	Improve the quality of services
Bahati sub-county hospital	Level III	Improve on infrastructure to be considered for level 4

The study sampled the study population using census sampling. Census sampling refers to the complete enumeration of the target population in the study. This approach ensured minimum sampling error and improved the generalizability of the study findings to the target population. The sample was proportionately distributed across the four selected level 4 hospitals in Nakuru County. Proportional distribution ensured that there was no selection bias and there was a proportional representation of study subjects as they appeared in the target population (Creswell, 2014). Table 3.1 shows the sample distribution in the four selected hospitals in Nakuru County.

Table 3.2: Sample Distribution

Target Hospitals	Number of HMT members	percentage
Naivasha level 4 hospital	53	34%
Molo level 4 hospital	31	20%
Olenguruone level 4 hospital	42	27%
Subukia Level 4 Hospital	30	20%
TOTAL	156	100%

3.7 Research instruments

Three data collection tools were used: a questionnaire and an interview schedule. The questionnaire was divided into four sections. The first section entailed the background information of the respondents, the second section collected data on the extent of use of routine health data, the third section collected data on the data quality factors and the last section focused on organizational factors. Key informant interviews were used to provide the views and opinions of the managers (Medical Superintendents, Hospital Administrators, and Health Records Department in charge). An observation checklist was used to identify the presence or absence of the list of items representing quality data and evidence of data. The observation checklist was in the form of structured questions that led to the submission of the evidence being assessed and ensured that all relevant aspects were considered and recorded.

3.8 Pre-Test Study

A pre-test was conducted on a group of 15 hospital management team members from Langa-Langa Hospital since it had relatable characteristics to the hospitals in the study. The process helped to evaluate the reliability and validity of the questionnaire and established the suitability of the instrument. Adjustments were made to rectify any errors or ambiguities noted in the questionnaire during the pre-test.

3.9 Validity

Construct and content validity of the instruments were measured by experts in data management from the HMIS county offices to assess whether they considered the instrument to measure what it was purposed to measure and whether it was representative of all aspects of the subject on data use. The recommended changes were effected before the study.

3.10 Reliability

Cronbach's alpha was employed to measure internal consistency of the questionnaires across items within a construct. A Cronbach reliability coefficient of 0.72 was achieved for each of the construct and thus considered reliable.

3.11 Data Collecting Technique

The study and data collection were permitted by NACOSTI and additional authorization from the four selected hospitals. The researcher applied a drop-and-pick method of administration where the researcher issued the questionnaires to the respondents and collected them after one week. Interviews for the key informants were scheduled and carried out on the appointed dates. The responses from the interviews were noted down in a systematic narrative form. The researcher identified the presence or absence of items representing quality data and evidence of data and marked it accordingly on the observation checklist.

3.12. Data Analysis

The completed questionnaires were first edited for completeness and consistency. Quantitative data collected was analyzed using Statistical Package for the Social Sciences (SPSS) version 25 through means, standard deviations, and frequencies. The data was split down into different aspects of strategy implementation. This offered a

systematic and qualitative aspect of the study objectives. Qualitative data was analyzed using the content analysis method and classification of qualitative data was done to generate homogenous groups/thematic areas.

To accommodate the majority of the quantitative data collected using a Likert scale, necessary data transformation was conducted to ensure compatibility with analysis in SPSS. Initially, responses within the scale were assigned numerical values corresponding to the strength of the response. For example, "strongly agree" was assigned the highest score of 5, followed by "agree" with 4, "neutral" with 3, "disagree" with 2, and "strongly disagree" with 1. By utilizing these numerical codes, the data became conducive to quantitative and regression analysis methods, facilitating a more streamlined and comprehensive examination of the collected data within SPSS.

The dependent variable was assessed with the help of fifteen questions. By summing together respondents' ratings for each item (which ranged from 1 to 5) and dividing the result by the total number of respondents, the mean score for health management teams' extent of data utilization was determined. The health management team was labeled as making good use of routine health data for decision-making if it scored above or equal to the mean value of the Likert scale questions (> 47.43%), while the health management team was labeled as making poor use of routine health data for decision making if it scored below the mean value of the Likert scale questions.

According to a study done by Kawakyu et al. (2023). testing the association of “data use” with data use determinants commonly transformed the data use measure into a binary variable (e.g., good/poor data use). Mean or median values were commonly used as the cut-off for defining binary variables. Studies were done in Ethiopia by

Dagnew et al. (2018) and Shiferaw et al. (2017) and had a 5-point agreement Likert scale for the measure of data use and any score above the mean was labeled as good data use to practice and any score equal to or below the mean was labeled a poor data use practice.

This method was also used in a study done by Ayele et al,2024 where 269(65.6%) of the respondents had a good utilization of routine health data since they scored above the mean value. This same method of determining the level of good or poor use was also in a study by Endriyas (2020), where the researcher labeled good data use as 75% and above, Fair data use as 50%-74%, and poor data use was below 50%.

The information was presented using bar charts, graphs and pie charts and in narrative form. Using the Pearson correlation technique and bivariate analysis, each of the independent variables was correlated with the dependent variable to determine which of the variables had the most significant relationship. The qualitative data was transcribed, analyzed thematically, and presented in narrative form.

3.13 Logistical and Ethical Consideration

The National Commission for Science, Technology, and Innovation (NACOSTI) granted the research authorization after receiving ethical clearance from the Kenyatta University Ethical Review Committee (K.U.E.R.C.) and approval to conduct the study from the graduate school at Kenyatta University. The county health and education administration as well as the appropriate medical superintendent of the hospitals were consulted for consent to conduct the research in Nakuru County; Naivasha, Subukia, Olenguruone, and Molo sub-county hospitals (Level 4 hospitals). Those who qualified for participation did so voluntarily. To enable their informed consent, the eligible participants were told of the study's goals and methodology and

instead of using the respondents' names, coding was used to ensure their anonymity and confidentiality.

CHAPTER FOUR: RESULTS

4.1 Introduction

This chapter presents the results as per the study objectives. First, the study looked at the response rate of the questionnaires returned, then organized the section as per the objectives. The first objective was the findings on the socio-demographic characteristics of the respondents and its bivariate analysis. Second was the overall extent of routine health data use and utilization per health facility, the third, was the overall assessment of data quality factors that influence data use, assessment per health facility, and its bivariate analysis. The fourth objective results were on organizational factors influencing data use, followed by the bivariate analysis. The last results presented in this section are those of the multivariable analysis involving all the independent variables.

4.2 Response Rate

The study sampled 156 HMT members in Subukia, Molo, Naivasha, and Olenguruone sub-county (Level 4) hospitals. A total of 156 questionnaires and 11 key informants who were part of the study population (Medical Superintendent, Hospital Administrator, and Health Records Department in charge) were administered. Of all the questionnaires administered during the period of data collection i.e. between the month of July 2022 to November 2022, 146 were completed and returned for analysis, translating to response rate of 93.6%. Similarly, out of the targeted 11 key informant interviews, 6 interviews were successfully conducted. The summary of the self-administered questionnaire response rate is provided in Table 4.1 below.

Table 4.1: Health Facility questionnaire return rate

Health Facility	**HMT members**	
	Sample size (n)	Response n (%)
Naivasha Level 4 Hospital	53	51(96.2%)
Molo Level 4 Hospital	31	28(90.3%)
Olenguruone Level 4 Hospital	42	39(92.9%)
Subukia Level 4 Hospital	30	28(93.3%)
Total	**156**	**146(93.6%)**

4.3 Socio-demographic characteristics influencing RHD use

Hospital management teams often include individuals of different genders with a range of ages, reflecting a mix of experienced professionals and younger leaders as well as varying educational qualifications.

In this study, as indicated in the table below, the socio-demographic factors considered were age, gender, highest education, HMT members' Position, and years of being in that position. A total of 146 participants comprised 57.5% (n=84) male respondents and 42.5% (n=62) constituted female respondents. The majority 54 (37%) of the respondents were aged 36-45 years while only 28 (19.2%) of the respondents were aged 26-35 years. Those aged 45-55 years were 36 (24.7%) while those aged above 55 years were 17 (11.6%) and 11 (7.5%) were below 25 years.

Table 4.2: Socio-demographic characteristics of the participants

Variable	Frequency (n)	Percent (%)
Gender		
Male	84	57.5
Female	62	42.5
Age of the respondents		
Below 25 years	11	7.5
26 - 35 years	28	19.2
36 - 45 years	54	37.0
45- 55 years	36	24.7
Above 55 years	17	11.6
Highest Level of Education		
Certificate	6	4.1
Diploma	35	24.0
Higher Diploma	52	35.6
Undergraduate Degree	39	26.7
Masters	11	7.5
PhD	3	2.1
Health Management Team Position		
Nursing Officer in-charge	5	3.4
Hospital Accountant	4	2.7
Procurement Department in-charge	5	3.4
Human Resource Officer	4	2.7
Laboratory Department in-charge	4	2.7
Radiology Department in-charge	3	2.1
Pharmacy Department in-charge	3	2.1
Physiotherapy Department in-charge	5	3.4
Head of Clinical Departments	57	39.0
Ward in-charge	56	38.4
Years of Holding the Position		
Less than 1 year	29	19.9
1-5 years	60	41.1
6-10 years	42	28.8
Above10 Years	15	10.3

As indicated in Table 4.2, the majority of respondents 52 (35.6%) held higher diploma qualifications, 39 (26.7%) held undergraduate degrees and 35 (24%) possessed diplomas while 11 (7.5%) had master's degrees, and only 3 (2.1%) had doctorate (PhD) qualifications. However, there were 6(4.1%) hospital management team members with certificate qualifications at the highest level of education. A majority (39%; n=57) of the HMT were heads of clinical departments followed by 38.4% (n=56) who were ward in-charges. These accounted for over three-quarters of the

HMT in the sampled hospitals. Further, 60 (41.1%) have held the position for 1-5 years, 42 (28.8%) for a period between 6-10 years, 29 (19.9%) for less than a year while 15 (10.3%) have held that position for more than 10 years.

