FACTORS INFLUENCING UTILIZATION OF ROUTINE HEALTH DATA IN EVIDENCE BASED DECISION MAKING IN HIV/AIDS SERVICES BY PUBLIC HEALTH FACILITIES IN NAKURU COUNTY

BY

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DECLARATION

This research project is my original work and has not been presented for a degree or any award in any other university.

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APPROVAL

This research project report has been submitted for examination with my approval as the University Supervisor

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DEDICATION

This research project is dedicated to my loving parents Mr. and Mrs. Carlo Njoka, who have nurtured and encouraged me as I undertook my academic work since childhood. I grateful to my dear wife EllyJoy Kendi for her invaluable support and encouragement during my research period. May God richly reward every one of you?

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ABBREVIATIONS AND ACRONYMS

AIDs	Acquired Immune Diseases
ART	Antiretroviral Therapy
CHRIO	County Health Records and Information Officer
DHIS	District Health Information System
GOK	Government of Kenya
HIS	Health Information Systems
HIV	Human Immunodeficiency Virus
AIDs	Acquired immune Deficiency Syndrome
HMIS	Health Management Information System
KNBS	Kenya National Bureaus of Statistics
MDGs	Millennium Development Goals
MOH	Ministry of Health
PMTCT	Prevention of Mother to Child Transmission
RHIS	Routine Health Information Systems
SCHRIO	Sub-County Health Records and Information Officer
SOP	Standard Operating Procedure
SPSS	Statistical Package for Social Science
WHO	World Health Organization

ABSTRACT

Most Ministries of Health across Africa invest substantial resources in some form of health management information system (HMIS) to coordinate the routine acquisition and compilation of monthly treatment and attendance records from health facilities nationwide. The relationship of improved information, demand for data, and continued data use creates a cycle that leads to improved health programs and policies. However, despite the expense of the HMIS, poor data coverage means they are rarely, if ever, used to generate reliable evidence for decision makers. The purpose of this study was to examine the factors influencing the utilization of routine health data in evidence based decision making by public health facilities offering HIV treatment services in Nakuru County. According to the Kenya HIV Estimates Technical Report of 2013, Nakuru County is one of the 10 counties with the highest number of people (61,598) living with HIV/AIDs in the county and therefore chosen as a study point. The study adopted a descriptive survey research design. The study was guided by the following objectives; to assess the influence of data quality on evidence based decision making; to establish the influence of data availability on evidence based decision making; to examine the influence of capacity on data use competencies in evidence based decision making and to investigate the influence of institutional support in evidence based decision making by public health facilities in Nakuru county. A structured questionnaire was used to collect data from 58 respondents from 33 health facilities providing HIV/AIDs treatment services. A stratified random sampling technique was used to achieve the desired representation of the various sub-groups within the population and simple random sampling was applied to identify respondents from the facilities. Data was analyzed using frequencies, percentages, mean, standard deviation, coefficient of variation and correlation coefficient with the aid of Statistical Packages for Social Sciences (SPSS) computer software version 20.0. The results were presented in tables. From the coefficient correlation analysis, only data quality and capacity on data use had significant positive relationship on evidence based decision making. I.e. data quality at r =.368** with p =.004 (<0.05) and capacity on data use competencies r =.323* with p =.013 (<0.05). There was no significant relationship between data availability r =.059 with p = 662 (>0.05) and institutional support r =.087and p = .514 (>0.05) with evidence based decision making. The study therefore recommends that there is need to develop and implement data quality protocols at the health facilities, train health care providers on synthesis and communication of routine health data using appropriate channels, need for training in leadership and advocacy skills for health managers to leverage on funding and sustaining data use and demand interventions and lastly, need to develop standard operating procedures that clearly state the role and value of data in organizational functioning. There is need for further research on the cost and effectiveness of using routine health data in planning and management.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Data are the lifeblood of decision-making and the raw material for accountability. Without high-quality data, providing the right information on the right things at the right time; designing, monitoring and evaluating effective policies becomes almost impossible. But too many people, organisations and governments are excluded because of lack of resources, knowledge, capacity or opportunity. There are huge and growing inequalities in access to data and information and in the ability to use it. Too often, existing data remain unused because they are released too late or not at all, not well- documented and harmonized, or not available at the level of detail needed for decision-making (Independent Expert Advisory Group, 2014).

Recent substantial increases in international funding for health have been accompanied by increased demand for statistics to accurately track health progress and performance, evaluate impact, and ensure accountability at country and global levels. The use of results-based financing mechanisms by major global donors has created further demand for timely and reliable data for decision-making (Boerma et al., 2009).

Public health decision-making has become increasingly complex, and the use of data has become essential in this information age. At the local level, data are used to monitor population health and to target interventions; at the national level, data are used for resource allocation, prioritization, and planning; and at the global level for estimates on the global burden of disease, to measure progress in health and development, and to contain emerging global health threats (van Panhuis et al., 2014).

Indeed, the health metrics network observed that the very countries that face the greatest health challenges generally have the weakest systems for gathering, managing and using information. This gap, often referred to as the “information paradox”, is most apparent in the reliable documentation of vital events, such as births and deaths (World Health Organization, 2011).

Information has been described as the glue that could and should hold the health sector together. Enormous amounts of information are generated in the health sector and almost all of this information is static; it is not indexed, cannot be readily sorted, searched, summarized or communicated electronically. Health care is information intensive but has thus far failed to come to grips with the problems of managing this information. The health care environment is bursting with information, but the sector lacks the capacity to find, communicate or use it effectively (Neame & Boelen, 1993). According to the report on mobilizing the data revolution for sustainable report (2004), the volume of data in the world is increasing exponentially: one estimate has it that 90% of the data in the world has been created in the last two years. The volumes of both traditional sources of data and new sources have been rising, and openness is increasing. This has been referred to as the "data revolution" i.e. the opportunity to improve the data that is essential for decision- making, accountability and solving development challenges (Independent Expert Advisory Group, 2014).

It has been noted that many developing countries face challenges in producing data of sufficient quality to permit the regular tracking of progress in scaling-up health interventions and strengthening health systems. Data gaps span the range of input, process, output, outcome and impact indicators (Boerma et al., 2009).

Most experts agree that routine health information systems in most countries, industrialized as well as third world countries, are woefully inadequate to provide the necessary information support to individual care and public health activities. In fact, poor use of information for evidence-based decision making is probably one of the main causes of the current lack of linkages between individual care and public health systems (Rhino, 2001).

Currently, Health Information System [HIS] in Kenya faces a number of challenges; the lack of or inadequacy of requisite skills at all levels coupled with a perception of non-usefulness of information and data collected at the lower levels have conspired to create an exceptionally low level of commitment from health providers. Programme focused strategies receive more support and recognition as a result of the lack of commitment. This has led to difficulties in coordination since programmes have differing priorities and the ultimate is to justify the use of resources put at their disposal (Ministry of Health, 2010).

An assessment conducted on the Kenya National Monitoring and Evaluation system and Health Information System identified various weaknesses in the HMIS; weak culture of data use for planning and decision-making at all levels, weak capacity in data management at all levels, few real-time or structured data products, little ready access to data and little or no data analysis and information usage at all levels (Blumhagen, Khan, Ndungu, & Settimi, 2010).

It has been observed that more diverse, integrated, timely and trustworthy information can lead to better decision-making and real-time citizen feedback. This in turn enables individuals, public and private institutions, and companies to make choices that are good for them and for the world they live in (Independent Expert Advisory Group, 2014).

Access to and capacity to use information more frequently and effectively will lead to decisions that improve health by improving the health system's ability to respond to health needs at all levels. The more positive experiences a decision maker has in using information to support a decision, the stronger will be the commitment to improving the quality and timeliness of data collection systems (Moreland, 2009). Infact, it has been argued by (Fapohunda, 2012) that, encouraging data-informed decision making promotes decisions that are objective, targeted and transparent. Data-informed decision making helps to ensure that programs monitor progress toward their objectives and meet their health goals.

1.2 Statement of the Problem

Significant human and financial resources have been invested worldwide in the collection of data on populations, facilities and communities. Unfortunately, this information is often not used by key stakeholders to effectively inform policy and programmatic decision making. The failure to consider all the empirical evidence before making decisions hinders the health system's ability to respond to priority needs throughout its many levels (Foreit, Moreland, & LaFond, 2006).

According to (Fapohunda, 2012), in the absence of using data to make decisions, decisions are based on anecdotes and gut feelings. In these situations, the health system fails to respond to the priority needs of the populations it serves.

While data collection can always be improved, there are many missed opportunities for using existing information to improve decision making. Many times these missed opportunities can be traced to limited demand, stemming from pervasive lack of "data ownership" (decision makers are not aware of existing data sources and/or do not fully understand their underlying technical issues), low value placed on data by decision makers (perceptions that the data are of poor quality and/or lack of understanding how the information could be useful), or failure to present the data in user-friendly, accessible formats (Harrison, 2008)

1.3 Purpose of the Study

The purpose of this study was to examine the factors influencing utilization of routine health data in evidence based decision making by public facilities providing HIV/AIDs treatment services in Nakuru County.

1.4 Objectives

The study was guided by the following objectives;

1 To assess the influence of data quality on evidence based decision making by public health facilities of Nakuru County

2 To establish the influence of data availability on evidence based decision making by public health facilities of Nakuru County

3 To examine the influence of data use capacity on evidence based decision making by public health facilities of Nakuru County

4 To investigate the influence of institutional support on evidence based decision making by public health facilities of Nakuru County

1.5 Research Questions

The study was guided by the following research questions:-

1. To examine what extent does Data quality influence evidence based decision making by public health facilities in Nakuru County
2. How does data availability influence evidence based decision making by public health facilities in Nakuru County

3. How does capacity in data use influence evidence based decision making by public health facilities in Nakuru County
4. To what extent does institutional support for data use influence evidence based decision making by public health facilities in Nakuru County

1.6 Significance of the Study

The ultimate objective of a routine health information system (RHIS) is to produce information for taking action in the health sector. The RHIS is an important mechanism to identify gaps in the management of the health system and to resolve them to maintain and improve performance. With timely, complete and accurate information, managers can identify strengths and weaknesses of health system functions and services, and take appropriate action to maximize success. For issues outside of their control, they can advocate for possible solutions and policy changes. It is hoped that this study will add knowledge on the data use interventions that will be helpful to health managers to improve utilization of routine health data in planning and management of health services.

The failure to consider empirical evidence regularly before making program and policy decisions is due primarily to the complex causal pathway between data collection, its use, and improvement in health outcomes. Further, specific and comprehensive guidance to improve data demand and use in the public health facilities is lacking. This study fills this gap by identifying gaps in implementing data use interventions and proposing specific recommendations on how to improve use of routine health data in evidence based decision making by public health facilities. This study will therefore strengthen the health information systems functioning by suggesting to health care managers and health care workers the best ways to improve use of routine health information data in evidence based decision making.

1.7 Delimitation of the Study

The study aimed at examining the factors influencing utilization of routine health data in evidence based decision making by public facilities providing HIV/AIDs treatment services in Nakuru County. Nakuru county was identified because it is one of the ten high burden counties in the country due to the large number of people (61,598) living with

HIV/AIDs. (Kenya HIV Estimates Technical Report 2013). There are various models that have been researched on the barriers for data demand and information use; technical, organizational and behavioral factors. Whereas assessment on the routine health information system (RHIS) is explicit on the data demand and use barriers, there has not been research done on the implementation and relevance of proposed data use activities. There are eight activities that have been proposed to promote data use, however, this study was limited in assessing the influence of four key interventions necessary for ensuring data demand and use specifically by GOK owned public health facilities offering HIV/AIDs treatment services in Nakuru County.

1.8 Limitations of the Study

The study respondents included selected health workers from GOK facilities providing HIV/AIDS treatment services in Nakuru County. This study cannot therefore be used to generalize the results of the study to the whole country as it may not be representative. The accuracy of the results depended on the willingness of the respondents to fill the questionnaire. The study controlled the limitations through proper planning and explaining on the need for providing correct information.

1.9 Assumptions of the Study

The study assumes that the respondents are interested in promoting data use for planning and managing HIV/AIDS services and would objectively answer the research questions which was confirmed by the significant response rate obtained.

1.10 Definitions of Significant Terms

Community Services:	Community based demand creation activities organized around Community Units
County referral services	Hospitals operating in and managed by a given county.
Data Availability:	Degree to which data can be instantly accessed
Data Demand:	Measure of the value that the stakeholders and decision makers place on Information

Data Use:	Analysis, synthesis, interpretation, and review of data for data-informed decision making processes regardless of the source of data
Data Quality:	Data that is fit for use for decision making and planning
Data use Capacity:	Skills and knowledge of health care workers in manipulating and using data
Decision Making:	The cognitive process leading to the selection of a course of action among alternatives.
Evidence Decision Making:	Proactive and interactive processes that consider data during program monitoring, review, planning, and improvement; advocacy; and policy development and review
GOK Health Facilities:	Facilities owned and supported by the Government of Kenya
Health Managers:	Staff that is part of the health management team at the facility, sub-County or county level
Information:	Product of transforming data by adding order, context and purpose in a way that adds to knowledge of the receiver.
National Referral services	Health facilities providing tertiary and highly specialized and complete the set of care available to persons in Kenya.
Primary Care Services	All dispensaries, health centres, maternity and nursing homes in the country.
Routine Health Information System:	Ongoing data collection of health status, health interventions, and health resources

1.11 Organisation of the Study

Chapter one covers the background to the study i.e. the status of data use in the health sector and the barriers to data use. It goes further to state the research problem, the purpose of the study, the research objectives and questions of the study. The chapter defines the delimitation of the study; it discusses the rational of the study and limitations of the study and concludes with definition of terms significant to the study.

Chapter two presents the literature review relevant to data quality in health sector globally, regionally and locally. The findings by other researchers are discussed and summary gaps captured.

Chapter three covers the research design, population of the study, the sample size and sample selection, validity and reliability of research instruments, procedures for data analysis, operational definition of variables and ethical considerations.

Chapter four presents data analysis, presentation, interpretation and discussion of study findings

Chapter five covers the summary of research findings, conclusions, recommendations and suggestions for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter highlights the HIV/AIDs burden in Kenya, the structure of routine health system in Kenya focusing on the decentralization of health services to the counties. The chapter further discusses the importance of using routine health data in planning for HIV services, the underlying challenges that hinder use of routine health data in decision making. The chapter also discusses the challenges of data quality, data availability, capacity on data use competencies and organizational data demand and use infrastructure.

2.2 Importance of using routine health data in evidence based decision making

Sound and reliable information is the foundation of decision-making across all health system building blocks, and is essential for health system policy development and implementation, governance and regulation, health research, human resources development, health education and training, service delivery and financing (World Health Organisation, 2008).

Improving a health system requires data, but too often they are unused or under-used by decision makers. Without interventions to improve the use of data in decision making, health systems cannot meet the needs of the populations they serve (Traore, Bosso, Nutley, & Mullen, 2014).

Accurate, timely and accessible health care data play a vital role in the planning, development and maintenance of health care services. Quality improvement and the timely dissemination of quality data are essential if health authorities wish to maintain health care at an optimal level. In recent years, data quality has become an important issue, not only because of its importance in promoting high standards of patient care, but also because of its impact on government budgets for the maintenance of health services. Authorities at all levels of health care, including hospitals, community health centres, outlying clinics and aid posts, as well as ministries or departments of health, should be concerned about poor data quality and the impact it has on the quality of health care. In many countries, administrators are dogged by poor medical/health record documentation, large backlogs of medical records waiting to be coded and inconsistent coding, plus poor access to, and utilization of, accurate and accessible morbidity data (World Health Organisation, 2003).