4.3.1 Routine health data use and socio-demographic characteristics

Further analysis with the aid of a chi-square test was carried out in order to establish an association between respondent's characteristics and the use of RHD for decision-making. The Pearson chi-square in Table 4.3 shows no statistically significant association between gender (x^2=3.124, p=0.077), age (x^2=3.124, p=0.0537) and level of education (x^2=1.241, p=0.743) on the RDH use.

Table 4.3: Influence of Socio-demographic factors on RHD use.

Variable	RHD use		df	Chi-square value	P-value
	Poor (n)	Good (n)			
Gender					
Male	35(41.7%)	49(58.3%)	1	3.124	0.077
Female	35(56.5%)	27(43.5%)			
Age					
Below 25 years	5(45.5%)	6(54.5%)			
26-35 years	11(39.3%)	17(60.7%)	5		
36-45 years	28(51.9%)	26(48.1%)		3.124	0.0537
45-55 years	20(55.6%)	16(44.4%)			
Above 55 years	6(35.3%)	11(64.7%)			
Level of education					
Diploma & below	20(48.8%)	21(51.2%)			
Higher Diploma	22(42.3%)	30(57.7%)	4		
Undergraduate Degree	21(53.8%)	18(46.2%)		1.241	0.743
Postgraduate	7(50%)	7(50%)			
Health facility					
Naivasha Hospital	27(52.9%)	24(47.1%)			
Molo Hospital	6(21.4%)	22(78.6%)	4	9.873	0.020*
Olenguruone Hospital	22(56.4%)	17(43.6%)			
Subukia Hospital	15(53.6%)	13(46.4%)			

The differences in routine health data utilization per health facility was noted to be statistically significant at a p =0.020 as shown in table 4.3.

4.4 Extent of Routine Health Data Utilization

Routine health data use was evaluated using a utilization index (mean) derived from nine usage regions as the Table 4.4 below. The respondents self-rated their extent of data use, on a scale of 1 to 5 (1 never; 2 Rarely; 3 sometimes; 4 often; 5 always). The rating score was from 0% to 100%, where 1 meant that the use of data was very low with a rating score of (0 – 20)%, 2 meant low with a rating score of (21 – 40)%, 3 meant data use was average with a rating score of (41 – 60)%, 4 meant high with a rating score of (61– 80)% and 5 meant very high with a rating score of (81-100)%.

The mean of all nine dimensions, which amounted to 62.9%, was used to construct the total routine data consumption index with a mean of 3.14.

Table 4.4: Extent of Routine Health Data utilization for decision-making

Ranking	Use area	Total scores	Mean (n=146)	Rating Score (%)
1.	Referrals of patients	560	3.84	76.7
2.	Supply & drug management	528	3.62	72.3
3.	Staff recruitment & trainings	476	3.26	65.3
4.	Outreach activities	449	3.08	61.5
5.	Review strategy/Performance	447	3.06	61.3
6.	Service improvement	445	3.05	61
7.	Funds Allocations	418	2.86	57.3
8.	Customer feedback	405	2.77	55.5
9.	Policies development	403	2.76	55.2
Routine Health Data utilization index			**3.1443**	**62.9**

On the areas of data use, Table 4.4's analytical findings implied that routine health data for referrals had a mean of 3.84 implying that 76.7% of the respondents used routine data for the referral of patients, on health-related activities,72.3% used data on supply & drug management (mean=3.62), 65.3% for staffing recruitment & training (mean = 3.26), 61.5% for outreach activities (mean = 3.08) while 61% of members

used routine data for service improvement with a mean of (mean = 3.05). However, 55.2% (mean = 2.76) utilized routine data in policy development which recorded the lowest use followed by 55.5% of the respondents using routine data for customer feedback and 57.3% for funds allocation.

4.4.1 Extent of Routine health data use among the Level 4 hospitals

In this study, good routine health data utilization was found among 76(52.1%) with (95% CI: 43.6%-60.4%) of the study participants (figure 4.1). Moreover, good routine data utilization was found among 78.6% (22) participants from Molo Level 4 hospital, while 56.4% (22) participants from Olenguruone Hospital, 53.6% (15) participants from Subukia Hospital and 52.9% (27) participants from Naivasha Hospital were found to have poor data utilization.

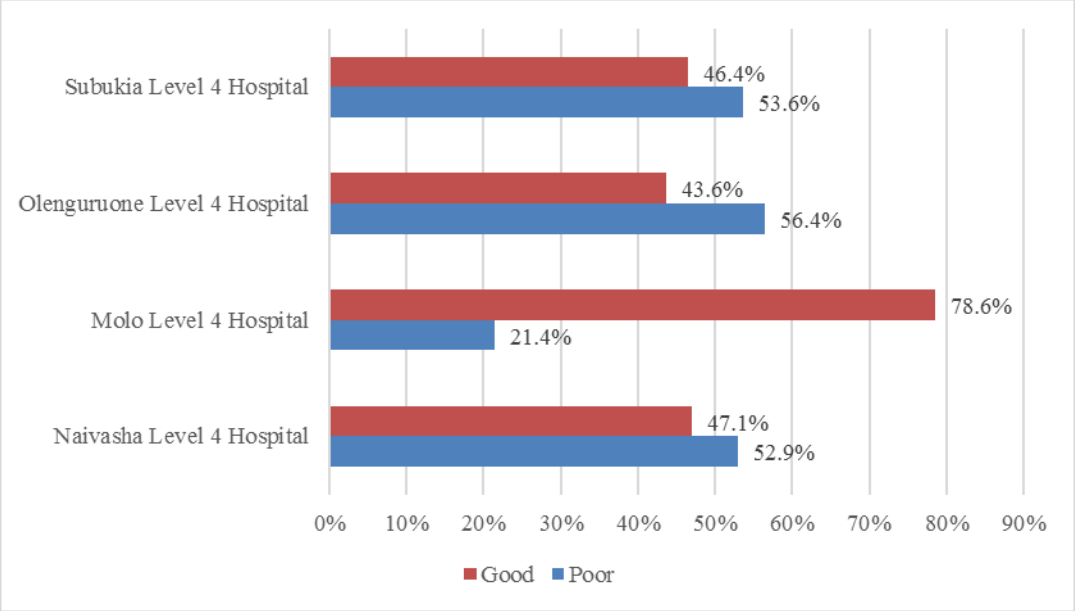

Figure 4.1: Routine health data utilization among the level 4 hospitals

4.5 Data quality factors influencing RHD use

Data quality factors require a concerted effort involving not only technology and systems but also ongoing training, staff engagement, and a commitment to continuous

improvement in data management practices. The study looked at the following factors under data quality; tool validity, accuracy, completeness, timeliness, and data management.

The data quality factors were measured by five-item Likert scale questions ranging from '1= Never '5= Always'. This study assessed the five data quality dimensions by use of a Likert scale, where questions regarding the type of data collected in the sampled facilities were asked. For accuracy, HMT members indicated their level of agreement with questions regarding accuracy, then the available registers were assessed and elements judged as correct were noted against the total fields assessed. Completeness was assessed by comparing the number of complete elements against the elements assessed. Timeliness was assessed when the submission of the data was done against when the HMT meeting was held. Consistency was assessed against the pre-set registers and the expected entries of each service.

Table 4.5: Level of data quality factors

Variable	Number	Percent (%)
Tool Validity		
No	25	17.1
Yes	121	82.9
Accuracy		
Good	78	53.4
Poor	68	46.6
Completeness		
Good	64	43.8
Poor	82	56.2
Timeliness		
Yes	46	31.5
No	100	68.5
Data Management		
Good	86	58.9
Poor	60	41.1

From Table 4.5 above, all respondents 121(82.9%) believed that the data collection tool captured data on all services offered in the health facility, and 78(53.4%) of the health management team responded that the data was current, accurate, and adequate.

About 64(43.8%) of the respondents indicated that the health facility ensured routine health data was complete before analysis while 46(31.5%) agreed that health routine data was available when needed. Only 86(58.9%) participants believed that data management is undertaken in their health facility. The table exhibits the summary of the level of agreement by the health management team on the level accuracy, completeness, timeliness, tool validity and data management in the health facility.

4.5.1 Level of data quality factors per Level 4 hospital

High-quality data allows the user, to extract clear and actionable insights that inform real-world strategies. With dirty data, one might miss important trends or patterns altogether. High-quality data is key and the basis for meaningful data-driven decisions.

In Figure 4.2 below, the level of data quality factors per hospital was assessed under the data quality attributes such as data management, timeliness, completeness, accuracy, and tool validity. None of the respondents in Olenguruone Hospital agreed that the data collection tool captured all the data for all the services offered. This was emphasized by a KII who stated that "these *tools are so many, repetitive, and only collecting what the donors or sponsors want, for example in our hospital we have many cases of assaults, attacks, animal products related diseases e.g. brucellosis, but none of the data collecting tools availed by the government captures that. (KII.,04)"*

The finding for Subukia Hospital on completeness of data was (71.4%) and tool validity (35.7%). Of the respondents, 71.4% of the Molo hospital health management team agreed that the hospital routine health data was accurate and 60.7% acknowledged that data management was carried out in the hospital regarding the routine health data policy. Naivasha Hospital performed averagely in all aspects of the

data quality. On average, on all data quality dimensions, Subukia Hospital had an average of 45.72%, Molo had 39.28%, Olenguruone had 42.58% and Naivasha had 38.04%.

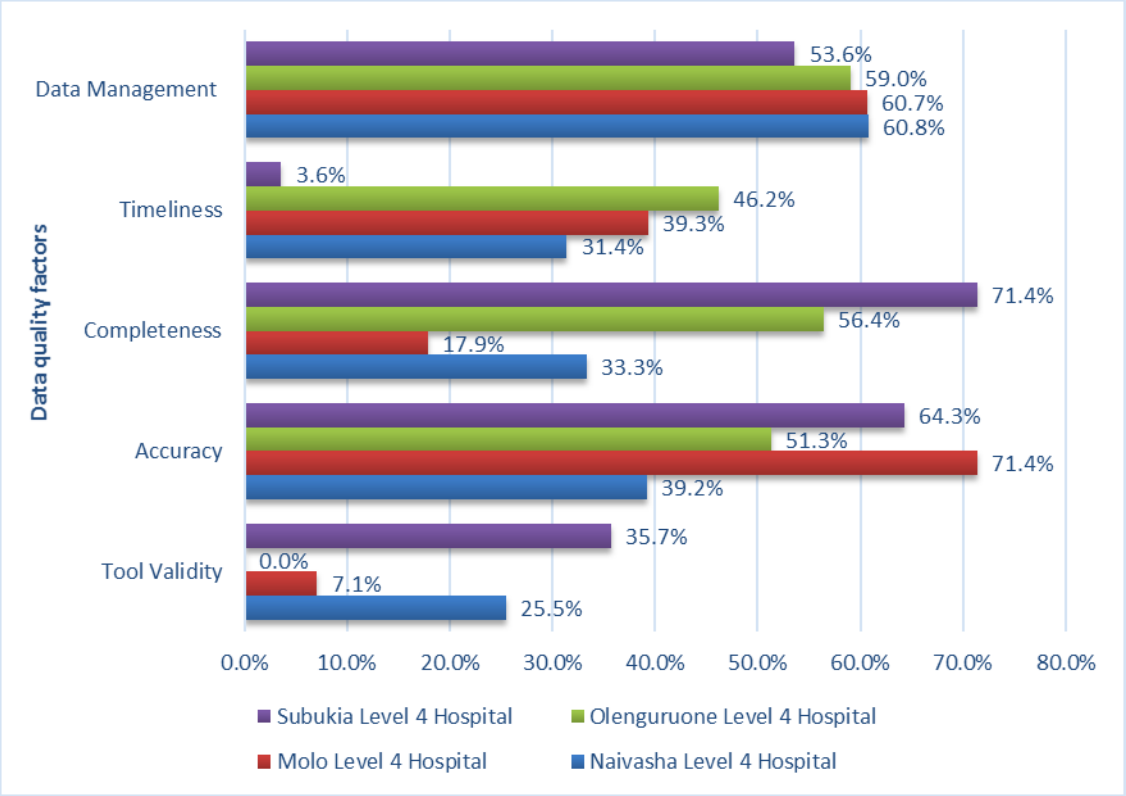

Figure 4.2: Dimensions of data quality factors per health facility

Additionally, an observation checklist (n=4) was used to identify the presence or absence of the list of items representing quality data and evidence of data. Figure 4.3 below indicated that all health facilities had storage facilities such as cabinets, shelves, or computers, evidence was also presented on the state of the available filled data collection tools (completeness, accuracy, last updates, etc.).There was evidence of a departmental meeting for data review and supervisor feedback held in the last 3 months, patient satisfaction survey questionnaires were filled in the last 3 months, the presence of a data office, and evidence of recorded meetings on data management. Two of the facilities had illustrations of data monitoring and analysis and two health

facilities had operational HMIS computers. However, in one facility it was noted that there were notable data entry errors in the tools submitted.

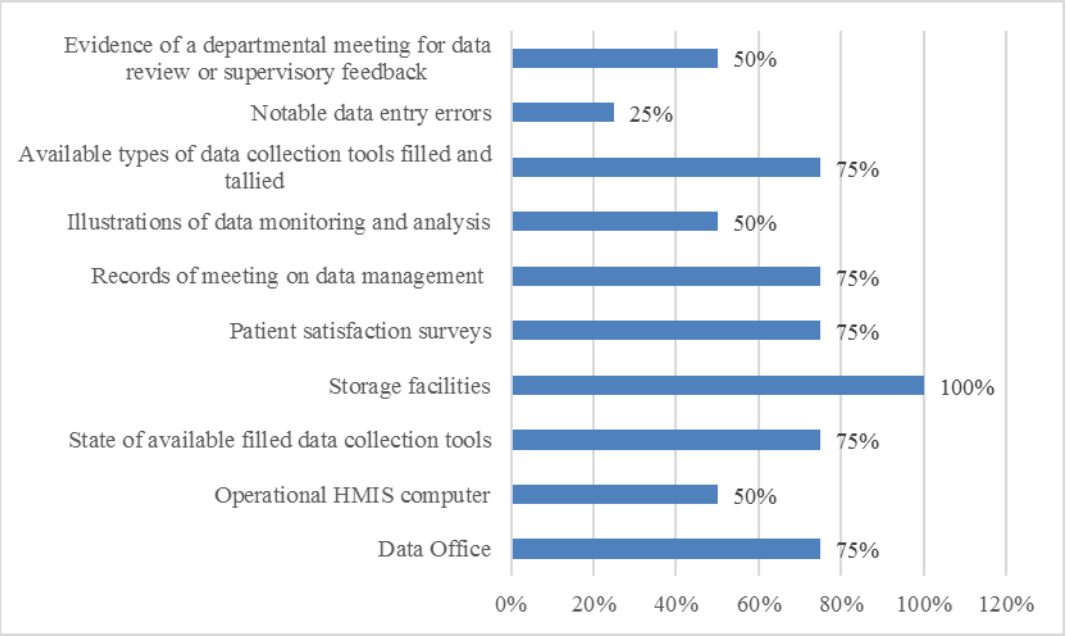

Figure 4.3: Evidence of quality data practices in health facilities

4.5.2 Routine health data use and data quality factors

In the bivariable logistic regression analysis, accuracy and data management were factors associated with good routine health data utilization at a p-value of 0.02. The findings indicated routine health data with good accuracy was 2.9 times more likely to be utilized for decision-making compared with data classified as poor accuracy. Similarly, routine health data that adhered to good data management was 1.8 times more likely to be utilized for decision-making than routine health data with poor data management practices. This was not statistically significant (p=0.079). Table 4.6 below shows the bivariate analysis of the data quality factors with routine health data utilization.

Table 4.6: Effect of Data quality factors on RHD use.

Variable	RHD utilization		Bivariate Logistic Regression	
	Poor (n)	Good (n)	COR (95% CI)	P-value
Tool Validity				
No	57(47.1%)	64(52.9%)	1	
Yes	13(52%)	12(48)	1.216	0.656
Accuracy				
Poor	42(61.8%)	26(38.2%)	1	
Good	28(35.9%)	50(64.1%)	2.885(1.471-5.655)	0.02*
Completeness				
Poor	40(48.7%)	42(51.2%)	1	
Good	30(46.9%)	34(53.1%)	1.079(0.561-2.077)	0.819
Timeliness				
Yes	24(51.2%)	22(47.8%)	1	
No	46(46%)	54(54%)	1.281(0.636-2.578)	0.488
Data Management				
Poor	34(56.7%)	26(43.3%)	1	
Good	36(41.9%)	50(58.1%)	1.816 (0.933-3.537)	0.079*

Further analysis was done by use of the coefficient of determination in order to predict the relationship between the dependent variable and data quality factors.

Table 4.7: Model Coefficients for Data Quality and Data Utilization

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0.196	0.239		-0.820	0.413
	Data Quality	1.052	0.075	0.763	14.104	0.000

a. Dependent Variable: Data Utilization

In Table 4.7 above, the analysis established that data quality was a significant predictor of the extent of data utilization since the p-value was 0.000. It was noted that one one-unit increase in data quality aspects resulted in a 1.052-unit increase in data utilization and vice versa with other factors held constant. This implied that data quality positively influenced the extent of routine health data use in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

4.6 Organizational Factors influencing RHD use

The third objective sought to identify organizational factors influencing the utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya. Organizational factors often play a crucial role in influencing the effective utilization of routine health data in Level 4 hospitals. These factors encompass various aspects such as the health facility characteristics, data collection tools, incentives, use of modern ICT in the facility and leadership style.

4.6.1 Health Facility Characteristics

The study sought to establish how long the hospitals under study had been in existence, what was the bed capacity of each hospital and what type of services each facility offered as well as the number of patients attended daily in these facilities. Table 4.8 below provides a summary of the characteristics of the sampled health facilities. A majority (54.1%; n=79) of health facilities had been in existence for over 10 years while 45.9% (n=67) had existed for a period between 6-10 years. About 45.9% (n=67) had a bed capacity of 50 beds or less, 19.2% (n=28) reported having 51-100 beds, and 34.9% (n=51) with 101-150 beds.

Table 4.8: Characteristics of the health facilities

Variable	Frequency (n)	Percent (%)
Years of Health Facility existence		
6-10 years	67	45.9
Above 10 years	79	54.1
Bed capacity of the facility		
1-50 beds	67	45.9
51-100 beds	28	19.2
101-150 beds	51	34.9
Services offered in the facility		
OPD	146	100
ANC	146	100
R.H	146	100
Drug Dispensing	146	100
Surgery	50	34.2
Laboratory	146	100
Inpatient	146	100
Daily patients' attendance		
26-50 patients	67	45.9
Above 50 patients	79	54.1

The HMT reported that the health facilities offered every service that information was sought apart from 34.2% (n=50) who indicated that surgery was provided in the health facility. Over half of the respondents reported that they attended to above 50 patients while 45.9% attended to 26 and 50 patients daily.