It has been argued that the effectiveness of HIV/AIDS programs throughout the world is dependent on the ability of program managers and providers to identify needs in the communities they serve and to understand the extent to which their programs address these needs. While there is a great deal of routine data collected at the health facility level, much of it is collated and sent elsewhere for reporting purposes. Too often program managers and providers do not have the capacity, time, or resources to analyze the data they collect to monitor service delivery or to assess problems and identify new strategies for improving health services (Nicole, 2010).

Correct and up-to-date data is critical, not only for the provision of high-quality clinical care, but also for continuing health care, maintaining health care at an optimal level, clinical and health service research, and planning and management of health systems. Accurate data about resources used and services delivered at all levels of health care is essential for resource management, use of clinical evidence and measurement of outcomes to improve the effectiveness of health care services (World Health Organisation, 2003).

Data for decision-makers are clearly important, but the circle of stakeholders for health-related information is much larger. Access to health care and to the benefits of scientific knowledge are human rights which encompass also the right to sound health information. The public has the right to know the status of public health. Communities have the right to know why people die before their time, why they get ill, what care is available and how they can protect themselves. Health information is too important to be left to statisticians and politicians. Strengthening health information systems is also about imagining and creating a better world for all (Jones, 2012).

Demand and supply deal with data, the raw materials of a health information system. In reality, raw data alone are rarely useful; they need to be converted into credible and compelling evidence that informs local health system decision-making. Only after data have been compiled, managed and analysed do they produce information. At present, health information systems in many low- and middle-income countries tend to be “data-rich” but “information-poor”. Information is of far greater value when it is integrated with other information and evaluated in terms of the issues confronting the health system (Commar, 2008)

It is not because countries are poor that they cannot afford good health information; it is because they are poor that they cannot afford to be without it. Good examples exist of the use of data for evidence-based decision-making leading to better health. The time has come to put serious effort and resources into building health information systems that can effectively support public health (AbouZahr & Boerma, 2005)

2.3 Structure of Health Information Systems in Kenya

The health care sector in a country consists of a large number of institutions ranging from small and simple health care centers up to large and technologically advanced hospitals. These institutions are managed by a number of overlapping institutional bodies, organized into geographic areas (district, province, nation), and according to vertical programs (HIV/AIDS, maternal health, vaccination) and services (primary health care, hospitals, laboratories, drug supply). Programs are influenced at the national level through various international donor organizations and the World Health Organization (Braa, Hanseth, Heywood, Woinshet, & Shaw, 2007)

In Kenya, the role of the Health Information System (HIS) in the health system is not just routine collection of health service data and dutiful conveyance of the same to higher levels of the health care system, but to facilitate evidence based decision-making at all levels especially at the point of collection the health Information System (Ministry of Health, 2010)

Health data is generated from many sources; individuals, health facilities, disease surveillance sites, the community and geographical (spatial) areas or units. The data is then summarized, analyzed and used at the sub-county, County and at the national levels depending on needs. Data is transmitted from these sources to the districts, then to the provinces and to the national level. Feedback loops exist at all levels. Within the health sector, data management is either paper based or electronic in different parts of the country. Data is collected manually (paper based) and reported to the districts where it is summarized and analyzed, then transmitted to the national level through the counties.

Key HIS statistical constituencies include: civil registration system whose vital events include registration of live births, deaths, marriages, divorces, adoptions, recognition, and legitimating; the Kenya National Bureaus of Statistics (KNBS) as the custodian of all Government Statistical information and therefore maintains a database for all national surveys including national population and housing censuses and population based health statistics derived from national surveys; Afri-Afya (African Network for Health Management and Communication), which is a consortium of seven Kenya-based health development agencies.

The Division of Health Information System (HIS) is charged with the responsibility of collecting, collating, analyzing, publishing and disseminating health and management data and information to all stakeholders (both public and private) for evidence based decision making. The information that is disseminated is used for planning and management of health services and programmes. HIS collects routine data from various sources such as: health facilities (both public and private); research institutions (e.g. KEMRI); disease/sentinel surveillance sites; civil registration; Kenya National Bureau of Statistics (surveys and censuses) and other Government Ministries (Ministry of Health, 2010)

2.4 Theoretical Framework

This study was based on the Rationality Decision making model as developed by Donelson Forsyth in 1990. The model postulates that effective decision making must be rational. People deciding rationally are attempting to reach goals in a systematic way; they collect all relevant information, they analyze information, they evaluate the information and make choices. Rationally based decisions are built on a foundation of measurable facts usually ordered in a systematic manner (Turpin & Marais, 2004).

Rational decision making favors objective data and a formal process of analysis over subjectivity and intuition. The model of rational decision making assumes that the decision maker has full or perfect information about alternatives; it also assumes they have the time, cognitive ability, and resources to evaluate each choice against the others. This model assumes that people will make choices that will maximize benefits for themselves and minimize any cost.

Embedded within the logic of normative decision theory is the presumption that decision-makers actually do use information when it is made available, and they behave that consistently towards it. However, for decades now it has been well acknowledged, from observations, that decision-makers gather information and ignore it; they make decisions first and look for the relevant information afterwards (Mutemwa, 2006).

Rational decision making is a multi-step process for making choices between alternatives. The process of rational decision making favors logic, objectivity, and analysis over subjectivity and insight. The word "rational" in this context does not mean sane or clear-headed as it does in the colloquial sense. The approach follows a sequential and formal path of activities. This path include; a) Formulating a goal(s) b) Identifying the criteria for making the decision c) Identifying alternatives c) Performing analysis and d) Making a final decision.

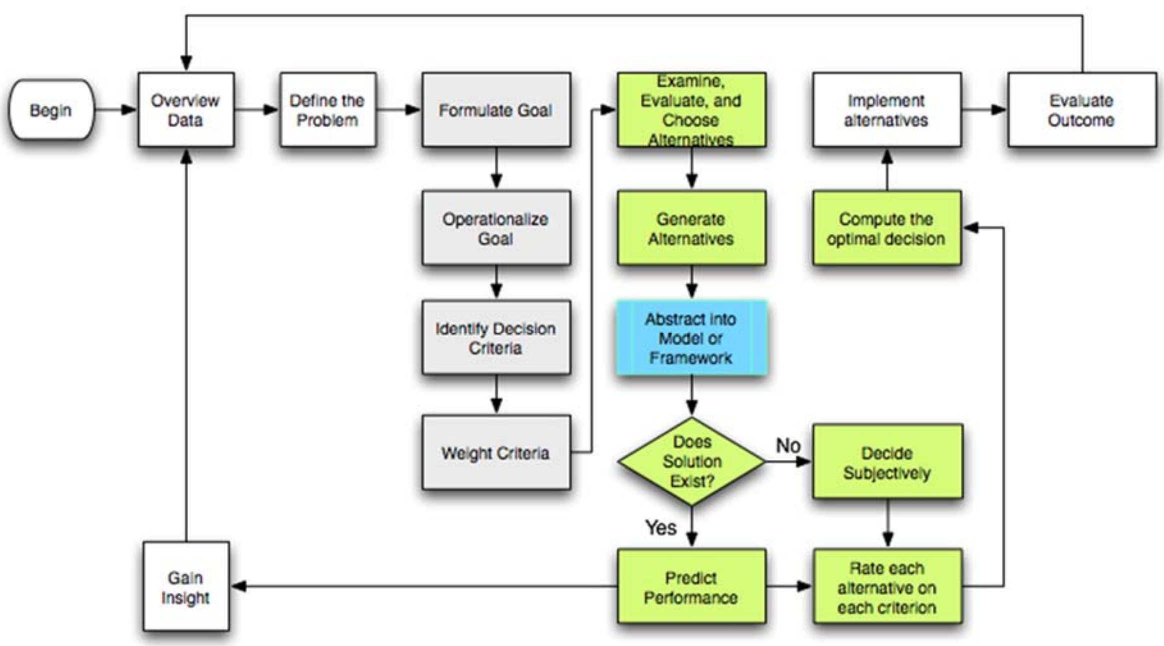

Figure 1: Rational Decision Making Model (1990)

The rational model of decision making assumes that people will make choices that maximize benefits and minimize any costs. The idea of rational choice is easy to see in economic theory. For example, most people want to get the most useful products at the lowest price; because of this, they will judge the benefits of a certain object (for example, how useful is it or how attractive is it) compared to those of similar objects. They will then compare prices (or costs). In general, people will choose the object that provides the greatest reward at the lowest cost.

The rational model also assumes that an individual has full and perfect information on which to base a choice, that a measurable criteria exist for which data can be collected and analyzed and that an individual has the cognitive ability, time, and resources to evaluate each alternative against the others.

The rational-decision-making model does not consider factors that cannot be quantified, such as ethical concerns or the value of altruism. It leaves out consideration of personal feelings, loyalties, or sense of obligation. Its objectivity creates a bias toward the preference for facts, data and analysis over intuition or desires. The main strength of a rational decision making model is that it provides structure and discipline to the decision making process. It helps ensure we consider the full range of factors relating to a decision, in a logical and comprehensive manner.

According to (Nutt, 2008), bad decisions are usually bad because two things are missing; adequate participation of stakeholders in the decision making process or sufficient time spent generating a range of possible solutions. Too often those who should have been involved weren't, and solutions were proposed and acted upon too quickly. Often with disastrous effects, a second weakness arises if we attempt to use the model in isolation. This is particularly important where complex or important decisions are involved.

The theory fits with the study because evidence based decision making is assumed to be the managers role and that it is their responsibility. The rational decision-making theory also establish a weighing mechanism between choice and value. Rational methodologies lead to the optimization of the outcomes by emphasizing the process of choosing rather than on what is chosen. A certain alternative is always selected whenever its expected value is greater than that of other potential choices.

2.5 Influence of Data Quality on evidence based decision making

The function of any health information system (HIS) to produce high quality primary data and to make this data available for measurement purposes. Data are a first step, but quality data is the real aim. Good quality and timely data from health information systems are the foundation of all health systems. However, too often data sit in reports, on shelves or in databases and are not sufficiently utilized in policy and program development, improvement, strategic planning and advocacy (Nutley & Reynolds, 2013a).

Data that are accurate, complete and delivered on time to users (as information) are an important aspect in health planning, management and decision making. Evidence-based plans and decisions must, of necessity, be based on accurate, complete and timely data. Despite concerns about the poor quality of data collected routinely through health facilities, the extent of reliability has not been well explored. Therefore, decisions to use or not to use these data are made subjectively (Simba & Mwangu, 2009). It has been argued that decision-makers often rely on data to support their decision-making processes. There is strong evidence, however, that data quality problems are widespread in practice and that reliance on data of poor or uncertain quality leads to less-effective decision-making. Addressing this issue requires first a means of understanding data quality and then techniques both for improving data quality and for improving decision-making based on data quality information (Price & Shanks, 2008)

According to the schematic framework of data quality, data quality is defined as how well the information system represents the real world, also, data quality is defined as, "the degree to which data items are accurate, complete, relevant, timely, sufficiently detailed, appropriately represented and retain sufficient contextual information to support decision making."(Rychetnik, Hawe, Waters, Barratt, & Frommer, 2004).

In the real world, activities are implemented in the field. These activities are designed to produce results that are quantifiable. On the other hand, information systems represent these activities by collecting the results that were produced and mapping them to some form of recording system. Seven data quality dimensions are identified; Accuracy, Reliability, Completeness, Precision, Timeliness and Integrity (Measure Evaluation, 2007)

Various scholars have come up with different dimensions to explain data quality. In the information systems literature, information quality and user satisfaction are two major dimensions for evaluating the success of information systems. These two dimensions generally include some data quality attributes, such as accuracy, timeliness, precision, reliability, currency, completeness, and relevancy Other attributes such as accessibility and interpretability are also used in the data quality literature (Wang & Strong, 1996)

Data quality dimensions are not independent of each other but correlations exist among them. If one dimension is considered more important than the others for a specific application, then the choice of favoring it may imply negative consequences on the others. Establishing trade-offs among dimensions is an interesting problem, and tradeoffs may need to be made (Scannapieco, Missier, & Batini, 2005)

Past research has illustrated that data quality maybe evaluated along several different quality dimensions. The three important and commonly addressed data quality dimensions are accuracy, timeliness, and completeness (Scannapieco et al., 2005).

According to (Measure Evaluation, 2007), accurate data are considered correct if the data measure what they are intended to measure. Accurate data minimize error (e.g., recording or interviewer bias, transcription error, sampling error) to a point of being negligible. Whereas, (Tejay, Dhillon, & Chin, 2006) postulate that data accuracy dimension is concerned with the conformity of the recorded value with the actual value. It is a widely accepted dimension of data quality. Accuracy implies that data is correct, flawless, precise, reliable and certified free of error.

The original data must be accurate in order to be useful. If data are not accurate, then wrong impressions and information are being conveyed to the user. Documentation should reflect the event as it actually happened. Recording data is subject to human error and steps must be taken to ensure that errors do not occur or, if they do occur, are picked up immediately (World Health Organisation, 2003).

For a typical health information system in a developing country, it is not easy to achieve data quality. Frequently, health data in developing countries are incomplete; they either miss a portion of the population or do not cover all relevant aspects of health. This is often through no fault of their own; they simply do not have the resources needed to achieve a comprehensive system instantaneously, but they can definitely work to improve what they have. There is also sometimes a lack of support from the supply perspective for improving data quality. There are few incentives to correct the crude data gathered for the health information system at a national or district level. This generates a perverse cycle in which decision-makers reacting to the quality problems in the data exclude those data from their decision-making. In turn, providers of data choose not to invest in improvements because nobody is consuming their products to begin with (Joan s. Ash, 2004).

Emphasis on improving data quality is increasingly becoming necessary because it is explicitly evidence based and results oriented. Good data are needed to inform the design of interventions and to monitor and evaluate the quantitative progress toward pre-determined treatment, prevention, and care targets. Ultimately, organizations should be committed to accuracy of information for purposes of accountability and, more importantly, for use of quality data to improve programs (Measure Evaluation, 2007)

Attention to data quality ensures that target-setting and results reporting are informed by valid and sensitive information, and that reporting partners and participating country programs are thinking about and collecting and organizing this information in the same manner. In this way, attention to data quality leads to improved program performance and to more efficient resource management (Measure Evaluation, 2007).

Poor data quality limits stakeholders' ability to use data for evidence-based decision making and has a negative impact on facilities' strategic planning activities and their efforts to advocate for resources. Inaccurate and incomplete data along with delayed reporting affects demand for data. Stakeholders who have had negative experiences with poor data quality are less likely to seek it for future decision making (Harrison, 2008)

Data quality is not only important for securing an accurate description of health status, service coverage, and performance, it also inspires faith in the routine health information system among data users. The better the quality of data, the more people will come to rely on it, value it, and use it as a tool in decision making and, ultimately, to improve the health of the community. Quality health data should be verifiable, accurate (using correct calculations and measuring the right things), complete (i.e., from all data sources and available to users), timely, and standardized (meet agreed standards as determined by client/user), relevant, true (reflect reality), and context specific. They also should allow for decision making with minimal risk and be unbiased, interpretable by all users, organized in such a way as to be manageable, objective and not subjective, comprehensive, feasible to collect, meaningful (reflecting what it wants to measure), specific, sharable, accessible, simple and easy to use, consistent with explanation for unexpected changes, and sensitive to changes (Setzer, 2003)

While relevant and timely information allows managers to make accurate decisions, irrelevant information makes decision making difficult, adds to confusion, and affects the performance of the company. Therefore it is crucial that managers are aware of what information they require, how to acquire it and how to maximize the use of it in order to survive and prosper in today's information-intensive environment. Managers need to use information not only for decision making and making sense of changes and developments in their external environment but also to generate new knowledge which can be applied to design new products and services, enhance existing offerings and improve organisational processes (Alwis & Higgins, 2001)

Various organizational activities require data in some form or manner. (Pipino, Lee, & Wang, 2002) give a grim warning that important corporate initiatives are at a risk of failure unless data quality is seriously considered and improved. Poor data quality would impact setting strategy, its execution, ability to derive value from data, and ability to align the organization (Tejay et al., 2006)

In a study conducted to evaluate the reporting of routine health delivery services in Tanzania and Mozambique in 2002 found that the health data being reported were not sufficient to support informed decision-making and health planning. The causes of the low quality of the data identified include incomplete, inaccurate, and untimely reporting; lack of resources and office space; existence of legacy information systems; and the existence of parallel reporting systems in the health information systems (Lungo, 2003)

Empirical studies conducted in Africa point to the fact that data completeness is a serious concern. According to a study conducted in South Africa on challenges for Routine Health System Data Management in a Large Public Programme to Prevent Mother-to-Child HIV Transmission in South Africa, results showed huge variations in the completeness of data reporting for selected PMTCT data elements. Analysis of all six data elements from 316 health facilities reported over 12 months to the DHIS showed that the data were complete (i.e. 50.3%) only half the time (Mate, Bennett, Mphatswe, Barker, & Rollins, 2009).

A study conducted in Kenya to assess the ability of the health information systems in 22 hospitals to support evidence-informed decisions found out that the HMIS does not deliver quality data and significant constraints exist in data quality assurance, supervisory support, data infrastructure in respect to information and communications technology application, human resources, financial resources, and integration (Kihuba et al., 2014).

Empirical findings from a rapid needs assessment on organisational HIV M&E capacity conducted in Kenya in 2013 indicated that the lack of written guidelines and/or standard operating procedures (SOPs) regarding data validation and routine data quality audits requires attention and also recognized that the absence of tools and training on the updated tools hinders the ability of the providers to encounter difficulty delivering accurate information on the HIV activities that they conduct in their facilities (Mbondo, Scherer, Aluoch, Sundsmo, & Mwaura, 2013).

Similarly, a descriptive cross-sectional research conducted to collect data from 178 facilities on data quality in Kenya in 2014 by the division of Health Informatics Monitoring and Evaluation concluded that the accuracy of summary data and DHIS data against the source documents was generally low and was aggravated by several systemic issues including lack of standardized tools, governance, standard operating procedures, indicator definitions, and unclear roles and responsibilities. There was only a slight improvement of accuracy of DHIS data against summary sheets despite having qualified HRIOs keying in this data due to lack of aggregation instructions and multiple service delivery sites generating data (Government of Kenya, 2014)

Accurate, consistent, complete and timely information is essential for public health decision making and action-taking such as policy making, planning, programming and monitoring. In a study conducted to assess the factors associated with low level of health information utilization in resources limited setting in Eastern Ethiopia in 2004 found out that 77.4% department heads agreed reports were submitted according to the schedule, which is within 20th to 22nd days of the month for health post and 20th to 24th for health centers and hospital. There was 82.0% department heads also claimed reports were completely filled before reporting while 78.7% of these reports was agreed to be consistent (Teklegiorgis, 2014).

Too often, the primary focus of data quality projects is to increase the internal controls involved in entering and editing data. As laudable as these efforts are, they are ultimately doomed to failure, as are one shot attempts to clean up data. The only way to truly improve data quality is to increase the use of that data. If an organization wants to improve data quality, it needs to insure that there is stringent use of each data element (Orr, 1998).

2.6 Influence of Data Availability on Evidence based decision making

According to the United Nations environmental programme for development (2015), information within many developing countries is not adequately managed, because of shortages of financial resources and trained manpower, lack of awareness of the value and availability of such information and other immediate or pressing problems. Even where information is available, it may not be easily accessible, either because of the lack of technology for effective access or because of associated costs, especially for information held outside the country and available commercially. The reasons for limited access to some data are privacy protection, fragmented health care system, poor quality of routinely collected data, unclear policies and procedures to access the data, and control on the freedom on publication. The primary objective of collecting health-care data in these economies is to aid the policymakers and researchers in policy decision making as well as create an awareness on health-care issues for the general public. The usage of data in monitoring the performance of the health system is still in the process of development (Aljunid et al., 2012).

For data to be useful in decision making, decision makers need to have access to all relevant data sources. Access to both summary reports and full data sets is critical in program management and improvement and policy formulation. For example; complete data is necessary to supporting trend, output and outcome monitoring; problem identification; target setting; site comparison and hypothesis testing. Without sufficient access to full and multiple data sources, data-informed decision making will be limited (Measure Evaluation, 2010).

According to (Kennerley & Mason, 2008), most organizations have an abundance of data available to them with which to make decisions with some complaining of “drowning in data whilst thirsting for information". If decision making is to be informed by information then clearly it is important that data is available. Not only does the availability of data enable a decision to be made, but in many circumstances data can indicate when a decision needs to be made (Chua & Degeling, 1993).

The World Health organisation asserts that health information is much more than collecting figures. Data have no value in themselves; value and relevance come when they are analysed, transformed into meaningful information and used. A health information system is thus not a static entity but a process whereby health-related data are gathered, shared, analysed, and used for decision-making in health – information is transformed into knowledge for action (Setzer, 2003).

High-quality health information is a critical input into clinical, local, national and global decision-making. The potential for good health information to help create a culture of evidence-informed decision-making for public health and medicine is well recognized. However, the current landscape is characterized by enormous gaps in the availability and timeliness of information. Information on basic health outcomes—including mortality rates, causes of death, and the incidence and prevalence of major diseases—is not available for many communities, countries and regions. Information on financial resources, human resources, and other inputs to health care and the quality and coverage of health interventions is even more deficient (Health, Systems, & Hub, 2009).

Well-designed information systems often include information technology infrastructure, policies, and report templates to support the communication of synthesized data through dissemination and feedback techniques. What is often under- developed in these systems is the availability for data users to be able to access and share data easily that may not be part of the regular dissemination process. This issue becomes more apparent when data users seek to access data that are not part of the routine HIS. The consideration of data synthesis, communication, and access need to be improved to support the use of the information in decision making (Nutley, 2012)

As the volume of data has grown and the methods of analyzing them have improved, organizations have been integrating data more firmly into the decision-making process. However, increasing numbers of traditional and non-traditional data sources are inundating companies with data in volumes and types they may not have seen before (Economist Intelligence Unit, 2013). The value of accurately recorded data is lost if it is not accessible. Data is accessible when; Medical/health records are available when and where needed at all times, Abstracted data are available for review when and where needed, In an electronic patient record system, clinical information is readily available when needed, Statistical reports are accessible when required for patient-care committees, planning meetings and government requirements (World Health Organisation, 2003).

According to (Deiters et al. 2003), not only is the right information needed, it is also needed at the right point in time and from the location the user happens to be at, at any given time. For health information systems to function effectively and efficiently health professionals need to be trained not only to collect and manage the information but also to analyze, interpret and disseminate it for use in decision making. For data to be used consistently, the entire health system must place a high value on health information and be structured in a way that supports and encourages evidence-based decision making

Public access to health data is essential to ensure accountability. The sharing of aggregate data, such as district level data on TB or vaccinations, or facility data on the number of antiretroviral therapy users, facilitates the compilation of reliable statistics, which can become the basis for effective advocacy, policy and action. In most countries however little data are publicly available. For example, very few countries make district reported health facility data on say immunization, TB treatment outcome or institutional deliveries available on their health ministry web site (World Health Organization, 2011)

Difficulties in conveying technical information effectively: Low numeracy skills limit the extent to which percentages, rates, and ratios can be used; low literacy levels may limit acceptance, understanding, and use of information; messages are misunderstood if they are not adapted to appropriate culture and language; they are ineffective if they stop short of suggesting an action; it is difficult to craft compelling messages on routine, “boring” subjects.

The organizational culture of expecting information from subordinates without providing feedback limits the provision of good-quality data (there is a tendency to punish poor reporting but not reward good reporting); red tape may block where information flows and if it flows at all (e.g., if important information is published on the Internet, “heads will roll”); political influence is often anti-technical, e.g., technical data on staffing needs may be overlooked and inappropriate persons appointed instead.

Fear of the misuse of information may impede its being communicated at all or may require that a spokesperson communicates only distilled information to the media; journalists may be “bloodhounds” who search for bad or sensational news; information is powerful and may be deliberately misused by the media to send the wrong message (Setzer, 2003).

To ensure that data are understood by potential users, data synthesis and communication need to be targeted and take into account users’ roles and information needs, the appropriate level of detail and complexity of the information being presented, and users’ intensity of interest in the topic (Davies, Hodge, & Aumua, 2011)

Kenya among other countries have started utilizing the District Health Information System Software (DHIS2) which is a free and open source database and application for collecting, processing, and analyzing health information, and whose development and implementation was started in 1998 by the Health Information System Programme (HISP) based in South Africa. The overall objective of DHIS2 implementation is to be able to generate, analyze and disseminate health information to facilitate effective policy formulation, management, planning, budgeting, implementation, monitoring and evaluation of health services and program interventions in the health sector.DHIS2 is able to support collection and analysis of routine health services data, as well as non-routine data such as population estimates, facility workload and survey data. The web-based DHIS2 is intended to capture health facility service delivery data and allow analysis at that level, promoting data use at all levels for decision making (Karuri, Waiganjo, Orwa, & Manya, 2014).

In addition, in countries which have registered apparent success in use of DHIS2, there are still challenges reported with regard to data quality as well as capacity of various health workers to analyze and use DHIS information. Additional challenges which have been identified in countries using DHIS include the fact that fragmentation of systems in the health sector still persists, and even where quality data is present, its use for rationalizing key health decisions is still limited. It is thus apparent that implementation of a technically sound system like DHIS is not an end in itself in ensuring improved reporting and use of

HIS data for rational health decision making. There is also the need for acceptance and adequate support from the national and local authorities (Karuri et al., 2014).

A vital aspect of analysis is synthesizing data from multiple sources examining inconsistencies and contradictions, and summarizing health situations and trends to produce consistent assessments. This will include the burden of disease, patterns of risk behaviour, health service coverage and health system metrics. Despite its importance, such data analysis capacity is often lacking at peripheral levels where the results of generated data are needed for planning and management. Developing this capacity will require careful planning and investment by multiple stakeholders. Information packaging is a key requirement for influencing decision- makers (World Health Organization, 2008)

One of the key steps in moving from information to evidence-based action is the communicating the information to relevant stakeholders. When communicating health information, one needs to present the information in a package that is understood by the target audience, whether it is the community or politicians. Many health workers and health information specialists (including district information officers) are not trained in communication. Sometimes the reverse occurs: communication has been a problem in some places because of the requirement to communicate information through a communication official who is not trained in health information (Setzer, 2003).

2.7 Influence of capacity on data use on evidence based decision making

Significant investments have been committed towards strengthening strategic information activities for the Ministry of Health in Kenya by the MOH and development partners (ADAM Consortium) among others. The support has focused on monitoring and evaluation of the national HIV/AIDs program and to better use data/information in its decision making process. The support to improve health care capacities in M&E is premised on the fact that, to improve sustainable demand for and use of data in data use core decision making, individual capacity in core competencies to demand and use data must exist at all levels of the health system. Competencies include skills in data analysis, interpretation, synthesis, and presentation, and the development of data-informed programmatic recommendations. For data producers, these competencies should be built as part of standard monitoring and evaluation (M&E) training or basic research training, but often training programs have a short-term perspective (1-4 weeks) with limited follow up. Skills are not fully developed and newly trained professionals are under- equipped to apply their new skills in the work setting (Nutley & Reynolds, 2013a).

Moreover, the target audience for M&E and research training is the data producer not the data user. Data users often struggle with an underdeveloped ability to understand analysis and interpret them in the programmatic context. This population also needs to be targeted with training in how to analyze, critically review, and interpret data and understand what data they need and when they can demand data. For data informed decision making to become normative and sustained, funding will be needed to implement and sustain the interventions outlined in this article. Training in leadership and advocacy skills is critical to equip managers to leverage the funding and buy-in needed to implement and sustain interventions to improve.

The lack of or inadequacy of requisite skills at all levels coupled with a perception of non-usefulness of information and data collected at the lower levels have conspired to create an exceptionally low level of commitment from health providers. Programme focused strategies receive more support and recognition as a result of the lack of commitment (Ministry of Health, 2010).

The Kenya health information policy (2010-2030), recognizes that capacity for data management and use within the HIS is critically limited at all levels of the system amongst HIS staff who are supposed to produce analyzed information for use amongst managers who should use the information jointly with facility staff who collect the data.

In developing countries, health workers at the district level and below are often responsible for the initial collection, recording, and reporting of health data. In several countries, some degree of analysis and use of information is expected at the district level. Yet, even when health workers are properly trained and have access to the tools needed to record, report, analyze, and use data, evidence points to low health worker motivation to provide quality data in a timely way and to use that information for evidence-based decision making. To these health workers, the information collected usually serves an unclear purpose and provides little benefit to them; its collection and use is perceived as a waste of time and resources, even when the data are available (Setzer, 2003).

In many organizations so much time and effort is spent gathering data that once the gather process is complete those responsible simply collate the data they have gathered into standardized templates and release the resultant performance reports with very little attempt to using the data (Kennerley & Mason, 2008).

Lack of general skills in the basics of M&E not only affects data quality but also the ability to use data in decision making. Specific training on completing data collection forms and data compilation, analysis and presentation are critical yet often underdeveloped skills. Moreover, the ability to interpret health information and apply it to the programmatic and policy context requires a skill set that is often never addressed in pre- or post-service training of health professionals (Harrison, 2008)

Interpretation of data is one of the key stages in the process of using data to inform decision making. Interpretation is to translate data into intelligible or familiar terms, it is at this point that data becomes information having been given context. Once the charts and graphs have been completed in the previous step, the question now becomes: what does that mean for the decision being made or objective we are seeking to achieve? This stage is crucial and attempts to deal with fundamental questions: What insights can we extract from the data? How will the message differ by changing the angle we look at data? This is converting information into knowledge and is done by adding the important elements of relevance and context which clarify the insights that are contained in the data (Kennerley & Mason, 2008). Spence (2001) refers to interpretation of information as achieving the Ah-ha moment. That is arriving at the moment at which the messages in the data become clear.

According to (Fapohunda, 2012), a common barrier to using data in decision making is the limited capacity of data users to interpret data in the context of program improvement. Program managers and policy-makers, the end data users, are seldom involved in the research and data collection process, thus limiting their understanding of how the data were collected, the questions the study addressed, and the limitations of the data.