4.6.2 Influence of Data Collection on RHD use

In this section, the study sought to establish the data-collecting tools used in these level 4 hospitals, and the cadres involved in data collection. According to Table 4.9 below,113(77.4%) of the respondents reported to use registers as data collecting tools, followed using computers at 105(71.9%). The rest of the respondents used tally sheets and summary forms at a rate of 20.5% and 21.9% respectively. The cadre majorly used to collect data was the health records officers at 96(65.8%), followed by nurses at 71(48.6%). The other cadres who sometimes collected data were doctors 18(12.3%, clinical officers 20(13.7%) and casuals at 8(5.5%)

Table 4.9: Data collection in the health facilities

Variable	Number	Percent (%)
Data collection tools		
Registers	113	77.4
Tally Sheets	30	20.5
Summary forms	32	21.9
Computers	105	71.9
Others	11	7.5
Cadre collecting data		
Nurses	71	48.6
Clinical officers	20	13.7
Doctors	18	12.3
Health records	96	65.8
Casuals	8	5.5

4.6.3 Incentives

The majority of the respondents reported that the HMT received mainly training & benchmarking (71.9%, n=105) as incentives followed by 57.5% (n=84) who claimed to have received job promotions while 47.9% (n=70) were given pay rise. A KII respondent stated that *"…we do try to encourage the health workers especially nurses and health records officers to capture all the services and relevant data as they go about their work, however the data captured is not comprehensive may be due to the shortage of staff on the ground visa vis the amount of work to be done. This makes it difficult to recognize those that collect and use data and also even the little motivation given is not appreciated due to fatigue and frustration at work."* Figure 4.4 below shows the summary of the incentives the HMT is receive.

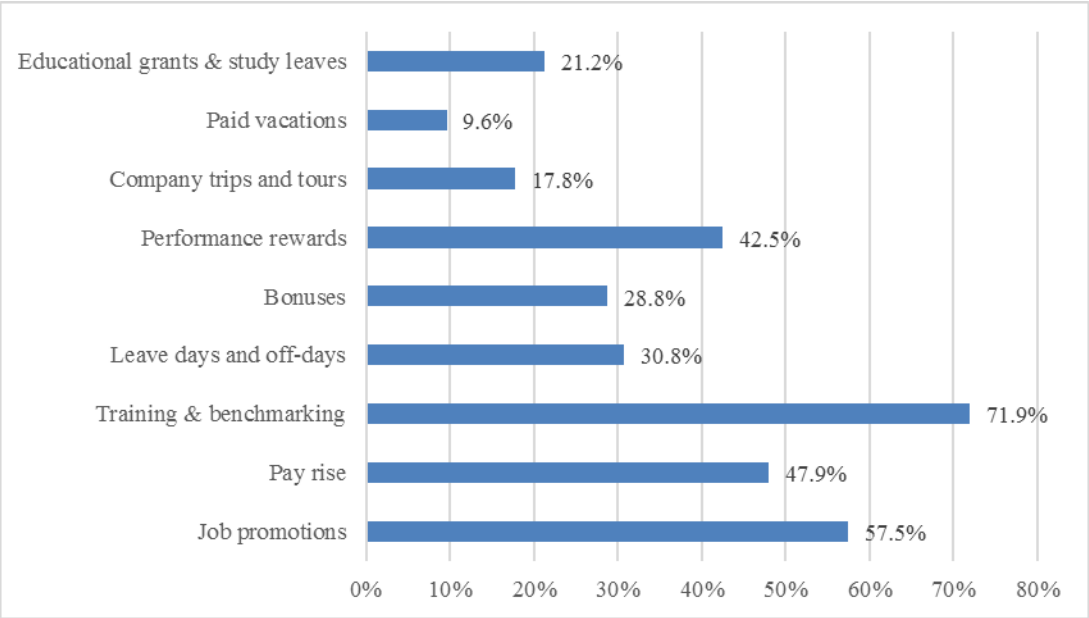

Figure 4.4: Incentives received by the hospital management team

4.6.4 Use of modern ICT in the facility

About 86.3% (n=126) use modern information and communication technology in its operations while only 13.7% (n=20) does the converse figure 4.5 below.

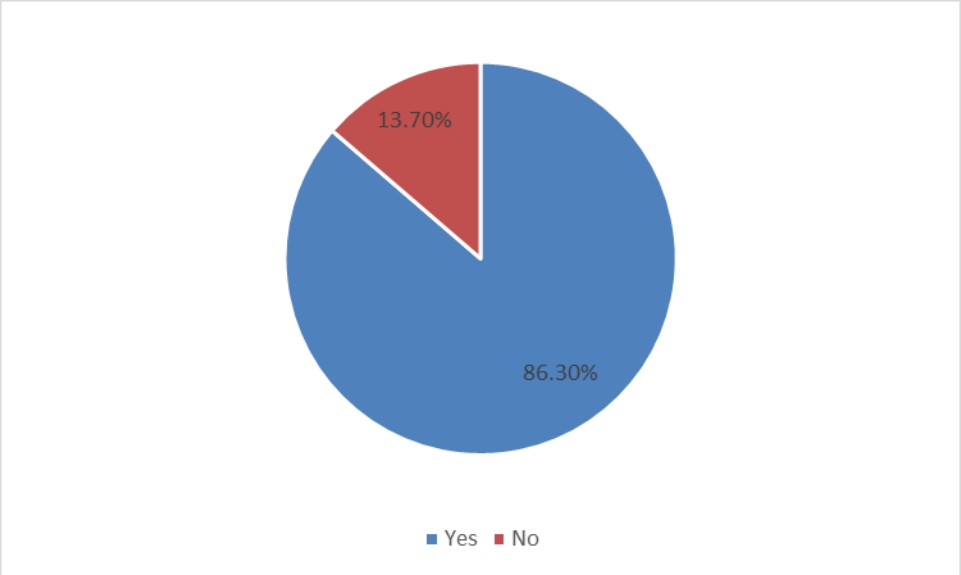

Figure 4.5: Use of modern technology

4.6.5 Leadership style

The leadership of the various hospitals was reported to be dominantly democratic (59.6%, n=87) while 24.7% believed it was transformational, 9.6% argued that it was transactional and only 2.1% believed it was autocratic as indicated in figure 4.6 below.

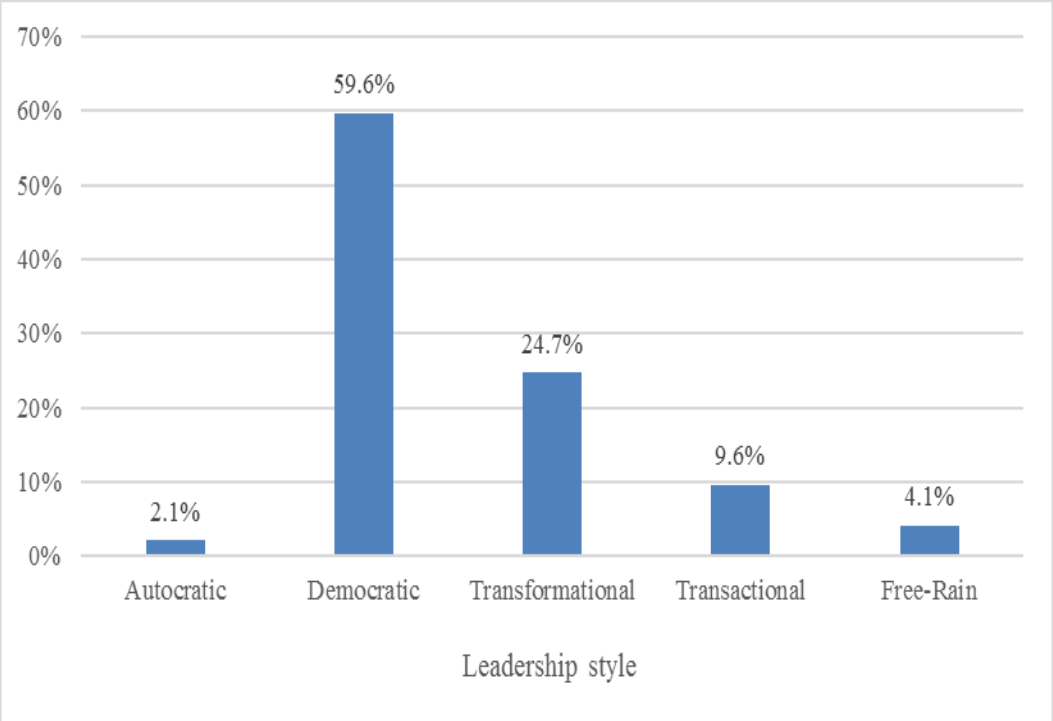

Figure 4.6: Leadership style

4.6.6 Routine health data use and Organizational factors

Organizations have the resources and structure to collect vast amounts of data from various sources. By centralizing and organizing this data, they can identify trends and patterns of patients and the community they serve. By fostering a culture where data is valued and used extensively for decision-making, employees at all levels would consider data when making choices and adopt a more objective and evidence-based approach. Table 4.10 below shows the findings of a bivariate regression analysis of organization factors and utilization of routine health data. Most of the factors such as facility years of existence were found not to be statistically significant at $p<0.05$.

Table 4.10: Effect of organizational factors on RHD use

Variable	RHD utilization		Bivariate Logistic Regression	
	Poor (n)	Good (n)	COR (95% CI)	P-value
Facility years of existence				
6-10 years	37	30	1	
Above 10 years	33	46	1.719(0.891-3.317)	0.106
Bed capacity of the facility				
1-50 beds	37	30	1	
51-100 beds	6	22	4.522(1.626-12.58)	0.04*
101-150 beds	27	24	1.096(0.528-2.277)	0.805
Use of register				
Yes	49	64	2.064 (1.125-5.643)	0.044*
No	21	12	1	
Leadership style				
Autocratic	2	1		
Democratic	30	57	3.8(0.331-43.634)	0.284
Transformational	28	8	0.571(0.046-7.143)	0.664
Transactional	7	7	2(0.146-27.447)	0.604
Free-rain	2	3	3(0.15-59.89)	0.472
Use of modern technology				
No	12	6	1	
Yes	56	70	2.5(0.883-7.81)	0.085

As reflected in the table above, facility with a bed capacity of 51-100 beds was discovered to be substantially connected to good routine health information use [COR= 4.522 95% CI (1.626, 12.58)] at p-value 0.04. From the bivariate regression analysis, the type of leadership was found not to influence the use of routine health data in decision-making. Most leadership styles were not statistically significant at the lowest p-value being 0.284. The use of modern technology was 2.5 times more likely to influence the use of routine health data compared to facilities without modern technology. However, this was found not to be statically significant, implying it is not an important factor in utilization of routine health data.