A good health information system should therefore present and disseminate data in appropriate formats for all audiences. Sound health information is a global public good and requires public and media support to ensure in strengthening health continued investment (World Health Organization, 2008).

Within the health sector itself, the need to build capacity for health information is often overlooked. The need for people with numeric and statistical skills to generate and analyze data is rarely mentioned in analyses of human resource requirements. The assumption seems to be that health-care workers can take on the duties of health information officers. Yet providers are understandably reluctant to divert their attention from patient care to data recording (Abouzahr & Boerma, 2005).

Health sector reform generally comprises decentralization of decision-making and resource allocation to the district level, yet neither the tools nor the capacities for information generation and analysis at this level have been sufficiently developed. Where capacity exists, is it is largely concentrated centrally.

A qualitative assessment of data management and reporting systems conducted in Botswana in 2014 found out that at the facility/community level, M&E and data management responsibilities were generally not clearly assigned, and there was often a lack of ownership of M&E-related tasks. Health workers did not necessarily view the recording of patient and health facility information in registers as one of their job responsibilities (Ledikwe et al., 2014).

From an action research study conducted on Improving quality and use of data through data-use workshops in Zanzibar in 2012, findings indicated that DHMT members' presentation skills were initially weak, as they were unused to drawing graphs, using PowerPoint, engaging in debate or offering constructive criticism. These skills improved dramatically as a result of the workshops, especially when standardized templates for presentations were developed. Local HMIS Unit and health zone personnel acquired sufficient skills to run the workshops without outside facilitators (Braa, Heywood, & Sahay, 2012).

2.8 Influence of Institutional support in evidence based decision making

Data is the "life blood" of an organization, for as it flows between systems, databases, processes, and departments, it carries with it the ability to make the organization smarter and more effective. Data is essential to making well-informed decisions that guide and measure achievement of organizational strategy. How an organization uses and manages the data is just as important as the mechanisms used to bring it into the environment. Having the right data of appropriate quality enables the organization to perform processes well and to determine which processes have the greatest impact. These fundamental objectives leverage data by transforming it into useful information. The highest performing organizations ensure that their data assets are accessible to the processes and individuals who need it, are of sufficient quality and timeliness, and are protected against misuse and abuse. Successfully leveraging data and information assets does not happen by itself; it requires proactive data management by applying specific disciplines, policies, and competencies throughout the life of the data (Mitre, 2013).

Information is used at various levels of the health system for health service and system management, planning, advocacy and policy development. The dynamic links between demand, supply and quality of information should be addressed by encouraging a culture in which information is demanded and its use promoted. In practical terms, this will require the establishment of institutional mechanisms and incentives to create a culture of evidence-based decision-making. Experience shows that the most effective mechanisms involve linking data & information to actual resource allocation (budgets) and developing indicator-driven planning. However, the capacity for data analysis is often lacking at peripheral levels where the data are generated and results should be used for planning and management. Bringing together a comprehensive analysis of the health situation and trends with data on health inputs (such as health expenditure and system characteristics) is particularly important. Developing such analytical capacity requires planning, investment and tools (World Health Organization, 2008).

For routine health information to be used in decision making, providers, M&E professionals and decision makers need to be supported in the collection, analysis and use of that information. Stakeholders need to understand each other's roles and responsibilities in producing and using data and they need specific guidance in implementing their roles and responsibilities. When organizational systems are in place to support a culture of data-informed decision making, data producers and users are better able to understand the value of data to the health system, data tends to be of higher quality, data is communicated and shared through the health system and, as a result, it is used in decision making (Harrison, 2008).

An unfortunate feature of health care systems in many parts of the world is that decisions are taken despite the absence of reliable information. In practice, decision-making in health is all too often based on political opportunism, expediency or donor demand. There is a growing awareness that this leads to inefficient and ineffective use of resources. Increasing emphasis on results-based management and performance-based funding is focusing minds on the need for sound data generated through reliable and transparent systems (Abouzahr & Boerma, 2005)

According to (Nutley & Reynolds, 2013a), all organizations are made up of people and the effectiveness of an organization is directly linked to the performance of its employees; most organizations are governed by rules, processes, values, and systems that have the ability to support or hinder an individual's ability to use data in decision making.

An organization that has structures and processes for improving the interaction of data users and producers, providing clear guidelines for data quality processes, and defining roles and responsibilities related to using data will strengthen other interventions put in place to improve data-informed decision making. An organization that has a guiding strategy and mission that clearly supports data-informed decision making will be better positioned to support data-informed decision making. Policies and standard operating procedures that govern how work is accomplished should clearly state the role and value of data in organizational functioning. By addressing organizational systems, such as those just mentioned, potential barriers to data use can be overcome and data-informed decision making can be improved and sustained (Michie & West, 2004).

In order to function, a health system needs staff, funds, information, supplies, transport, communications, and overall guidance and direction and it needs to provide services that are responsive, financially fair, and that treat people with respect. Despite the apparent suitability of an HMIS for monitoring a wide range of important health system metrics, and the substantial resources invested in their development and operation, the extent to which data from HMISs are used to generate statistics of use to decision makers is extremely limited (World Health Organization, 2008).

According to the Ministry of health (2010), inadequate funding for collecting, consolidating, integration and strengthening of the monitoring and evaluation systems within the decentralized health system has not been fully targeted such that at the various levels, funding and other resources are made available even if managers fail to report adequately on performance.

As a signatory to the 2001 Abuja Declaration, Kenya committed to allocating at least 15 percent of its national budget to health. Not only is Kenya spending a relatively low amount as a percentage of GDP on healthcare, but the allocation of funds to public facilities has been uneven. According to a 2011 Healthy Action report, secondary and tertiary facilities have historically been allocated 70 percent of the health budget. The same report notes that allocation of funds to primary care facilities has been "poor" this despite the significant role these facilities play as the first point of contact in the provision of healthcare services (KPMG, 2013)

In a study conducted by (Kihuba et al., 2014) to assess the ability of health information systems in hospitals to support evidence informed decisions in Kenya found out that at hospital level, HMIS departments were generally poorly financed. On average 3% of the total annual income, from cost sharing and government grants, was allocated to the HMIS departments with a range of 18% compared with a policy requiring that at least 10% should be allocated to information services.

Most health facilities have invested in some forms of information technologies to manage their routine health data, human resources and finances. However, while advances in information technology can enable large volumes of data to be processed and analyzed quickly, the success is highly dependent on having adequate hardware, sufficient internet access, and common data architecture between systems, IT professionals, and support to ensure systems maintain functionality. These critical success factors remain a big challenge in many resource-limited settings (Ledikwe et al., 2014).

From a rapid assessment study conducted by (Mbondo et al., 2013) on the organizational HIV monitoring and evaluation capacity in Kenya noted a shortage of HRIOs, ICT officers, and statisticians within HIS at the decentralized level. It further affirmed that most staff had basic data capture and reporting skills, but had limited ability to check data quality, undertake basic data analysis and interpretation, and use the data generated for decision making.

Without sufficient staff to lead, implement, and supervise an M&E system, data will not be available for use in decision making. An insufficient number of skilled M&E professionals, particularly at the regional level, posed challenges for further RHIS strengthening (Traore et al., 2014). We also recognize that for people to use data in decision making in a sustainable way, their organizations need to support them with clear processes and systems that help them to undertake data-use tasks.

2.9 Knowledge gaps

The following observations were made from the literature review. Much of the empirical studies carried out were in the developing countries and have been conducted on with the broader perspective of assessing the performance of the national routine health information systems. This study sought to fill the existing research gaps by conducting a study to examine the factors that influence the utilization of routine health data for evidence based decision making by public health facilities in Kenya. Specifically, the study sought to assess data quality, data availability, capacity on data use competencies and organisational data use & demand infrastructure as key activities that are critical in promoting the use of routine health data in evidence based decision making.

Table 1: Knowledge Gaps

Variable	**Author and Year**	**Focus of study**	**Findings**	**Knowledge gap**
Data Quality	Kihuba et al (2014	Assessing the ability of health information systems in hospitals to support evidence-informed decisions	Study findings indicate that the HMIS does not deliver quality data. Significant constraints exist in data quality assurance, supervisory support, data infrastructure in respect to information and communications technology application, human resources, financial resources, and integration	There is need to assess the association and interactions between human factors, availability of resources, and accuracies of the reported routine data estimates.
Data Availability	Wilkins, Nsubuga, Mendlein, Mercer, & Pappaioanou , 2008	The Data for Decision Making project: assessment of surveillance systems in developing countries to improve access to public health information	The assessments identified no fewer than eight problem areas that impeded decision makers' access to information as follows; (lack of timeliness, accuracy, simplicity, flexibility, acceptability, usefulness. The most common deficiencies were concerning the design of the system, ongoing training of personnel and dissemination of data from the system	This study seeks to focus more on lack of timeliness and accuracy

Capacity in Data Use competencies	Nutley & Reynolds, 2013	Improving the use of health data for health system strengthening	The logic model provides specific and comprehensive guidance to improve data demand and use. It can be used to design, monitor and evaluate interventions, and to improve demand for, and use of, data in decision making. As more interventions are implemented to improve use of health data, those efforts need to be evaluated.	There is limited understanding in general whether data use interventions resulted in anticipated changes in improving data demand and use
Institutional Support	Ledikwe et al (2014)	Improving the quality of health information: A qualitative assessment of data management and reporting systems.	Limited ownership of M&E-related duties within facilities, a lack of tertiary training programs to build M&E skills, few standard practices related to confidentiality and document storage, limited dissemination of indicator definitions, and limited functionality of electronic data management systems.	The study seeks to investigate capacity on data use and assignment of data use roles and responsibilities by the facilities.

2.10 Conceptual Framework

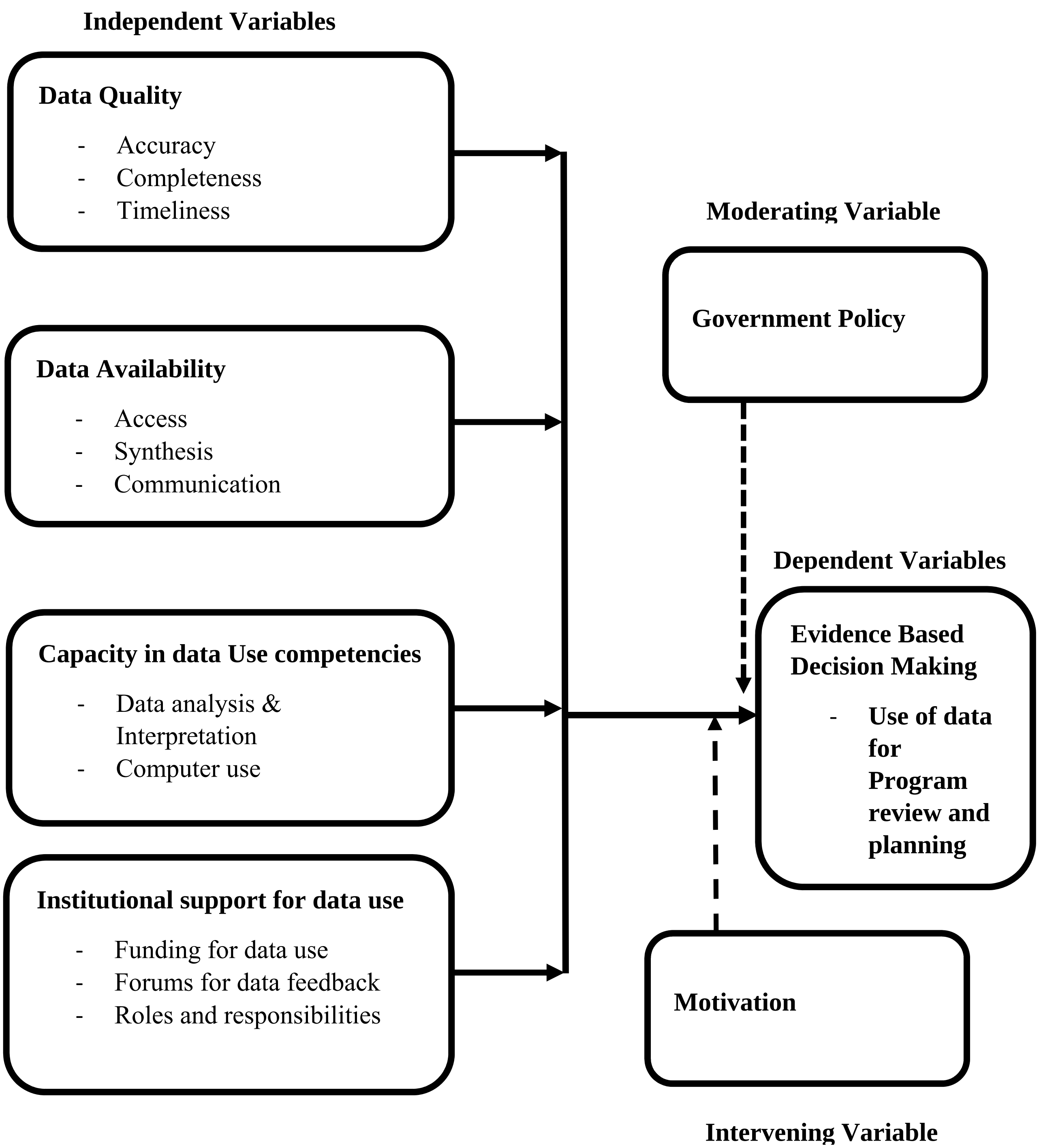

Figure 2: Conceptual Framework

A systematic review of literature on data quality indicated that for consistent data use to occur, routine health data need to be of high quality so that data users are confident that the data they are consulting are accurate, complete, and timely. Without quality data, demand for data drops, data-informed decision making does not occur, and program efficiency and effectiveness will suffer. Its influence has however not been properly contextualized. The influence of data quality on evidence based decision making and the extent of their relationship was tested in objective one.

Data availability, defined by authors as data synthesis, data communication, and access to data need to be improved to support the use of the information in decision making. To ensure that data are understood by potential users, data synthesis and communication need to be targeted and take into account users' roles and information needs, the appropriate level of detail and complexity of the information being presented, and users' intensity of interest in the topic. The influence of data availability on evidence based decision making will be tested in objective two.

To improve sustainable demand for and use of data in decision making, individual capacity in core competencies to demand and use data must exist at all levels of the health system. Competencies include skills in data analysis, interpretation, synthesis, and presentation, and the development of data-informed programmatic recommendations. Data users often struggle with an underdeveloped ability to understand analyses and interpret them in the programmatic context. For data-informed decision making to become normative and sustained, funding will be needed to implement and sustain the interventions. The influence of capacity on data use on evidence based decision making will be tested in objective three.

Empirical literature suggest that organizations that have structures and processes for improving the interaction of data users and producers, providing clear guidelines for data quality processes, and defining roles and responsibilities related to using data will strengthen other interventions put in place to improve data-informed decision making. The influence of institutional support on evidence based decision making will be tested in objective four.

2.11 Chapter Summary

The literature review comprised the theoretical framework, empirical review and conceptual framework. The researcher reviewed the importance of Health Information Systems, the structure of HIS in Kenya, the importance of various empirical literature carried out on data quality, data availability, capacity on data use and institutional support for evidence based decision making . The exact influence will be unequivocally explained in this study. Interrelationships of variables and indicators constituting those variables were undertaken in great detail through a conceptual framework. The chapter concluded by identifying knowledge gaps.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the methodological approaches used to answer the research questions and achieve the objectives of the study will be discussed. As previously stated, the primary objective of this research study was to assess the factors influencing utilization of routine health data in evidence based decision making for HIV treatment services in Nakuru County. It is against this background that the various methodologies adopted for this study are presented below. This chapter covers the research design, research methods and strategies, the study population, sampling frame, sampling procedure, operationalization of variables, research instruments and procedures of data collection, ethical issues as well as methods for data analysis.

3.2 Research Design

The research study adopted a descriptive survey research design whereby data was collected from a cross-section of health care providers and health facility managers from Nakuru County.

The purpose of descriptive research is to observe, describe and document aspects of a situation as it naturally occurs(Polit & Beck, 2004). A descriptive research design is a scientific method which involves observing and describing the behaviour of a subject without influencing it in any way (Martyn, 2008). On the other hand, descriptive survey studies are used to describe an event or process in its natural ambit and the main objective is to answer how, who, and what questions(Robert K. Yin, 2003).

The study adopted the descriptive survey design because it provided the opportunity for the researcher to explore and explain while providing additional information or meaning about the research topic. The research design was helpful at describing what was happening in more detail, filling in the missing parts and expanding understanding of the research topic.

3.3 Target Population

The research study targeted 68 health care workers (facility in-charges, departmental heads in HIV/AIDs departments and Health records information officers) who are the key decision makers with respect to planning and programming for HIV treatment services at the respective facilities.

Table 2: Sampling Frame

Sample	No of Institutions	No Per Institution	Population Size
Dispensaries	15	1	15
Health Centres	23	2	46
Sub-County Hospitals	6	3	18
County Hospitals	1	3	3
Total	**45**	**9**	**82**

Source: DHIS2 for Health Facilities

3.4 Sample size and Sampling Procedure

This study adopted the stratified sampling method. According to Kothari (2004), stratified sampling technique provides more reliable and detailed information. The research study used stratified random sampling technique as it improves the representation of particular strata (groups) within the population, as well as ensuring that these strata are not over-represented. Stratified sampling also helps to compare strata, as well as make more valid inferences from the sample to the population. As shown in table 2, the population was put in four strata. A list of all GOK owned public health facilities providing HIV/AIDs treatment services were listed from the DHIS2 and stratified depending on their level of care (i.e. dispensaries, health centres, sub-county hospitals and county hospitals). Simple random sampling technique was used to arrive at a representative sample from each of the strata.

In determining the sample size, the study used the Slovens formula for calculating sample size as follows;

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

Where;

n =Desired Sample Size,

N=Population Size= 82

e = Level of precision (error Margin) =0.05 NB: The study used a confidence level of 95%.

n = Sample Size (68 respondents)

3.5 Research Instruments

Primary data was collected using a structured questionnaire developed to answer to the study objectives. A structured questionnaire was preferred in this study because since it offers an effective way of collecting information from large samples in a short period of time and at a reduced cost. Additionally, a questionnaire facilitates easier coding and analysis of data collected. Additionally, questionnaires are standardized so it is not possible to explain any points in the questions that participants might misinterpret. Responses will be measured on an ordinal (Likert) scale for the closed ended questions.

The study questionnaire was self-administered by the respondents. The methods of administration was appropriate for the study because of the diverse experiences and roles the respondents had with respect to utilizing data for decision making, the huge spread of the facilities in the population, cost effectiveness and for increased chances for a higher response rate. A letter introducing the objective of the research accompanied the questionnaire.

3.6 Validity and Reliability

Validity determines whether the research truly measures that which it was intended to measure or how truthful the research results are whereas, reliability is the extent to which results are consistent over time and an accurate representation of the total population under study is referred to as reliability and if the results of a study can be reproduced under a similar methodology, then the research instrument is considered to be reliable. Joppe (2000).

Kirk and Miller (1986) identifies three types of reliability referred to in quantitative research, which relate to: the degree to which a measurement, given repeatedly, remains the same, the stability of a measurement over time and the similarity of measurements within a given time period. Reliability of instruments is important as it provides assurance that instrument will represent the true position is accurately recorded. The reliability of the instrument was enhanced by adopting an appropriate sampling technique.

The study used Cronbach alpha to measure internal consistency of results across items within a test i.e. how closely related a set of items are as a group. The Cronbach alpha was interpreted as the mean of all possible split-half coefficients and was considered to be a measure of scale reliability. A Cronbach reliability coefficient of .70 or higher was to be considered "acceptable"

A coefficient of 0.808 was obtained from the measurement and this meant that the tool had relatively high internal consistency: Table 3 below shows the reliability statistics computed from the study;

Table 3: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of Items
.808	.742	67

3.7 Operational Definition of Variables

This section defines the variables in terms of measurable indicators. The independent variables are operationalized as shown in the table below;

Table 4: Operational Definition of Variables

Research Objective	Variable	Indicator(S)	Measurement	Measurement Scale	Data Collection tool	Type of analysis
1. To assess the influence of data quality in planning for HIV services in public health facilities of Nakuru County	Data Quality	Accuracy of data	Level of data accuracy	Ordinal	Questionnaire	Descriptive Statistics
		Completeness of data	Level of data completeness			
		Timeliness of data	Level of data timeliness			
2. To establish the influence of data availability in evidence based decision making by public health facilities of Nakuru County	Data Availability	Access to data	Ease of data access	Ordinal	Questionnaire	Descriptive Statistics
		Data synthesis	Ability to synthesize data			
		Data communication	Ability to use different forms for data communication			
3. To examine the influence of capacity on data use competencies in evidence based decision making by public health facilities of Nakuru County	Capacity for data use competencies	Data analysis& Interpretation	Capacity of staff to conduct data analysis Ability to interpret charts and graphs	Ordinal	Questionnaire	Descriptive Statistics
		Computer use	Frequency of using computers to perform basic tasks			
4. To investigate the influence of institutional support on evidence based decision making by public health facilities of Nakuru County	Institutional support for data use	Funding for data use	Allocation of funds allocated for data use activities	Ordinal	Questionnaire	Descriptive Statistics
		Forums for data use feedback	Presence of data feedback forums			
		Data use roles and responsibilities	Allocation of data use responsibilities by management			

3.8 Methods of Data Analysis

Data analysis was done using descriptive statistics. This involved coding the collected data and entering it into SPSS Version 20.0. Information for the different variables was obtained by computing the variables, recoding the variables and synthesizing the information from the data collected for meaning. In the data analysis, the researcher examined each piece of information in the instrument for completeness, errors and inconsistencies. Missing data was verified with the original questionnaires. Outputs for the data were generated in the form of frequencies, means, standard deviation, coefficient of variation and Pearson's product moment correlation coefficient denoted as r for the sample statistic so as to assess possible linear relationship between the independent and dependent variables. The significance level was set at probability $p < 0.05$ for every statistical set. The results were then presented in the form of tables for ease of interpretation

3.9 Ethical Issues

The researcher sought authorization from the relevant bodies and letters from the authorities were appended to the to the research project before commencement of data collection. Institutional entry protocol will be adhered to and a letter of introduction will be sent to the sub-county MOH in-charges in advance. The study assured the respondents that all the information provided will be treated with confidentiality. The researcher further ensured that the results were generalised without referring to a specific facility or person.

3.10 Summary

The chapter covers the methodology to be used to conduct the research on the factors influencing utilization of routine health data in planning for HIV services in Nakuru County. A descriptive case study research design is to be used for the study. The population of the study was identified as 82 health facility staff working in GOK public health facilities providing HIV/AIDS treatment services in Nakuru County.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION AND INTERPRETATION

4.1 Introduction

This chapter presents the research findings related to the factors influencing the utilization of routine HIV/AIDS health data in evidence based decision making in public health facilities in Nakuru County. The findings are presented according to the following thematic areas: Respondents general information, influence of data quality on evidence based decision making, influence of data availability on evidence based decision making, influence of capacity on data use competencies on evidence based decision making and the influence of organisational data demand and use infrastructure on evidence based decision making.

4.2 Respondents General Information

4.2.1 Response Rate

A total of 68 questionnaires were distributed and out of which 58 were duly filled and returned

Table 5.1 Response Rate

Type of Facility	Number of questionnaires given out	Number of questionnaires returned	Response Rate
Dispensary	12	7	58.3%
Health Centre	36	34	94.4%
Sub County Hospital	15	12	80.0%
County Referral Hospital	5	5	100.0%
Total	**68**	**58**	**85.3%**

This gives a response rate of 85.3% as shown in Table 4.1. The response rate was generally good and conforms to Mugenda and Mugenda (2003) stipulation, that a response rate of 50% is adequate for analysis and reporting; a rate of 60% is good while a response rate above 70% is excellent. A majority of the respondents 58.6% were working at the health centres, 20.7% were working at sub-county hospitals, 12.1% respondents were from dispensaries and 8.6% of the respondents were from the county referral hospital.

4.2.2 Background Information of Survey respondents

The study sought the background characteristics of the respondents. This information was important to understand the general demographic features of the respondents. The respondents were asked to choose their designation, professional background, highest level of education, number of years they had been employed in current job and an age bracket that they currently are in and the following is the findings;

Table 4.2: Gender Composition

Gender	Frequency	Percentage
Male	23	39.7
Female	35	60.3
Total	**58**	**100%**

Table 4.2 shows that there were more female respondents 60.3%, compared to 39.7% male respondents. The study further sought to know from the respondents their designation as health care workers.

Table 4.3: Designation of Respondents

Designation	Frequency	Percentage
Facility In charges	20	34.5
Departmental heads	24	41.4
HRIOs	7	12.1
Service Providers	7	12.1
Total	**58**	**100%**

Table 4.3 indicates that the majority of respondents were departmental heads 41.4%, followed by facility in charges 34.5%, Health records information officers 12.1% and service providers 12.1%.

The study further sought to know from the respondents their duration of employment into the current position as health care workers.

Table 4.4: Duration of employment in current job

Duration of employment in current job	Frequency	Percentage
Less than 1 Year	5	8.6
Between 2-3 Years	7	12.1
Between 4-6 Years	24	41.4
Between 7-10 Years	14	24.1
Above 10 Years	8	13.8
Total	**58**	**100%**

Table 4.4 shows that 8.6% of the respondents have been employed in their current position for less than a year, 12.1% had been in employment for between 2-3 years, 41.4% had been in employment for 4-6 years, 24.1% were employed in their current job for between 7-10 years and 13.8% were employed in their current job for over 10 years.

The respondents were asked to choose from which age bracket they fall in as health care workers.

Table 4.6: Age of Respondents

Age	Frequency	Percentage
Below 25 Years	1	1.7
26-35 Years	18	31.0
36-45 Years	31	53.4
46-55 Years	8	13.8
Total	**58**	**100%**

Table 4.5 shows that majority of the respondent 53.4 % were in age bracket of 36-45 years, 31.0% were in age bracket of 26-35 years, 13.8% were in age bracket 46-55 years, while 1.7 % were below 25 years and none was above 55 years old.

4.3 Influence of data quality on use of data for decision making

The study sought to find out the influence routine health data quality on evidence based decision making focusing on three dimensions of data quality i.e. data accuracy, data completeness and data timeliness in public health facilities in Nakuru County. The respondents were asked to rate the extent to which they agreed or disagreed to the listed domains using a five point likert scale of strongly disagree, disagree, neutral, agree, strongly agree.

4.3.1 Data accuracy

The respondents were asked to rate data accuracy for the routine health data generated by the routine health system using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.7: Data Accuracy

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. I have encountered inaccurate data during decision making process	0 (0.0%)	2 (3.4%)	5 (6.9%)	24 (39.7%)	27 (50.0%)
2. Inaccurate data has hindered me from routinely using data to make decisions	1 (1.7%)	4 (6.9%)	4 (6.9%)	24 (41.4%)	25 (43.1%)
3. I take corrective action to address noted data accuracy issues before use	1 (2%)	0 (0.0%)	2 (3.4%)	40 (69.0%)	15 (25.9%)
4. I have used/relied on other data sources and not routine health data to make decisions	9 (15.5%)	11 (19.0%)	3 (5.2%)	31 (53.4%)	4 (6.9%)

Average	**4.8%**	**7.3%**	**5.6%**	**50.9%**	**31.5%**
Standard Deviation	**6.6%**	**7.9%**	**2.9%**	**25.6%**	**21.8%**
Coefficient of Variation	**137.2%**	**107.6%**	**51.7%**	**50.3%**	**69.4%**

Table 4.6 summarizes the distribution of respondents' opinions. On the statement, I have encountered inaccurate data during decision making, respondents were of different opinions as follows; strongly disagree 0%, disagree 3.4%, neutral 6.9%, agree 39.7% and strongly agree 50.0%. Concerning the statement inaccurate data has hindered me from routinely using data to make decisions, the responses were as follows; strongly disagree 1.7%, disagree 6.9%, neutral 6.9%, agree 41.4% and strongly agree 43.1%. Concerning the statement I take corrective action to address noted data accuracy issues before use, the responses were as follows; strongly disagree 2%, disagree 0%, neutral 3.4%, agree 69.0% and strongly agree 25.9%. The study findings further show that on the statement of I have used/relied on other data sources and not routine health data to make decisions, the responses were as follows; strongly disagree 15.5%, disagree 19.0%, neutral 5.2%, agree 53.4% and strongly agree 6.9%.On average, responses on data accuracy were as follows; strongly disagree 4.8%, disagree 7.3%, neutral 5.6%, agree 50.9% and strongly agree 31.5%. Coefficients of Variation computed for data accuracy were as follows: strongly disagree 137.2%, disagree 107.6%, neutral 51.7%, agree 50.3% and strongly agree 69.4%.

4.3.2 Data completeness

The respondents were asked to rate the completeness of data for the routine health data generated by the facility using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.8: Data Completeness

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. Reported data includes all the necessary dataset reports	0 (0.0%)	9 (15.5%)	0 (0%)	31 (53.4%)	18 (31.0%)
2. Reported data is sufficiently complete for our needs	2 (3.4%)	5 (8.6%)	8 (8.6%)	21 (36.2%)	22 (38.9%)
3. Reported data summarizes the work of the department	1 (1.7%)	1 (1.7%)	1 (1.7%)	27 (46.6%)	28 (48.3%)
4. Routine health data is not relevant to my current data analysis and aggregation needs	36 (62.1%)	14 (24.1%)	4 (6.9%)	2 (3.4%)	2 (3.4%)
5. There is no added value due to aggregating inconsistent data	29 (50.0%)	11 (19.0%)	5 (8.6%)	7 (10.3%)	6 (10.3%)
Mean	**23.4%**	**13.8%**	**5.2%**	**30.0%**	**26.4%**
Standard Deviation	**30.1%**	**8.8%**	**4.0%**	**22.1%**	**19.0%**
Coefficient of Variation	**128.4%**	**63.8%**	**78.3%**	**73.8%**	**72.1%**

Table 4.7 summarizes the distribution of respondents' opinions. On the statement reported data includes all the necessary data set reports, respondents were of different opinions as follows; strongly disagree 0%, disagree 15.5%, neutral 0%, agree 53.4% and strongly agree 31.0%. Concerning the statement reported data is sufficiently complete for our needs, the responses were as follows; strongly disagree 3.4%, disagree 8.6%, neutral 8.6%, agree 36.2% and strongly agree 38.9%. Concerning the statement reported data summarizes the work of the department, the responses were as follows; strongly disagree 1.7%, disagree 1.7%, neutral 1.7%, agree 46.6% and strongly agree 48.3%. Concerning the statement routine health data is not relevant to my current data analysis and aggregation needs, the responses were as follows; strongly disagree 62.1%, disagree 24.1%, neutral 6.9%, agree 3.4% and strongly agree 3.4%. The study findings further show that on the statement there is no added value to aggregating inconsistent data, the responses were as follows; strongly disagree 50.0%, disagree 19.0%, neutral 8.6%, agree 10.3% and strongly agree10.3%. On

average, responses on data completeness were as follows; strongly disagree 23.4%, disagree 13.8%, neutral 5.2%, agree 30.0% and strongly agree 26.4%. Coefficients of Variation computed for data completeness were as follows: strongly disagree 128.4%, disagree 63.8%, neutral 78.3%, agree 73.8% and strongly agree 72.1%.