4.7 Socio-demographic, data quality and organizational factors and RHD use.

Binary logistic regression was used throughout the investigation to find the variables connected to regular usage of the health information system. As candidate variables for the multivariate analysis, the variables with a p-value of <0.2 were chosen.

Finally, during the multivariable analysis, factors with a p-value of <0.05 were regarded as statistically significant. Odds ratios with a 95% Confidence Interval are used to quantify the strength of the link between dependent and independent variables to measure the significance of the association. With a 95% confidence interval, the crude odds ratio (COR) and adjusted odds ratio (AOR) were both computed to indicate the strength of relationships.

Table 4.11: Determinants of RHD use.

Variable	B	p-value	AOR	95% C.I AOR	
				Lower	Upper
Gender					
Male			1		
Female	-0.321	0.417	0.725	0.334	1.575
Age					
Below 25 years			1		
26 - 35 years	0.068	0.935	1.070	0.210	5.447
36 - 45 years	-0.136	0.862	0.873	0.188	4.059
45- 55 years	-0.396	0.625	0.673	0.137	3.300
Above 55 years	0.394	0.664	1.483	0.250	8.784
Accuracy					
Poor			1		
Good	0.861	0.025*	2.365	1.113	5.023
Data Management					
Poor			1		
Good	0.376	0.324	1.456	0.691	3.069
Facility years of existence					
6-10 years			1		
Above 10 years	0.274	0.504	1.315	0.590	2.929
Bed capacity of the facility					
1-50 beds			1		
51-100 beds	0.991	0.060	2.694	0.825	8.795
101-150 beds	0.037	0.101	1.038	0.431	2.497
Use of registers					
No			1		
Yes	0.827	0.043*	2.286	1.026	5.092
Use of modern technology					
No			1		
Yes	0.891	0.152	2.437	0.721	8.239

Table 4.11 shows results indicating that accuracy was strongly related to Routine health data use [AOR= 2.365; 95% CI (1.113, 5.023)] at a p-value of 0.025. The likelihood of using high-quality routine health data for decision-making was 1.474 times greater among those who agreed that the hospital gathered current, accurate, and appropriate data than among those who disagreed. The use of registers for data collection was shown to be substantially connected to Routine health data use [AOR= 2.286; 95% CI (1.026, 5.092)] at a p-value of 0.043. Those who used data collected on registers were 2.286 times more likely to practice and use good routine health data than those who used other data collection tools. The majority of the factors such as

gender, age, data management, facility years of existence, bed capacity, and use of modern technology were found not to be statistically significant with good practice of routine health data use among health management teams.

CHAPTER FIVE: DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

This chapter presents the major findings of the study and is divided into 5 major sections where the first discusses the demographic characteristics of the respondents the following three sections address the three objectives and the last sections were conclusions that were based on the objectives, recommendations were based on the conclusion and lastly, the suggested further studies.

5.1 Discussion of the findings

5.1.1 Response rate

The respondent rate in Naivasha Level 4 Hospital was 96.2%, Molo Level 4 Hospital was 90.3%, Olenguruone Level 4 Hospital had a rate of 92.9% and 93.3% of the respondents were from Subukia Level 4 Hospital. A response rate of at least 80% is recommended for social studies and generalization of study findings. The majority of the respondents were from Naivasha Level 4 Hospital. This could have been because Naivasha Level 4 Hospital is the largest among the four hospitals where the study was carried out. A study by Sebsbie (2021) indicated that the capacity of the health facility contributes to the utilization of routine health data in decision-making.

5.1.2 Demographic characteristics of the respondents

The results showed that most of the Hospital management team members were male, between the ages of 36 to 45 years with at least 1 to 5 years of experience. Most of them were higher diploma holders with only 2.1% being Ph D holders and 4.1 % had a certificate as their highest level of education. Socio-demographic characteristics were considered as important because according to a study done by Morike (2023), the level of education was seen to play a significant role in data use at a p-value of

0.0001, and female gender was seen to be proactive in data use as compared to male gender. Ayele (2024), asserted that job positions and experience had a statistical significance to data use at a p-value of 0.25, while Negera et al. (2023) found that health workers under the age of 30 years were 60% less likely to utilize routine health data for decision making than those above 30 years of age.

According to Onchonma et al. (2018), health care leadership of this era must have management talent, and be cultured enough to be able to handle the complexity of the healthcare environment in the study done in Nigeria, a conclusion was derived that there was a positive effect of higher education on administrator's competency. This was supported by findings that showed a significant competency difference between 1st degrees and those with higher degrees (p=.048). However, this study disagreed with the finding as no statistical significance was found between the level of education (x^2=1.241, p=0.743) and RHD use. Another study done by Njuguna et al. (2023), showed that age, duration at the facility, and working experience of the health worker were not significantly related to the use of routine data for decision-making. In this study, the same findings were noted as Age (□2=6.761; p=0.149), duration at the facility (□2=10.684; p=0.099), and working experience (p=0.763) had no statistical relationship to use of routine data for decision making, thus does not influence utilization of routine data.

5.1.3 Extent of health data use in decision making

The value of health data and information is demonstrated through the outcomes derived during decision-making. Shiferaw et al. (2017) noted that Health data use among health managers in Africa ranged between 10 to 56% with the major reasons given as lack of capacity to use data. A similar study by Mekuria (2023) in Eastern Ethiopia indicated Good RHIS utilization among health professionals at 57.7%. This

study, however, revealed a positive culture of data use amongst hospital management team members with a utilization index of 62.9%, which translated to often use of data. This was also reflected by one of the KII who said "*The culture of information use is average at all levels, starting from level 6 hospitals to level 4 otherwise directions on areas to improve in data use would trickle down from higher facilities to lower level facilities and help improve service delivery in the peripheral facilities" (KII 02).* The activities in which data was seen to be highly utilized was patients referral at 76.7% however, a KII had a different view, "… *most of the time there is no data available or accessible to refer to when making urgent decisions such as referrals, therefore when a patient requires services we do not offer, we immediately refer, unfortunately, nothing is done to correct the shortcomings,….policies are made as per whoever is in office and may change with the change of office bearer" (KII 06).* Supply and drug management was at 72.3%, meaning that procurement and distribution of medical supplies were based on the consumption and demand rate per department, the referrals of patients to other facilities were based on the available services and equipment in their facility. Development of policies, decisions based on customer feedback, and fund allocation were at an average of 55%, meaning that those decisions were only sometimes based on data.

Similar studies done in Kitui County indicated a utilization index of 34% and on the various hospital management activities had an average of 35% Karijo (2021), in Mombasa County, the index use was higher at 69.6% with the highest use of data on supply of drugs at 74% Mboro (2017), in Kisii county the RHD use was at 30%, Obwocha (2016), and now Nakuru county at a possible average of 63%.In the African countries discussed earlier, Tanzania had an index use of 42%, Uganda at 59%, Liberia at 58%, South Africa at 65%, and in Ethiopia, a study indicated an index use

of 82% rating as the highest user of data in decision making among the studies sampled. According to Mekonnen (2021), Some of the factors identified as associated with utilization of routine health information were supportive supervision (AOR = 2.25; 95% CI: 1.80, 2.82), regular feedback (AOR = 2.86; 95% CI: 1.60, 5.12), availability of standard guideline (AOR = 2.53; 95% CI: 1.80, 3.58), data management knowledge (AOR = 3.04; 95% CI: 1.75, 5.29) and training on health information (AOR = 3.45; 95% CI: 1.96, 6.07). Another factor that was seen to improve data quality for use was staff training management as a study done by in Nigeria showed that there was a statistically significant increase in completeness of reporting ($p = 0.02$), overall accuracy rate ($p < 0.001$), timeliness rate of reporting ($p = <0.001$) and feedback ($p = 0.012$) after the staffs were trained on data management. Just as the difference in data use was noted among the various counties sampled, the study also found that there were significant differences ($p=0.020$) in the extent of utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County.

5.1.4 Data Quality Factors Influencing Utilization of RHD

Health data quality ensured a reflection of the true and precise health status of patients, and this led to reliable insights and informed decision-making by healthcare professionals. According to Lemma et al. (2020), Sound decisions are based on sound data and the foundation of health care is quality and timely data from our health facilities, since they inform management of the five health systems' building blocks as recommended by WHO strengthening health systems framework. The definition of data quality was in several dimensions, this study focused on Tool validity, accuracy, completeness, timeliness, and data management. The finding was that the majority (82.9%) of the HMT members believed that the data collection tool did not capture

data on all services offered in the health facility, and thus the data would not create the actual picture of the service delivery. A similar problem was seen in many other African settings as discussed by Hassanien (2018), where the researcher stated that the health data collecting tools caused fragmentation, bifurcation, and replication of data with no single source resulting in imprecise and imperfect health care profiles.