4.3.3 Data Timeliness

The respondents were asked to rate the timeliness of the routine health data generated by the facility using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.9: Data Timeliness

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. Reporting from the facility is always on time	0 (0.0%)	7 (12.1%)	1 (1.7%)	21 (36.2%)	29 (50.0%)
2. Corrective actions are always taken within reasonable time?	1 (1.7%)	9 (15.5%)	1 (1.7%)	32 (55.2%)	15 (25.9%)
3. When making decisions, i always use current data?	0 (0%)	2 (3.4%)	1 (1.7%)	38 (65.5%)	17 (29.3%)
4. Data is always available on time for decision making?	0 (0%)	10 (17.2%)	2 (3.4%)	34 (58.6%)	12 (20.7%)
Mean	**0.4%**	**12.1%**	**2.1%**	**53.9%**	**31.5%**
Standard Deviation	**0.9%**	**6.1%**	**0.9%**	**12.5%**	**12.8%**
Coefficient Variation	**200.0%**	**51.0%**	**40.0%**	**23.3%**	**40.8%**

Table 4.8 summarizes the distribution of respondents' opinions. On the statement reporting from the facility is always on time, the respondents were of different opinions as follows; strongly disagree 0%, disagree 12.1%, neutral 1.7%, agree 36.2% and strongly agree 50.0%. Concerning the statement corrective actions to address data quality are always taken within reasonable time, the responses were as follows; strongly disagree 1.7%, disagree 15.5%, neutral 1.7%, agree 55.2% and strongly agree 25.9%. Concerning the

statement when making decisions, I always use current data, the responses were as follows; strongly disagree 0%, disagree 3.4%, neutral 1.7%, agree 65.5% and strongly agree 29.3%. Concerning the statement data is always for decision making, the responses were as follows; strongly disagree 0%, disagree 17.2%, neutral 3.4%, agree58.6% and strongly agree 20.7%. On average, responses on data timeliness were as follows; strongly disagree 0.4%, disagree 12.1%, neutral 2.1%, agree 53.9% and strongly agree 31.5%. Coefficients of Variation computed for data timeliness were as follows: strongly disagree 200.0%, disagree 51.0%, neutral 40.0%, agree 23.3% and strongly agree 40.8%.

4.4 Influence of data availability on use of data for decision making

The study sought to find out the influence of routine health data availability on evidence based decision making focusing on three dimensions of data quality i.e. data access, data synthesis and data communication by public health facilities in Nakuru County. The respondents were asked to rate the extent to which they agreed or disagreed to the listed domains using a five point likert scale of strongly disagree, disagree, neutral, agree, strongly agree.

4.4.1 Data Access

The respondents were asked to rate the accessibility of routine health data generated by the facility using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.10: Data Access

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. It takes a lot of time to find required data to make timely decisions	21 (36.2%)	27 (46.6%)	1 (1.7%)	8 (13.8%)	1 (1.7%)
2. Data is stored in a way that is difficult to access	39 (67.2%)	18 (31.0%)	0 (0%)	1 (1.7%)	0 (0%)
3. Data is inaccessible due to technological limitations?	9 (15.5%)	21 (36.2%)	2 (3.4%)	25 (43.1%)	1 (1.7%)
4. There is no obvious way to access data?	38 (65.5%)	16 (27.6%)	1 (1.7%)	3 (5.2%)	0 (0%)
5. I need special clearance to access routine health data?	39 (67.2%)	13 (22.4%)	2 (3.4%)	4 (6.9%)	0 (0%)
6. I have limited capacity to understand the data to enable summarising into understandable formats?	14 (24.1%)	23 (39.7%)	3 (5.2%)	18 (31.0%)	0 (0%)
7. Available routine health data does not support my tasks?	41 (70.7%)	16 (27.6%)	1 (1.7%)	0 (0%)	0 (0%)
8. I have access to the district health information system (DHIS)?	31 (53.4%)	10 (17.2%)	3 (5.2%)	7 (12.1%)	7 (12.1%)
9. I have the capacity to manipulate the DHIS to generate data reports?	35 (60.3%)	10 (17.2%)	3 (5.2%)	5 (8.6%)	5 (8.6%)
Mean	**51.1%**	**29.5%**	**3.1%**	**13.6%**	**2.7%**
Standard Deviation	**20.7%**	**10.0%**	**1.9%**	**14.3%**	**4.5%**
Coefficient of Variation	**40.4%**	**34.0%**	**62.2%**	**105.4%**	**167.9%**

Table 4.9 summarizes the distribution of respondents' opinions. On the statement it takes a lot of time to find required data to make decisions, the respondents were of different

opinions as follows; strongly disagree 36.2%, disagree 46.6%, neutral 1.7%, agree 13.8% and strongly agree 1.7%. Concerning the statement data is stored in a way that is difficult to access, the respondents were of different opinions as follows; strongly disagree 67.2%, disagree 31.0%, neutral 0%, agree 1.7% and strongly agree 0%. Concerning the statement data is inaccessible due to technological limitations, the respondents were of different opinions as follows; strongly disagree 15.5%, disagree 36.2%, neutral 3.4%, agree 43.1% and strongly agree 1.7%.On the statement there is no obvious way to access data, the respondents were of different opinions as follows; strongly disagree 65.5%, disagree 27.6%, neutral 1.7%, agree 5.2% and strongly agree 0%.On the statement I need special clearance to access routine health data, the respondents were of different opinions as follows; strongly disagree 67.2%, disagree 22.4%, neutral 3.4%, agree 6.9% and strongly agree 0%.On the statement, I have limited capacity to understand the data to enable summarising into understandable formats, the respondents were of different opinions as follows; strongly disagree 24.1%, disagree 39.7%, neutral 5.2%, agree 31.0% and strongly agree 0%.On the statement available routine health data does not support my tasks, the respondents were of different opinions as follows; strongly disagree 70.7%, disagree 27.6%, neutral 1.7%, agree 0% and strongly agree 0%. When asked if the respondents had access to the district health information system (DHIS), the responses were as follows; strongly disagree 53.4%disagree 17.2%, neutral 5.2%, agree 12.1% and strongly agree 12.1%. Lastly, the respondents were asked if they had the capacity to manipulate the DHIS to generate data reports and their responses were as follows; strongly disagree 60.3%, disagree 17.2%, neutral 5.2%, agree 8.6% and strongly agree 8.6%. On average, responses on data access were as follows; strongly disagree 51.1%, disagree 29.5%, neutral 3.1%, agree 13.6% and strongly agree 2.7%. Coefficients of Variation computed for data access were as follows: strongly disagree 40.4%, disagree 34.0%, neutral 62.2%, agree 105.4% and strongly agree 167.9%.

4.4.2 Data Synthesis

The respondents were asked to rate their capacity to synthesize routine health data on the highlighted domains using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.11: Data Synthesis

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. There is a facility set of indicators with targets and annual reporting to inform annual health sector reviews and other planning cycles	6 (10.3%)	3 (5.2%)	2 (3.4%)	26 (44.8%)	21 (36.2%)
2. The facility/department routinely calculates performance of indicators using the catchment population	20 (34.5%)	6 (10.3%)	2 (3.4%)	21 (36.2%)	9 (15.5%)
3. The facility makes comparison with sub county/county national set targets	22 (37.9%)	2 (3.4%)	6 (10.3%)	20 (34.5%)	8 (13.8%)
4. The facility makes comparison among the different types of service coverage	9 (15.5%)	1 (1.7%)	2 (3.4%)	37 (63.8%)	9 (15.5%)
5. The facility makes comparison of routine health data over different time	6 (10.3%)	1 (1.7%)	4 (6.9%)	35 (60.3%)	12 (20.7%)
6. Facility staff are able to synthesize data into understandable and actionable narrative and graphical forms for different target audience	4 (6.9%)	20 (34.5%)	11 (19.0%)	20 (34.5%)	3 (5.2%)
Mean	**19.2%**	**9.5%**	**7.7%**	**45.7%**	**17.8%**
Standard Deviation	**13.5%**	**12.7%**	**6.2%**	**13.3%**	**10.3%**
Coefficient of Variation	**70.0%**	**133.9%**	**79.8%**	**29.1%**	**57.9%**

Table 4.10 summarizes the distribution of respondents' opinions on their capacity to synthesize data. On the question if there is a facility set of indicators with targets and annual reporting to inform annual health sector reviews and other planning cycles, the responses

were as follows; strongly disagree 10.3% disagree 5.2%, neutral 3.4%, agree 44.8% and strongly agree 36.2%. On the question if the facility/department routinely calculates performance of indicators using the catchment population, the responses were as follows; strongly disagree 34.5% disagree 10.3%, neutral 3.4%, agree 36.2% and strongly agree 15.5%. On the question if the facility makes comparison with sub county/county national set targets, the responses were as follows; strongly disagree 37.9% disagree 3.4%, neutral 10.3%, agree 34.5% and strongly agree 13.8%. On the question if the facility makes comparison among the different types of service coverage, the responses were as follows; strongly disagree 15.5% disagree 1.7%, neutral 3.4%, agree 63.8% and strongly agree 15.5%. On the question if the facility makes comparison of routine health data over different time, the responses were as follows; strongly disagree 10.3% disagree 1.7%, neutral 6.9%, agree 60.3% and strongly agree 20.7%. Lastly, the question if the facility staff are able to synthesize data into understandable and actionable narrative and graphical forms for different target audience, the responses were as follows; strongly disagree 6.9% disagree 34.5%, neutral 19.0%, agree 34.5% and strongly agree 5.2%. On average, responses on data synthesis were as follows; strongly disagree 19.2%, disagree 9.5%, neutral 7.7%, agree 45.7% and strongly agree 17.8%. Coefficients of Variation computed for data synthesis were as follows: strongly disagree 70.0%, disagree 133.9%, neutral 79.8%, agree 29.1% and strongly agree 57.9%.

4.4.3 Data Communication

The respondents were asked to rate their capacity to communicate the synthesized routine health data based on the highlighted domains using a five point scale of strongly disagree, disagree, neutral, agree and strongly agree.

Table 4.12: Data Communication

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. Facility has identified HIV/AIDs performance indicators for routine monitoring	12 (20.7%)	3 (5.2%)	2 (3.4%)	23 (39.7%)	18 (31.0%)
2. Graphs/charts/data tables are displayed in the departments to show performance of the identified HIV/AIDs indicators	13 (22.4%)	7 (12.1%)	2 (3.4%)	18 (31.0%)	18 (31.0%)
3. Facility has capacity to identify potential target audiences or users of data	14 (24.1%)	10 (17.2%)	5 (8.6%)	25 (43.1%)	4 (6.9%)
4. There is systematic communication of data analysis findings through a variety of communication channels	21 (36.2%)	7 (12.1%)	7 (12.1%)	19 (32.8%)	4 (6.9%)
Mean	**25.9%**	**11.7%**	**6.9%**	**36.7%**	**19.0%**
Standard Deviation	**7.0%**	**4.9%**	**4.3%**	**5.7%**	**13.9%**
Coefficient of Variation	**27.2%**	**42.3%**	**62.0%**	**15.6%**	**73.4%**

Table 4.11 summarizes the opinions of the respondents on data communication. On the question if the facility had identified HIV/AIDs performance indicators for routine monitoring, the responses were as follows; strongly disagree 20.7%, disagree 5.2%, neutral 3.4%, agree 39.7% and strongly agree 31.0%. When asked if Graphs/charts/data tables are displayed in the departments to show performance of the identified HIV/AIDs indicators, the responses were as follows; strongly disagree 22.4%, disagree 12.1%, neutral 3.4%, agree 31.0% and strongly agree 31.0%. On the question if facility has capacity to identify potential target audiences or users of data, the responses were as follows; strongly disagree 24.1%, disagree 17.2%, neutral 8.6%, agree 43.1% and strongly agree 6.9%. Further when respondents were asked if there was a systematic communication of data analysis findings

through a variety of communication channels, the responses were as follows; strongly disagree 36.2%, disagree 12.1%, neutral 12.1%, agree 32.8% and strongly agree 6.9%. On average, responses on data communication were as follows; strongly disagree 25.9%, disagree 11.7%, neutral 6.9%, agree 36.7% and strongly agree 19.0%. Coefficients of Variation computed for data communication were as follows: strongly disagree 27.2%, disagree 42.3%, neutral 62.0%, agree 15.6% and strongly agree 73.4%.

4.5 Influence of capacity in data use for decision making

The study sought to find out the influence of capacity on data use competencies by the health facility staff focusing on their opinions on capacity to conduct basic data analysis, data interpretation where the respondents were asked to rate their capacity using a five point likert scale of poor, below par, average, good and exemplary. On the other hand, the respondents were asked to rate their frequency of using computers to perform basic data analysis tasks using a scale of daily, at least once a week, at least once a month and never.

4.5.1 Data Analysis & Interpretation Capacity

The respondents were asked to rate the extent to which they agreed or disagreed to the listed domains using a five point likert scale of poor, below par, average, good and exemplary.

Table 4.13: Data Analysis Capacity

	Poor	Below Par	Average	Good	Exemplary
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. Capacity to calculate percentages or rates correctly	0 (0%)	9 (15.5%)	17 (29.3%)	23 (39.7%)	9 (15.5%)
2. Capacity to plot data by weeks, months or years	1 (1.7%)	8 (13.8%)	20 (34.5%)	20 (34.5%)	9 (15.5%)
3. Capacity to plot data into bar charts	1 (1.7%)	9 (15.5%)	20 (34.5%)	21 (36.2%)	7 (12.1%)

4. Capacity to interpret charts and their implications	2 (3.4%)	6 (10.3%)	21 (36.2%)	26 (44.8%)	3 (5.2%)
Mean	**1.7%**	**13.8%**	**33.6%**	**38.8%**	**12.1%**
Standard Deviation	**1.4%**	**2.5%**	**3.0%**	**4.5%**	**4.9%**
Coefficient of Variation	**81.6%**	**17.8%**	**8.9%**	**11.7%**	**40.2%**

Table 4.12 summarizes the opinions of the respondents on their data use capacity. On the question of capacity to calculate percentages or rates correctly, the responses were as follows; poor 0% below par 15.5%, average 29.3%, good 39.7% and exemplary 15.5%. Concerning their capacity to plot data by weeks, months or years, the responses were as follows; poor 1.7% below par 13.8%, average 34.5%, good 34.5% and exemplary 15.5%. Concerning their capacity to plot data into bar charts their responses were as follows; poor 1.7% below par 15.5%, average 34.5%, good 36.2% and exemplary 12.1%. Lastly when asked their opinion on their capacity to interpret charts and their implications, the responses were as follows; poor 3.4% below par 10.3%, average 36.2%, good 44.8% and exemplary 5.2%.On average, responses on data analysis capacity were as follows; poor1.7%, below par13.8%, average33.6%, good38.8% and exemplary 12.1%. Coefficients of Variation computed for data analysis capacity were as follows: poor 81.6%, below par 17.8%, average 8.9%, good 11.7% and exemplary 40.2%.