Only 53.4% (n=78) of HMT members were in support of the availability of accurate and adequate data for use in their facility, a score slightly above average contrary to the expectation of high data accuracy for decision-making. This narrative was confirmed by a comment made by a KII who reported data fabrication due to workload and multiple reports. A study by Otieno et al. (2020) confirmed this finding as 71% of health workers in Mombasa County reported having encountered inaccurate data during decision-making, translating to only 29% of health workers who thought the data to be accurate. Another study by Mboro (2017) in Tharaka Nithi county, indicated an average of 46 % response on poor status of data quality data factors i.e. timeliness, accuracy, and completeness. Analysis per hospital showed that Molo level 4 hospital and Subukia had the highest rates of data accuracy both at 71.4%, and this may bring up a study on impact made by use of accurate in decisions.

Among the five dimensions of data mentioned, the most challenged factors were the completeness and timeliness of data where 56.2%(n=82) and 68.5% (n=100) respectively. In a study done in Mombasa, a linear regression analysis indicated that approximately 36.2% of the variation in data use was attributed to changes in data quality factors Otieno et al. (2020). This concurred with this study's finding that established that data quality factors such as accuracy and data management were associated with good RHD use ($p<0.2$) and that data with good accuracy was 2.9

times likely to be utilized($p<.05$), while data with good management was 1.8 times likely to be utilized for decision making ($p=0.079$).

5.1.5 Organizational factors influencing utilization of RHD

An organization can influence data use in several ways such as shaping how data is collected, analyzed, and ultimately applied to decision-making. Further, data use can also be influenced by institutional data-collection policies, data-collection methods, investment in Technology, data quality monitoring, analysis tools, and data training. Organizations should therefore establish a culture where data is valued and used to guide decision-making across all levels. Leadership buy-in plays a crucial role in promoting and maintain a positive culture.In a study by Mboera et al.(2021), institutional factors such as bed capacity and availability, number of patients, level of hospital, and number of years of existence were seen to only influence data use in terms of how much data was generated. The study showed that the amount of data generated did not influence data use in facilities where data demand and use culture were missing.

From the findings in this study, the sampled facilities were seen to be average above 10 years in existence with 1-50 bed capacity, offering services ranging from outpatient to inpatient except for major surgeries. The facilities served more than 50 patients a day and the common data collecting tool used were the registers (77.4%), followed by computers (71.9%). WHO,(2022) indicated that weaknesses in data quality were distinctive to systems that depend on paper transmission, manual aggregation and analysis of data. Wamae (2015) stated that Kenya has 66% of its health data collected on paper first and then transferred to electronic system while 34% of the data is captured only on paper. Paper based data management technique is

fraught with storage and retrieval problems which eventually lead to inaccurate and incomplete data.

The cadres involved in data collection were seen to be health record officer (65.8%) followed by nurses at (48.6%) contrary to the expectation as nurses are assumed to be more in numbers and the key service providers thus is the first contact. In a study done in Uasin Gishu showed that the cadre involved in data collection were nurses at 70% (Cheburet, 2016), in Tharaka-Nithi it was casual laborer at 95.2% (Mucee, 2016).The findings are supported by Tulu et al. (2021) who established that effective organizational structures contributed to cost-effectiveness by optimizing resource utilization, reducing unnecessary expenses, and improving overall financial sustainability. According to Bagyendera et al. (2023), the interoperability of the RHIS increased utilization and enabled healthcare professionals to make informed decisions by analyzing real-time health data, leading to more effective and personalized patient care. It also facilitated early detection of health issues and diseases, allowing for timely interventions and preventive measures to improve patient outcomes.

Human resource support on data use was done through incentives with 71.9% of HMTs reporting to have been sent for training while above half of them were promoted. The effectiveness of this strategies would then have been expected to be seen in the utilization index which was still low at 62.9%. Three quarter of the respondents reported to have been using modern technology e.g. in data analysis, presentation and dissemination, patient monitoring and diagnostics. This finding was however not fully supported by a KII who stated that the kind of training done was not necessarily on the data management processes. In the KII's review, in the last 2 years there had not been any training regarding data. This was unfortunate as studies

show training increase data use in decision making as according to a study done by Nwankwo & Sambo (2018) who asserted that training workers was seen to increase the completeness of reporting at a p value of 0.02, increase the overall accuracy rate ($p < 0.001$), timeliness rate of reporting ($p = <0.001$) and feedback ($p = 0.012$).

A study done by Rosing (2022), on leadership styles and performance, revealed that autocratic rather than democratic leadership elevated trust in the workforce during a crisis period that required urgent decisions, while democratic rather than autocratic leadership enhanced trust in the workforce when the decision decision-making process was more reflective such as policy development. Thus, all leadership styles were important and useful in particular situations. Maybe then this discussion would be helpful to the management teams as the leadership style noted to prevail was democratic which was at 59.6% and would then be expected to be open to suggestions on training the health workers on data management, to improve decision making even at the point of care.

In organizational factors seen to influence data use, the study revealed that data use was not affected by the facility's' years of existence, leadership style or use of modern technology. However, the bed capacity of 51-100 of a facility as well as use of registers as the major data collection tool was statistically significant at $p=0.04$ and $p=0.044$ respectively.

5.1.6 Summary of the study Findings

The study finding established that Nakuru county had good data use practices at a score of 62.9% and this finding were supported by a study done by Nguefack (2020) in Cameroon that indicated that a good score on data use was a score greater than or equal to 60% and a poor data use score was a score less than 60%. The areas of data

use deprived of evidence-based support were policy developed which was the lowest in data utilization at 55.2%,then customer satisfaction at 55.5% and funds allocation at 57%.On the socio-demographic data, the study revealed that though the male gender (good use was 49(58.3%)was seen to utilize data more than the female, and good use of data was seen to be highest among respondents above 55 years, as well as among this with higher diplomas, the bivariate analysis findings showed that there was no statistical significance to data use at p-values of 0.077, 0.057 and 0,743 respectively.

On the data quality factors influencing data use for decision making, Majority of the respondents,121(82.9%) agreed that the data collecting tools used were able to collect what was intended. Though negligible 17.1% reported of the tools to be poor on validity, this was supported by a key informant who reported the tools to have been repetitive and focused more on particular programs thus missing out on some unique services offered per facilities. This reason amongst others could affect the Completeness, and timeliness of the data reported. Of the five data quality dimensions tested, only data accuracy was found to have a statistical significance to data use at a p-value of 0.02. Of the 4 hospitals Subukia was seen to have the highest score in data quality at 45.58% higher than Naivasha Hospital at 38.04% yet it was the largest hospital that covered a larger population in comparison to the other study areas.

On organizational factors influencing data use, the bed capacity of the health facility was seen to have a statistical significance to data use while the years of facility existence, cadre collecting data, incentives, and leadership style had no statistical significance to data utilization. However, most researchers agreed that motivation to data use was crucial in the improvement of data management for quality service delivery. The two major cadres found to collect data were HROs and Nurses with

rewards to performance at a rate of 42.5%. This led to demotivation as stated by an informant who complained of high workload, and increased data registers with no appreciation from the management.

5.2 Conclusion of the study

The study conclusion was based on study objectives;

5.2.1 Extent of health data use in decision making

The study concluded that the average data utilization index of 62.6% identified in this study was slightly higher than most indexes seen in other Kenyan counties and as much as 62.9% was considered as good data use as per analysis of the study, it is prudent to note that it was way below the recommended data use of 95%(WHO,2022) thus interventions are paramount to improve data use for evidenced based decisions.

On the specific areas of data use performance in policy development, customer care feedback and funds allocation were poor.

5.2.2 Socio-demographic factors influencing utilization of RHD

The study concluded that age, gender, position held, or the number of years one had held the position had no statistical significance to data use. Thus, the socio demographic characteristic was not seen to influence the managers ability to utilize data. Of importance to note was that in a profession assumed to have more female than male, the male gender had more members in the leadership of the health facilities that the female gender. The study also concluded that good data use practices was noted among the managers with advanced age as compared to the middle aged respondents.

5.2.3. Data quality factors influencing utilization of RHD

The finding revealed that some of the HMT members believed that the data collection tool did not capture data on all services offered in the health facility, and thus the data

would not create the actual picture of the service delivery. The utilization of routine health data in level 4 hospitals is highly dependent on the quality of the data. It was established the data collecting tool commonly used were the registers, followed by computers. The complaint by KII on proliferation of this registers, increased workload, lack of motivation leading to increased cases of incompleteness was noted to be the key challenge in achieving quality data for use in decision making.

5.2.4 Organizational factors influencing utilization of RHD

The study concluded that there were statistically significant differences in the routine health data utilization in decision-making by management teams in selected level 4 hospitals in Nakuru County based on the bed capacity of the health facilities and the type of data collecting tools. The study further concluded that there was no significant relationship between the number of services offered at the health facility, the cadres collecting data, the number of patients attended daily, the number of incentives, the different leadership styles and the extent of utilization of the routine health data.

5.3 Recommendations

5.3.1 Recommendation from the study

Based on the conclusions reached by this study, the following recommendations were made:

i. The HMT members with support from the CHMT should set a standard reference score for data use and also develop Standard Operating Procedures that clearly outlines the role of data in policy development, interventions towards customer feedback and allocation and utilization of hospital funds for quality health service delivery.

ii. The HMT should aim to empower more women into leadership as the male gender was seen to take lead in a female dominated profession,

iii. The HMT of each facility should customize data collecting tools for specific services to avoid repetitive data, automate the data management process to reduce errors emanating from paper-based records and also develop a data quality assessment tool to be utilized in every department before submitting monthly data at the facility level and to the county HMIS.

iv. The HMT through the support of CHMT should ensure all level four hospitals meet the requirements of a sub-county level as guided by the government's' level 4 checklist including the required bed capacity and also equip the facilities with connectivity and train health care providers in data management to promote evidence-based decision making.

5.3.2 Recommendation for Further Studies

The study makes the following suggestions for further studies.

i. A comparative study on routine health data utilization between private and public hospitals and its effect on service delivery in Kenya.

ii. A study on the impact of routine health data use on service delivery in Primary Health Care facilities in other counties for purpose of UHC achievement.