4.5.2 Computer use

The respondents were asked to rate their frequency of using computers to perform basic data analysis tasks using a scale of daily, at least once a week, at least once a month and never.

Table 14: Frequency of Computer Use

	Daily	At least once a week	At least once a month	Never
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. Frequency of using computers to type documents	13 (22.4%)	12 (20.7%)	9 (15.5%)	24 (41.4%)
2. Frequency of using computers for data analysis	2 (3.4%)	2 (3.4%)	17 (29.3%)	37 (63.8%)
3. Frequency of using computers for presenting data	1 (1.7%)	0 (0%)	19 (32.8%)	38 (65.5%)
4. Frequency of using computers to access internet browsing	19 (32.8%)	0 (0%)	16 (27.6%)	23 (39.7%)
Mean	**15.1%**	**6.0%**	**26.3%**	**52.6%**
Standard Deviation	**15.1%**	**9.9%**	**7.5%**	**13.9%**
Coefficient of Variation	**100.1%**	**164.5%**	**28.6%**	**26.5%**

Table 4.13 summarizes the opinions of the respondents on their frequency of using computers for basic data use purposes. On the question of frequency of using computers to type documents, the responses were as follows; daily 22.4%, at least once a week 20.7%, at least once a month 15.5% and never 41.4%. Concerning their frequency of using computers for data analysis, daily 3.4%, at least once a week 3.4%, at least once a month 29.3% and never 63.8%. Concerning their frequency of using computers for presenting data, their responses were as follows; daily 1.7%, at least once a week 0%, at least once a month 32.8% and never 65.8%. Lastly, concerning their frequency of using computers to access internet browsing; their responses were as follows; daily 32.8%, at least once a week 0%, at least once a month 27.6% and never 39.7%.On average, responses on computer use were as follows; daily 15.1%, at least once a week 6.0%, at least once a month 26.3%, never 52.6%. Coefficients of Variation computed for data analysis capacity were as follows: daily 100.1%, at least once a week 164.5%, at least once a month 28.6%, never 26.5%.

4.6 Influence of institutional support on decision making

The study sought to find out influence of data demand and use infrastructure on evidence based decision making by asking the respondents the degree to which they strongly disagree to strongly agree from the listed factors influencing evidence based decision making in their facilities.

4.6.1 Data Activities funding

The study sought to understand the opinions regarding the influence of funding for data use activities on evidence based decision making.

Table 4.15: Data Activities Funding

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. The facility supports departments with airtime or internet bundles	19 (32.8%)	9 (15.5%)	3 (5.2%)	10 (17.2%)	17 (29.3%)
2. The facility has allocated funds for data quality assessment (DQA) activities	17 (29.3%)	13 (22.4%)	8 (13.8%)	5 (8.6%)	15 (25.9%)
3. The facility has funding for monthly quality improvement meetings	16 (27.6%)	12 (20.7%)	7 (12.1%)	11 (19.0%)	12 (20.7%)
4. The facility has funding for monthly data review meeting	18 (31.0%)	15 (25.9%)	7 (12.1%)	10 (17.2%)	8 (13.8%)
5. The facility has a recognition or reward system in place for good performance	33 (56.9%)	22 (37.9%)	3 (5.2%)	0 (0%)	0 (0%)
6. There is dedicated resources (staff, time, money) to support data analysis and data use	11 (19.0%)	17 (29.3%)	5 (8.6%)	20 (34.5%)	5 (8.6%)
Mean	**32.8%**	**25.3%**	**9.5%**	**16.1%**	**16.4%**
Standard Deviation	**12.8%**	**7.8%**	**3.7%**	**11.5%**	**11.1%**

Coefficient of Variation	**38.9%**	**30.7%**	**39.3%**	**71.7%**	**67.5%**

Table 4.14 summarizes the opinions of the respondents with regards to receiving funding for data use activities. On the question of if the facility supports the departments with airtime or internet bundles, the responses were as follows; strongly disagree 32.8%, disagree 15.5%, neutral 5.2%, agree 17.2% and strongly agree 29.3%. On the question if facility has allocated funds for data quality activities (DQA), the responses were as follows; strongly disagree 29.3%, disagree 22.4%, neutral 13.8%, agree 8.6% and strongly agree 25.9%. On the question if facility has funding for monthly quality improvement meetings, the responses were as follows; strongly disagree 27.6%, disagree 20.7%, neutral 12.1%, agree 19.0% and strongly agree 20.7%. When asked if the facility has funding for monthly data review meetings, the responses were as follows; strongly disagree 31.0%, disagree 25.9%, neutral 12.1%, agree 17.2% and strongly agree 3.87%. Concerning the question of facility has a recognition or reward system in place for good performance, the responses were as follows, strongly disagree 56.9%, disagree 37.9%, neutral 5.2%, agree 0% and strongly agree 0%. Lastly asked if there was dedicated resources to support data analysis and data use, the responses were as follows; strongly disagree 19.0%, disagree 29.3%, neutral 8.6%, agree 34.5% and strongly agree 8.6%.On average, responses on data activities funding were as follows; strongly disagree 32.8%, disagree 25.3%, neutral 9.5%, agree 16.1% and strongly agree 16.4%. Coefficients of Variation computed for data funding activities were as follows: strongly disagree 38.9%, disagree 30.7%, neutral 39.3%, agree 71.7% and strongly agree 67.5%.

4.6.2 Forums for data use feedback

The study sought to understand the opinions of the respondents regarding the influence of feedback on evidence based decision making.

Table 4.16: Forums for Data Use Feedback

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	**Freq (%)**	**Freq (%)**	**Freq (%)**	**Freq (%)**
1. Appropriate data users and producers regularly participate in the collection, analysis and use of data	21 (36.2%)	12 (20.7%)	10 (17.2%)	13 (22.4%)	2 (3.4%)
2. The facility keeps an official record of health management meetings	1 (1.7%)	1 (1.7%)	3 (5.2%)	37 (63.8%)	16 (27.6%)
3. The facility management provides immediate written support supervision feedback to the staff	2 (3.4%)	31 (53.4%)	4 (6.9%)	19 (32.8%)	2 (3.4%)
4. The facility management routinely seeks feedback from staff	9 (15.5%)	23 (39.7%)	3 (5.2%)	21 (36.2%)	2 (3.4%)
5. The facility engages stakeholders in the interpretation of analysis to extract meaning	28 (48.3%)	5 (8.6%)	11 (19.0%)	13 (22.4%)	1 (1.7%)
Mean	**21.0%**	**24.8%**	**10.7%**	**35.5%**	**7.9%**
Standard Deviation	**20.5%**	**21.5%**	**6.8%**	**17.0%**	**11.0%**
Coefficient of Variation	**97.8%**	**86.7%**	**63.7%**	**47.8%**	**139.7%**

Table 4.15 summarizes the opinions of the respondents with regards to forums for data feedback. On the question of if appropriate data users and producers regularly participate in the collection, analysis and use of data, the responses were as follows; strongly disagree 36.2%, disagree 20.7%, neutral 17.2%, agree 22.4% and strongly agree 3.4%. With regards to the question of the facility keeps an official record of health management meetings, the responses were as follows; strongly disagree 1.7%, disagree 1.7%, neutral 5.2%, agree 63.8% and strongly agree 27.6%.Concerning the facility providing immediate written

support supervision feedback, the responses were as follows; strongly disagree 3.4%, disagree 53.4%, neutral 6.9%, agree 32.8% and strongly agree 3.4%. Concerning the facility routinely seeking feedback from staff, the responses were as follows; strongly disagree 15.5%, disagree 39.7%, neutral 5.2%, agree 21% and strongly agree 3.4%. Lastly on the question if the facility engages stakeholders in the interpretation of analysis to extract meaning of these data for programs and policies, the responses were as follows; strongly disagree 48.3%, disagree 8.6%, neutral 19.0%, agree 22.4% and strongly agree 1.7%.On average, responses on forums for data use feedback were as follows; strongly disagree 21.0%, disagree 24.8%, neutral 10.7%, agree 35.5% and strongly agree 7.9%. Coefficients of Variation computed for forums for data use feedback were as follows: strongly disagree 97.8%, disagree 86.7%, neutral 63.7%, agree 47.8% and strongly agree 139.7%.

4.6.3 Roles and responsibilities

The study sought to understand the opinions of the respondents regarding the influence of roles and responsibilities on evidence based decision making.

Table 4.17: Roles and Responsibilities

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. There is designated staff responsible for reviewing aggregated data prior to submission to the next level	9 (15.5%)	22 (37.9%)	2 (3.4%)	17 (29.3%)	8 (13.8%)
2. Responsibility for monthly reporting of service delivery data has been clearly assigned to relevant staff	3 (5.2%)	21 (36.2%)	0 (0%)	20 (34.5%)	14 (24.1%)
3. Facility health providers are aware of their roles and	13 (22.4%)	6 (10.3%)	25 (43.1%)	0 (0%)	14 (24.1%)

responsibilities in data management					
Mean	**14.4%**	**28.1%**	**15.5%**	**21.3%**	**20.7%**
Standard Deviation	**8.7%**	**15.5%**	**24.0%**	**18.6%**	**5.9%**
Coefficient of Variation	**60.2%**	**55.0%**	**154.6%**	**87.5%**	**28.8%**

Table 4.16 summarizes the opinions of the respondents with regards to roles and responsibilities. On the question if there is designated staff responsible for reviewing aggregated data prior to submission to the next level, the responses were as follows; strongly disagree 15.5%, disagree 37.9%, neutral 3.4%, agree 29.3% and strongly agree 13.8%. On the question if responsibility for monthly reporting of service delivery data has been clearly assigned to relevant staff, the responses were as follows; strongly disagree 5.2%, disagree 36.2%, neutral 0%, agree 34.5% and strongly agree 24.1%. On the question if facility health providers are aware of their roles and responsibilities in data management, the responses were as follows; strongly disagree 22.4%, disagree 10.3%, neutral 43.1%, agree 0% and strongly agree 24.1%.On average, responses on roles and responsibilities were as follows; strongly disagree 14.4%, disagree 28.1%, neutral 15.5%, agree 21.3% and strongly agree 20.7%. Coefficients of Variation computed for roles and responsibilities were as follows: strongly disagree 60.2%, disagree 55.0%, neutral 154.6%, agree 87.5% and strongly agree 28.8%.

4.7 Evidence Based Decision Making

The study sought to investigate the opinions of the respondents on the basis for decision making, their opinions whether data is used to inform selected program activities and their opinions on the key data use obstacles.

4.7.1 Basis for Decision Making

The study sought to investigate the opinions of the respondents on what forms the basis for decision making.

Table 4.18: Basis for Decision Making

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Freq (%)	Freq (%)	Freq (%)	Freq (%)	Freq (%)
1. Decisions are based on Personal liking	41 (70.7%)	11 (19.0%)	4 (6.9%)	2 (3.4%)	0 (0%)
2. Decisions are based on superiors directives	28 (48.3%)	18 (31.0%)	3 (5.2%)	7 (12.1%)	2 (3.4%)
3. Decisions are based on facts	0 (0%)	1 (1.7%)	5 (8.6%)	23 (39.7%)	29 (50.0%)
4. Decisions are based on political directives	31 (53.4%)	6 (10.3%)	16 (27.6%)	4 (6.9%)	1 (1.7%)
5. Decisions are based on experience/gut feeling	4 (6.9%)	8 (13.8%)	13 (22.4%)	29 (50.0%)	4 (6.9%)
6. Decisions are based on donor demands	4 (6.9%)	5 (8.6%)	17 (29.3%)	29 (50.0%)	3 (5.2%)
Mean	**31.0%**	**14.1%**	**16.7%**	**27.0%**	**11.2%**
Standard Deviation	**30.0%**	**10.1%**	**11.0%**	**21.9%**	**19.2%**
Coefficient of Variation	**96.7%**	**71.7%**	**65.9%**	**81.1%**	**171.1%**

Table 4.18 summarizes the opinions of the respondents with regards to the motivation for making decisions. On the question if decisions are based on Personal liking, responses were as follows; strongly disagree 70.7%, disagree 19.0%, neutral 6.9%, agree 3.4% and strongly agree 0%. On the question if decisions are based on superior's directives, responses were as follows, strongly disagree 48.3%, disagree 31.0%, neutral 5.2%, agree 12.1% and strongly agree 3.4%. On the question if decisions are based on evidence/facts, responses were as follows, strongly disagree 0%, disagree 1.7%, neutral 8.6%, agree 39.7% and strongly agree 50.0%. On the question if decisions are based on political directives, responses were as follows, strongly disagree 53.4%, disagree 10.3%, neutral 27.6%, agree 6.9% and strongly agree 1.7%. On the question if decisions are based on experience/gut feeling, responses were as follows, strongly disagree 6.9%, disagree 13.8%, neutral 22.4%, agree 50.0% and strongly agree 6.9%. Lastly on the question if decisions are based on donor demands, the response was as follows; strongly disagree 6.9%, disagree 8.6%,

neutral 29.3%, agree 50.0% and strongly agree 5.2%.On average, responses on basis for decision making were as follows; strongly disagree 31.0%, disagree 14.1%, neutral 16.7%, agree 27.0% and strongly agree 11.2%. Coefficients of Variation computed for basis for decision making were as follows: strongly disagree 96.7%, disagree 71.7%, neutral 65.9%, agree 81.1% and strongly agree 171.1%.

4.7.2 Data use for action

The study sought to find out the extent to which data is used for different programmatic functions by the health care workers.

Table 4.19: Data Use for Action

	Always	**Sometimes**	**Never**
	Freq (%)	**Freq (%)**	**Freq (%)**
1. Data is used for day to day program management	44 (75.9%)	14 (24.1%)	0 (0%)
2. Data is used to review financial statements and budget preparations	41 (70.7%)	16 (27.6%)	1 (1.7%)
3. Data is used for medical supply and drug management	50 (86.2%)	8 (13.8%)	0 (0%)
4. Data is used for deciding budget allocation	33 (56.9%)	21 (36.2%)	4 (6.9%)
5. Data is used for formulating plans	41 (70.7%)	16 (27.6%)	1 (1.7%)
6. Data is used for human resources management	37 (63.8%)	20 (34.5%)	1 (1.7%)
7. Data is used for monitoring key objectives	37 (63.8%)	19 (32.8%)	2 (3.4%)
Mean	**69.7%**	**28.1%**	**2.2%**
Standard Deviation	**9.5%**	**7.6%**	**2.4%**
Coefficient of Variation	**13.7%**	**27.2%**	**108.1%**

The findings in Table 4.19 indicate the extent to which data is used for different programmatic functions. When asked if data is used for day to day program management, respondents answered as follows; always 75.9%, sometimes 24.1% and never 0%, on the question if data is used to review financial statements and budget preparations, response was as follows; always 70.7%, sometimes 27.6% and never 1.7%. On the question if data is used for medical supply and drug management, responses were as follows; always

86.2%, sometimes 13.8% and never 0%. On the question if data is used for deciding budget allocation, responses were as follows; always 56.9%, sometimes 36.2% and never 6.9%. On the question if data is used for formulating plans, responses were as follows; always 70.7%, sometimes 27.6% and never 1.7%. On the question if data is used for human resource management, responses were as follows; always 63.8%, sometimes 34.5% and never 1.7%. Lastly when asked if data is used for monitoring key objectives, responses were as follows; always 63.8%, sometimes 32.8% and never 3.4%.On average, responses on data use for action were as follows; always 69.7%, sometimes 28.1%, never 2.2%. Coefficients of Variation computed for data use for action were as follows: always 13.7%, sometimes 27.2% and never 108.1%.