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APPENDICES

Appendix I: Consent Form

My name is KAGWIRI MARY; I am a Master of public health (Epidemiology and Disease control) student at Kenyatta University. I am carrying out research on "**Utilization of routine health data in decision making by management teams in selected level 4 hospitals in Nakuru County."**

You are graciously asked to take part in this research since you are one of the sample respondents thought to have relevant knowledge about the study issue.

The objective of this study is to help develop interventions to make better use of the routine data generated in health facilities during decision making.

The data gathered for this research will be kept in strict confidence and will not be shared with anyone else for any reason not related to this investigation.

Names are not required on this form as you will use codes allocated by the researcher.

Your participation is optional, and if there are any questions you feel uncomfortable answering, you may choose not to participate.

I value your cooperation and assistance in completing this questionnaire.

Thank you.

The Participant: I was given an opportunity to choose whether or not to participate after being informed of the study's goals and nature (Please tick √ one box below)

1. Yes, I agree to participate ☐

2. No, I do not agree to participate ☐

For any questions or clarification, please feel free to contact me through 0727811268.

Appendix II: Questionnaires

Questionnaire Code: ---------- Facility Name: ----------

Part A: Demographic data

Instructions: (Tick the most appropriate response)

1. What is your gender?

Male ☐ Female ☐

2.In what age bracket are you?

Below 25years ☐ 45- 55years ☐

26 - 35years ☐ Above 55years ☐

36-45years ☐

3. What is your highest educational level?

Certificate ☐ Undergraduate Degree ☐

Diploma ☐ Master's Degree ☐

Higher Diploma ☐ PhD ☐

4.What is your profession?

.....

5.What position do you hold in the Hospital management team?

.....

6.For how long have you held that position?

Less than 1year ☐ 6-10 years ☐

1-5years ☐ Above10 ☐

Part B. Extent of Routine Health Data Use in Decision Making

The first objective of the study aimed to determine the extent to which routine health data is utilized for decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya. Please rate the extent to which routine health data is used for decision-making by management teams in your hospital using the following 5-Point Likert Scale, where;

$1 = \text{Never}, 2 = \text{Rarely}, 3 = \text{Sometimes}, 4 = \text{Often}, 5 = \text{Always}$

S/N	Statement	1	2	3	4	5
7.	Our facility performs a satisfaction survey of patients to assess their experiences about health care services offered in the facility					
8.	Staff recruitment is based on the number of staffs to client ratio available per department					
9.	Funds allocations are based on the need analysis per department					
10.	The procurement and distribution of medical supplies are based on the consumption and demand rate per department					
11.	The decisions made and filed in meetings are derived from submitted hospital data reports					
12.	The policies developed and projects undertaken in our facility are based on analyzed routine health data					
13.	The referrals of patients to other facilities are based on the available services and equipment in our facility					
14.	Our facility develops data analysis reports that illustrate performance as per routine health data collected					
15.	The outreach activities undertaken by our facility are informed by data collected on disease prevalence or community health need analysis					
16.	The trainings done to staffs are informed by data analysis that detect the weakest areas in need of					

S/N	Statement	1	2	3	4	5
	improvement					
17.	Decision makers in our facility evaluate the consequences of their decision by use of the collected data					
18.	Decision to offer new or improve services in our facility is based on the customers' feedback					
19.	Cost-Benefit analysis is done to ensure all the services offered are profitable					
20.	Pricing of our services and drugs is based on the prevailing market rates					
21.	Consensus is sought before implementation of decisions made by the management team					

Part C: Data Quality Factors

The second objective of the study was to ascertain data quality factors influencing utilization of routine health data in decision making by management teams in selected level 4 hospitals in Nakuru County, Kenya. In this section, rate the data quality factors that your health facility focuses on using the following 5-Point Likert Scale, where; $1 = \text{Never}, 2 = \text{Rarely}, 3 = \text{Sometimes}, 4 = \text{Often}, 5 = \text{Always}$

S/N	Statement	1	2	3	4	5
22.	Data collection tools captures data on all services offered in our health facility					
23.	Our facility collects current data on daily services offered in the facility					
24.	Our facility ensures that all routine health data is accurate					
25.	Our facility ensures that all routine health data is complete before analysis					
26.	Our facility takes corrective actions for incomplete or inaccurate data					
27.	There is supervision and follow-up on quality of data					
28.	There are mechanisms in place to prevent unauthorized changes to data					
29.	Our facility ensures that health routine data is available when needed					
30.	The data is adequately analyzed to reflect all reports from all departments in our health facility					
31.	Data analysis reports/summaries are frequently done (weekly or monthly reports)					
32.	There are review meetings about data use or data analysis					
33.	The health reports are submitted or shared with all relevant stakeholders					
34.	Our facility adheres to all data ethics and privacy					
35.	There are systems for data storage and management					

S/N	Statement	1	2	3	4	5
36.	Our facility carries out training for personnel involved in data collection, analysis and management					

Part D: Organizational Factors

The third objective sought to identify organizational factors influencing utilization of routine health data in decision making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

37. How long has the facility been in existence?

1-5 years ☐

6-10 years ☐

Above 10 years ☐

38. What is the bed capacity of your facility?

1-50 beds ☐ 101-150 beds ☐

51-100 beds ☐ 151-200 beds ☐

39. What services are offered in your facility? (Tick all that apply)

OPD ☐ Drug dispensing ☐ Laboratory ☐

ANC ☐ Surgery ☐ Inpatient ☐

R.H ☐

40. Approximately how many patients are attended daily in the outpatient department? 1-25patients ☐ 26 -50 patients ☐ Above 51 patients ☐

41.In your facility, what data collecting tools are used to collect data?

Registers ☐ Summary forms ☐

Tally sheets ☐ Computers ☐

Other, Specify……

42.What cadre collects routine data? (Tick all that apply)

Nurses ☐

Clinical officers ☐

Doctors ☐

Health records ☐

Casuals ☐

Other, specify ……..

43. What incentives does the management team receive? (Tick all that apply)

Job promotions ☐

Pay rise ☐

Training & Benchmarking ☐

Leave days and off-days ☐

Bonuses ☐

Performance rewards ☐

Company trips and tours ☐

Paid Vacations ☐

Educational grants & study leaves ☐

Other, specify……

44. How can you describe the leadership of the facility?

Autocratic ☐

Democratic ☐

Transformational ☐

Transactional ☐

Free-Rain ☐

45. Does your facility use modern information and communication technology in its operations?

☐ Yes ☐ No

THE END

Thank you for your feedback

Appendix III: Key Informants Guide

Hospital's Name _____

Department _____

Position Held _____ Job title _____

Theme 1: Extent of Data use

Probe 1: What data is mostly collected in your facility?

Probe 2: Describe how data is used in decision making on but not limited to the following aspects or activities?

i) Customer satisfaction
ii) Staff recruitment
iii) Funds allocations
iv) Procurement and distribution of medical supplies
v) Policies development
vi) Project and services offered
vii) Referrals of patients
viii) Trainings
ix) Introduction or improvement of services or projects
x) Cost-Benefit analysis
xi) Pricing of our services and drugs

Probe 3: What more can be done to improve the data use for decision making in your facility?

Theme 2: Data Quality factors

Probe 1: Describe the quality of data in your facility on but not limited to the following aspects;

i) Data collection tools
ii) Data accuracy
iii) Completeness
iv) Timeliness
v) Supervision and monitoring of data
vi) Data Analysis
vii) Data reporting and sharing
viii) Data Storage and Management

Probe 2: What more can be done to improve quality of data in your facility?

Theme 3: Organizational factors

Probe 1: How does the organization demonstrate commitment in enhancing data use in decision making? You may speak on but not limited to the following aspects;

i) Hospital Size (bed capacity, departments, number of patients, number of employees etc.)
ii) Services Offered
iii) Leadership & Management
iv) Employee Motivation
v) Technology integration
vi) Working Environment

Probe 2: What organizational factors can be enhanced in order to improve data use for decision making in your facility?

Appendix IV: Observation Guide

Name of hospital _____

Department _____

ITEMS TO CHECK	YES	NO
Is there a data office?		
Is there an operational HMIS computer?		
What is the state of the available filled data collecting tools (completeness, accuracy, last updates?)		
What storage facilities are in place? (Cabinets or shelves or computers)		
Are there patient's satisfaction survey questionnaire filled in the last 3 months?		
Are there records of meeting on data management? When was the last meeting held? Is there any evidence of data use?		
Are there illustrations of data monitoring and analysis in form of graphs, charts etc.? MOH 217		
Are the available types of data collecting tools filled and tallied in the last 3 months?		
Are there any notable data entry errors in the data tools submitted in the last 3 months?		
Is there any evidence of a departmental meeting for data review or supervisory feedback done in the last 3 months		

Appendix V: Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **349892**

Date of Issue: **04/March/2022**

RESEARCH LICENSE

This is to Certify that Ms.. mary kagwiri of Kenyatta University, has been licensed to conduct research in Nakuru on the topic: UTILIZATION OF ROUTINE HEALTH DATA IN DECISION MAKING BY NAKURU COUNTY, KENYA MANAGEMENT TEAMS IN SELECTED LEVEL 4 HOSPITALS IN for the period ending : 04/March/2023.

License No: **NACOSTI/P/22/15936**

349892

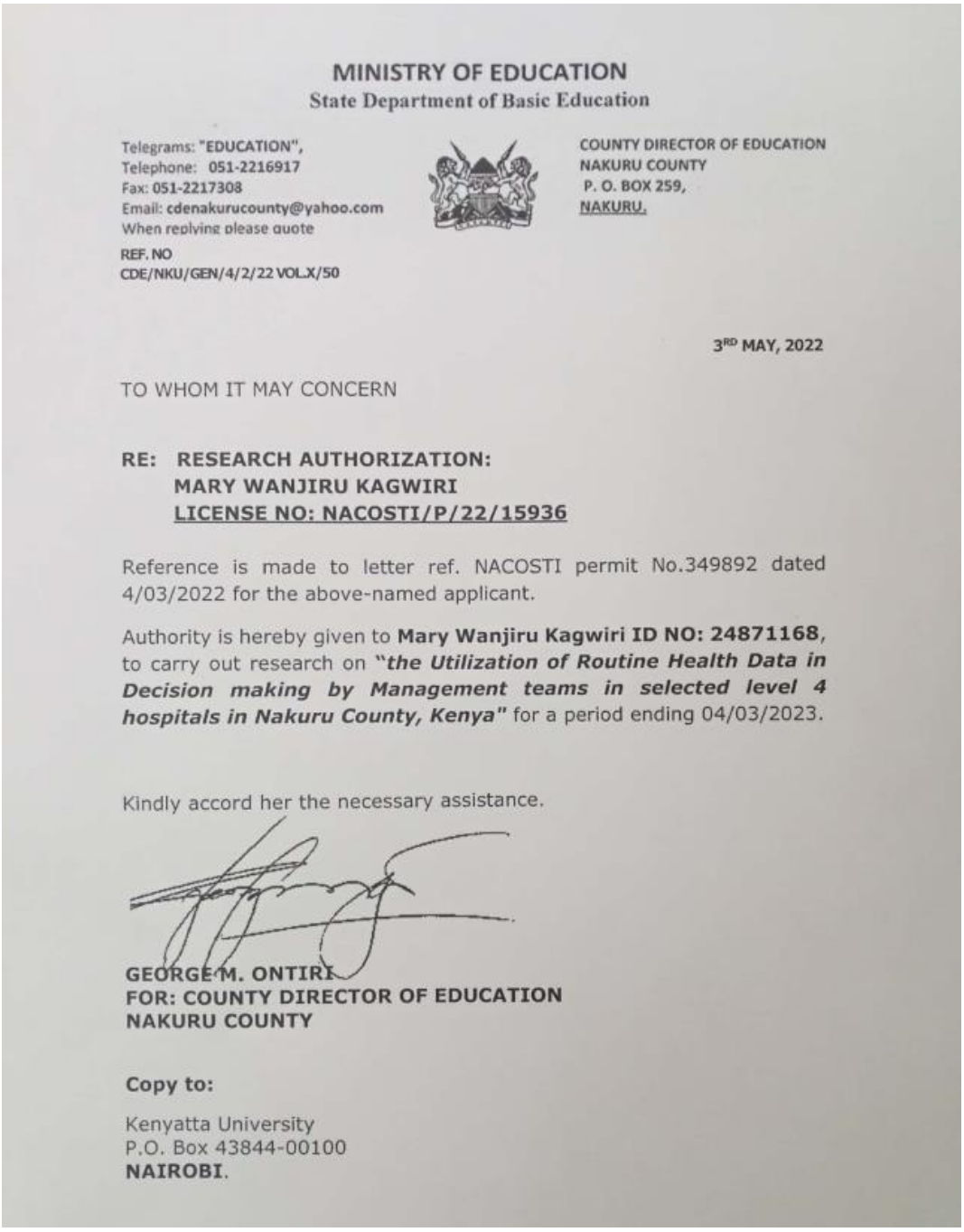
Applicant Identification Number

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 VI: Research Authorization Education Department



MINISTRY OF EDUCATION
State Department of Basic Education

Telegrams: "EDUCATION",
Telephone: 051-2216917
Fax: 051-2217308
Email: cdenakurucounty@yahoo.com
When replying please quote

REF. NO
CDE/NKU/GEN/4/2/22 VOL.X/50

COUNTY DIRECTOR OF EDUCATION
NAKURU COUNTY
P. O. BOX 259,
NAKURU.

3RD MAY, 2022

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION:
MARY WANJIRU KAGWIRI
LICENSE NO: NACOSTI/P/22/15936

Reference is made to letter ref. NACOSTI permit No.349892 dated 4/03/2022 for the above-named applicant.

Authority is hereby given to **Mary Wanjiru Kagwiri ID NO: 24871168**, to carry out research on ***"the Utilization of Routine Health Data in Decision making by Management teams in selected level 4 hospitals in Nakuru County, Kenya"*** for a period ending 04/03/2023.

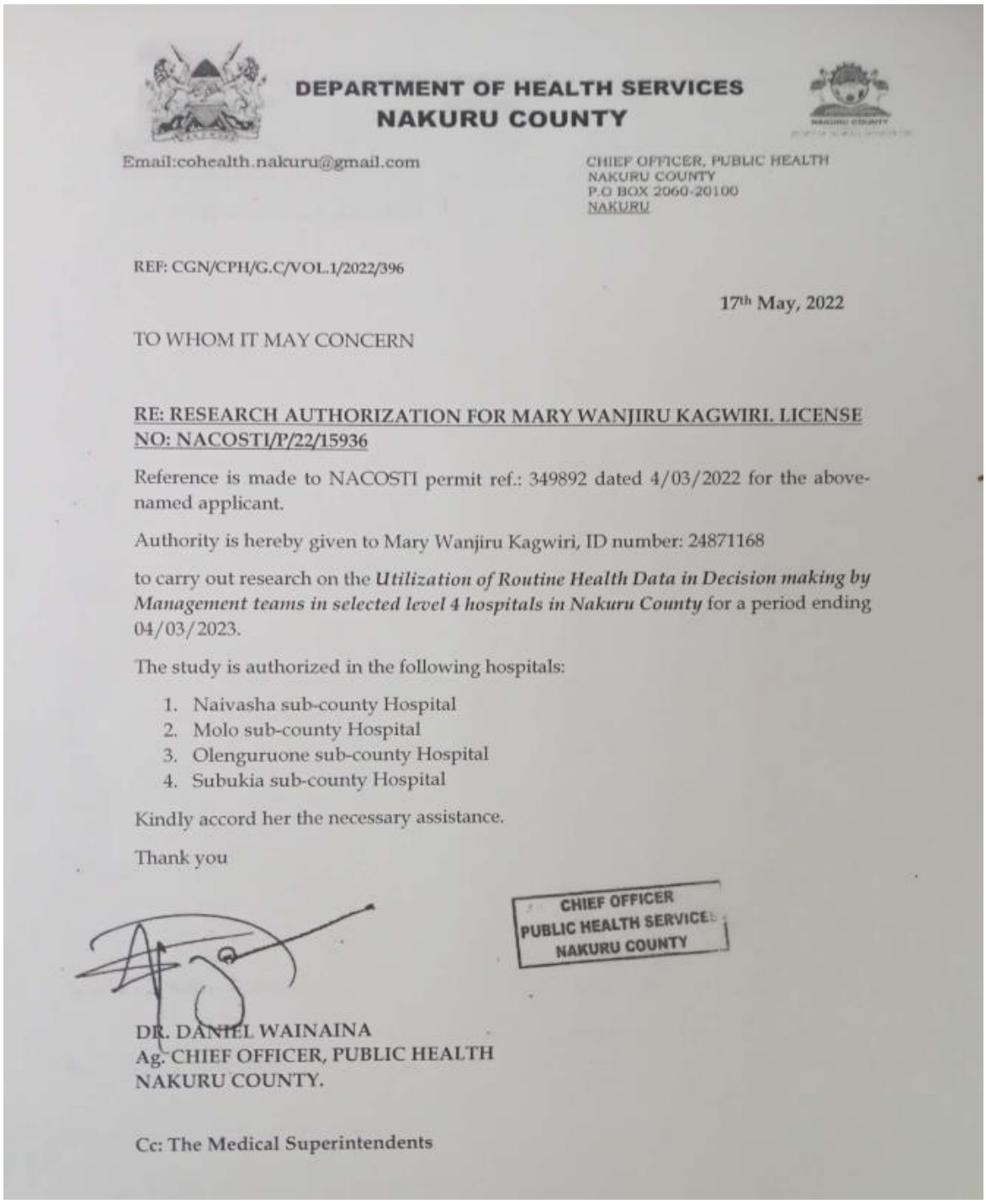
Kindly accord her the necessary assistance.

GEORGE M. ONTIRI
FOR: COUNTY DIRECTOR OF EDUCATION
NAKURU COUNTY

Copy to:

Kenyatta University
P.O. Box 43844-00100
NAIROBI.

Appendix VII: Research Authorization Health Department



DEPARTMENT OF HEALTH SERVICES
NAKURU COUNTY

Email:cohealth.nakuru@gmail.com

CHIEF OFFICER, PUBLIC HEALTH
NAKURU COUNTY
P.O BOX 2060-20100
NAKURU

REF: CGN/CPH/G.C/VOL.1/2022/396

17th May, 2022

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION FOR MARY WANJIRU KAGWIRI. LICENSE NO: NACOSTI/P/22/15936

Reference is made to NACOSTI permit ref.: 349892 dated 4/03/2022 for the above-named applicant.

Authority is hereby given to Mary Wanjiru Kagwiri, ID number: 24871168

to carry out research on the ***Utilization of Routine Health Data in Decision making by Management teams in selected level 4 hospitals in Nakuru County*** for a period ending 04/03/2023.

The study is authorized in the following hospitals:

1. Naivasha sub-county Hospital
2. Molo sub-county Hospital
3. Olenguruone sub-county Hospital
4. Subukia sub-county Hospital

Kindly accord her the necessary assistance.

Thank you

CHIEF OFFICER
PUBLIC HEALTH SERVICES
NAKURU COUNTY

DR. DANIEL WAINAINA
Ag. CHIEF OFFICER, PUBLIC HEALTH
NAKURU COUNTY.

Cc: The Medical Superintendents

Appendix VIII: Map Showing the Study Area