Table 4:20: Correlation Coefficient of Variables

		Data Quality	Data Availability	Capacity on data use	Institutional Support	Evidence based Decision Making
Data Quality	Pearson Correlation	1	.356**	.314*	.342**	.368**
	Sig. (2-tailed)		.006	.016	.009	.004
	N	58	58	58	58	58
Data Availability	Pearson Correlation		1	.134	.767**	.059
	Sig. (2-tailed)			.316	.000	.662
	N			58	58	58
Capacity on data use	Pearson Correlation			1	.166	.323*
	Sig. (2-tailed)				.212	.013
	N				58	58
Institutional Support	Pearson Correlation				1	.087
	Sig. (2-tailed)					.514
	N					58
Evidence based Decision Making	Pearson Correlation					1
	Sig. (2-tailed)					
	N					58

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

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

CHAPTER FIVE

SUMMARY OF FINDINGS, DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter discusses findings by comparing and contrasting research findings with other empirical findings in chapter two. The findings detail concurrence or with the existing body of knowledge. At the end of the chapter, recommendations are made based on the research findings.

5.2 Summary of Findings

The analysis involved the use of arithmetic means, percentages, frequencies and coefficient of variations. Tables were used to present results.

The study assessed the influence of routine health data quality on evidence based decision making by the public facilities providing HIV/AIDs treatment services in Nakuru County. It was established that a significant proportion of the respondents 89.7% had encountered inaccurate data during decision making process, and 84.5% of the respondents were thus hindered from making decisions using the routine health data. As a result, 60.3% of the respondents relied on other data sources and not routine health data to make decisions. On data completeness, 84.5% agreed that reported data had all the dataset reports, and 75.1% were of the opinion that reported data was sufficiently complete for their data use needs. On data timeliness, a significant number of respondents 86.2% were of the opinion that reporting from the facility was always on time, 81.1% ensured corrective actions were taken within reasonable time to address data quality issues, 94.8% used current data to make decisions and 79.3% were of the opinion that data was always available on time for decision making. The correlation coefficient analysis revealed a weak positive linear relationship between data quality and evidence based decision making at r =.368** and p =.004 (<0.05). This study therefore concludes that there is a strong evidence that data quality has a positive effect on evidence based decision making.

Findings on the influence of routine health data availability on evidence based decision making by the public facilities providing HIV/AIDs treatment services in Nakuru County established that 44.8% of the respondents were of the opinion that data access was limited due to technological limitations. Also, 70.6% of the respondents reported to not having access to the district health information system (DHIS) and 77.5% did not have the capacity to manipulate the DHIS to generate data reports. On the ability to synthesize data, 44.8% of the respondents were of the opinion that the facility did not have routinely calculate performance of indicators using the catchment population and 41.4% were of the opinion that facility staff are not able to synthesize data into understandable and actionable narratives for the different target audiences. Further, on data communication, 48.3% of the respondents were of the opinion that there was no systematic communication of data analysis findings. The study established a weak positive linear relationship between data availability and evidence based decision making at r = .059 and a p = .662 (>0.05). This means that there is no significant relationship of data availability and evidence based decision making.

The study assessed the influence of capacity on data use competencies on evidence based decision making by the public facilities providing HIV/AIDs treatment services in Nakuru County. With regards to the capacity of the respondents to conduct analysis and interpretation of data, 50.9% of the respondents were of the opinion that they had above average data analysis and interpretation skills, with only 15.5% with below average capacity to conduct data analysis and interpretation. On the use of computers to perform basic data analysis tasks, 63.8% of the respondents had never used a computer to conduct data analysis, 65.5% had never used a computer to present data. The study found a weak positive linear relationship between capacity on data use and evidence based decision making at r = .323 and p = .013 (<0.05).This implies that an increase in capacity on data use leads to an increase in evidence based decision making.

The study assessed the influence of institutional support on evidence based decision making by the public facilities providing HIV/AIDs treatment services in Nakuru County. With regards to funding for data use activities, the study found out that 32.8% strongly disagreed and 25.3% disagreed that here was funding for data use activities. When asked if the facility had a recognition/reward system for good performance, 94.8% of the respondents were of the opinion that there was none in place. With regards to creating opportunity for data use feedback, 56.9% of the respondents were of the opinion that appropriate data users and data producers did not participate regularly in analysis and use of data. It was further noted that 57.8% of the respondents felt that the facility management do not provide immediate written feedback after support supervision to the staff and 54.9% were of the opinion that the facility does not engage the stakeholders in the interpretation of analysis to extract meaning from the data so as to inform programs and policies. With regards to roles and responsibilities, 53.4% disagreed that there was designated staff responsible for reviewing data before submission to the next level and 41.4% disagreed that responsibility for monthly reporting had been clearly assigned to relevant staff. A significant proportion of the respondents 43.1% were neutral when asked if they were aware of their roles and responsibilities in facilitating data management at the facility. The study established a weak positive relationship between institutional support and evidence based decision making at $r = .087$ and $p =.514$ (>0.05). This means that there is no significant relationship between institutional support and evidence based decision making.

5.3 Discussion of the research findings

The study sought to examine the extent data quality influences evidence based decision making by public health facilities in Nakuru county. Data quality was measured using three indicators i.e. data accuracy, data completeness and data timeliness. The study findings indicated that a majority of the respondents 89.7% had encountered inaccurate data during decision making and 84.5% of the respondents indicated that inaccurate data hindered them from routinely using data to make decisions. Also 60.3% of the respondents relied or used other data sources and not routine health data to make decisions.

From the study, a partly 20.6% of the respondents were of the opinion that there was no added value due in aggregating inconsistent data an indication that most of the health care workers are cognizant of the need to generate accurate data and 94.9% of the respondents took corrective actions to address noted data accuracy issues before use. The findings concur with results from a study conducted to assess the ability of the health information system to support evidence based decision making in 22 hospitals (Kihuba et al., 2014). The results indicated that the HMIS does not deliver quality data and significant constraints exist in data quality assurance. Also, observations from a study conducted in Tanzania and Mozambique in 2002 by Lungo (2003) found out that health data being reported was not sufficient enough to support informed decision making due to inaccurate and untimely reporting.

Study findings on data completeness, indicated that a majority of the respondents 84.4% were of the opinion that reported data included all the necessary dataset reports and 75.1% were of the opinion that reported data was sufficiently complete for their needs. This contrasts sharply with empirical evidence from a study conducted in South Africa assessing the challenges of a large PMTCT program which found that data was incomplete only half the time (50.3%). This points to the fact that facilities in Kenya have fully utilized the district health information system (DHIS) in reporting for routine health data. Significant number of respondents 86.2% were of the opinion that reporting from the facility is always on time, 94.8% of the respondents used current data to make decisions and 79.3% of the respondents indicated that data is always available on time for decision making. The findings concur with study results from Ethiopia which found that 77.4% of the departmental heads agreed reports were submitted on time and that 82.0% of the reports were completely filled. The findings indicate that health facility staff adhere to the set reporting timelines set by the ministry of health (i.e. 5^{th} of every month).

The research also investigated how data availability influences evidence based decision making in public health facilities in Nakuru County. The study focused on access to routine health data, synthesis of routine health data and ability to communicate results to stakeholders. Study findings indicate that 44.8% were of the opinion that data was inaccessible to them due to technological limitations, 70.6% of the respondents did not have access to the district health information system (DHIS) and 77.5% did not have the capacity to manipulate the DHIS to generate data reports. Information availability is a key to its widespread use, according to (Karuri et al., 2014), the web-based DHIS2 is intended to capture health facility service delivery data and allow analysis at that level, promoting data use at all levels for decision making, however, findings from the research study indicate that access to routine health data is greatly compromised and therefore the value of accurately recorded data is lost if it is not accessible. The findings concur with (Karuri et al., 2014) who averred that implementation of a technically sound system like DHIS is not an end in itself in ensuring improved reporting and use of HIS data for rational health decision making.

Results on ability of the respondents to synthesize data indicated that 81% of the respondents were of the opinion that their facilities had identified indicators with targets that informed review and planning, 79.3% of the respondents opined that their facilities makes comparison among the different types of service coverage and 81.0% of the respondents were of the opinion that the facilities made comparison of routine health data over different time. However, a significant proportion of the respondents 44.8% were of the opinion that their facility or department did not routinely calculate performance of indicators using the catchment population and 41.3% of the respondents were of the opinion that their facilities did not make comparison with sub county and or county national set targets. According to the World Health Organisation (2008), a vital aspect of analysis is synthesizing data from multiple sources examining inconsistencies and contradictions, and summarizing health situations and trends to produce consistent assessments. This will include the burden of disease, patterns of risk behaviour, health service coverage and health system metrics. However, such data analysis capacity is often lacking at peripheral levels where the results of generated data are needed for planning and management.

Study findings on data communication indicated that 48.3% of the respondents were of the opinion that there was no systematic communication of data analysis findings through a variety of communication channels from their facilities and 41.3% of the respondents were of the opinion that the facilities had no capacity to identify potential target audiences or users of data. According to (Setzer, 2003), one of the key steps in moving from information to evidence-based action is communicating the information to relevant stakeholders by presenting information in a package that is understood by the target audience. However, many of the health workers and health information specialists (including district information officers) are not trained in communication.

The study sought to understand how capacity in data use competencies influences evidence based decision making by public health facilities in Nakuru County. The study assessed the capacity of the health care provider's capacity to analyse and interpret data. It also sought to find out their competence in using computers and the frequency of using computer use to perform basic data management activities. According to the findings of the study, 50.9% of the respondents had above average capacity to calculate percentages or rates correctly, plot data by weeks/months/years, capacity to plot data into bar charts and ability to interpret charts, 33.6% of the respondents had average capacity to perform the same tasks and 7.7% of the respondents had below average capacity to perform the same tasks.

With regards to computer use, 52.6% of the respondents had never used computers to type, conduct data analysis, present data or access to internet. A partly 26.3% had used a computer at least once a month, 6.0% at least once a week and 15.1% had used a computer daily to type, conduct data analysis, present data or access to internet. According to (Nutley & Reynolds, 2013a), the 'use' of data is the analysis, synthesis, interpretation, and review of data as part of a decision-making processes, regardless of the source of data. Local use of data collected at lower levels of the health system is a key step for improving overall data quality. Furthermore, aggregate patient information collected at various points of service delivery and made interoperable with routine HIS improves the quality and use of health information. The study findings are in agreement with (Karuri et al., 2014) who observed that health workers had minimal skills and competencies in the area of data analysis and interpretation; the lack of training on how to use health information for planning and other decision making and the complex process usually required to access the processed health data.

This limited capacity thus hinders their ability to understand analysis and interpret data in a programmatic context. There is a strong need to develop innovative approaches to health information that "tell the story" in ways that are simple, direct and easily comprehensible, and to report information through traditional channels such as research journals or routine annual reports.

The study also sought to examine the extent of institutional support influence on evidence based decision making by public health facilities in Nakuru County. The study zeroed down on funding for data use activities, availability of forums to give data feedback and allocation of data use roles and responsibilities. According to the study results, 60.0% of the respondents were of the opinion that the facility does not support them with airtime or internet bundles, facility does not allocate funds for data quality assessment & quality improvement activities, no funding for monthly data review meetings and no recognition or reward system in place. The findings are similar to (Kihuba et al., 2014)who found out that at the hospital level, HMIS departments were generally poorly financed. With regards to creating forums for data feedback, the study found out that 56.9% of the respondents were of the opinion that appropriate data user and producers do not regularly participate in the collection, analysis and use of data. 56.8% of the respondents were of the opinion that facility management does not provide immediate written support supervision feedback to the staff, 55.2% of the respondents felt that the facility management does not routinely seeks feedback from staff and 56.9% of the respondents were of the opinion that the facility does not engage stakeholders in the interpretation of analysis to extract meaning of these data for programs and policies.

According to the study findings, 53.4% were of the opinion that there were no designated staff responsible for reviewing aggregated data prior to submission to the next level and 43.1% were neutral on if the facility health providers were aware of their roles and responsibilities in data management. The findings are consistent with a study conducted in Ethiopia which found out that 37% of the health facilities had staff designated to undertake health information tasks. According to the Health Metric Network (2008), a good health information system brings together all relevant partners to ensure that users of health information have access to reliable, authoritative, useable, understandable, comparative data. A stronger engagement with data users can lift the quality of official statistics in ways that go beyond improving their relevance. Dialogue can lead to new conversations about existing data that can help to uncover problems. According to (World Health Organization, 2014) one important finding in most reviews and assessments of national health information systems is that the links between suppliers/producers, consumers and users of different types of health information are weak.

According to Nutley and Reynolds (2013), when data users and data producers work together, they become more aware of the data collection processes and methods, the available data sources, and the quality of those data. They have the opportunity to address barriers to data use and improve the sharing of data resources. They can also discuss concerns and seek clarification about the data collection process, and identify key programmatic questions and link these questions to the data available in their settings. They can jointly analyze and interpret data to answer programmatic questions.

5.4 Conclusions of the study

The study examined the extent to which data quality, data availability, capacity on data use competencies and data demand and use infrastructure influenced the use of routine health data in evidence based decision making by public health facilities providing HIV/AIDs treatment services in Nakuru County. The study was successful in addressing the research objectives and the research questions.

Quality data from the health information system is needed to inform the design of interventions and to monitor and evaluate plans and quantify progress towards treatment, prevention, and care targets. Attention to data quality ensures that target-setting and results reporting are informed by accurate and reliable information, and that reporting health units (facilities and communities) are collecting and organizing this information in a consistent manner. Attention to data quality leads to improved program performance and to more efficient resource management. From the findings of the study, a weak positive relationship between data quality and evidence based decision making. This therefore means that the health facilities need to focus more in improving data accuracy of the routine health data so as to enable its reliance on informing decision making.

There is little doubt that access to and use of timely and reliable health information from all sources is essential for ensuring adequate health system performance in developing countries. Sound evidence underpins decisions about policy direction, resource allocation, and management. No health system can operate effectively without access to health and health system-related information. The DHIS2 system recently implemented in Kenya has presented unprecedented potential for Kenya to move from the era of unreliable and fragmented HIS system to the more ideal situation of availability and use for quality health information for decision making, however, its access at the lower level facilities is hindering such efforts and therefore more funding will be required to ensure comprehensive access to the use of computerized data management tools such as the DHIS2 is expected to enhance the capacity for workers at all levels to analyze and interpret routine health information data.

The capacity for data use is critical so that data can be collected, organized, displayed, analyzed, and interpreted so that evidence based decision-making is accurate and meaningful. Competencies include skills in data analysis, interpretation, synthesis, and presentation, and the development of data-informed programmatic recommendations. Meeting the challenge of adequate capacity goes beyond training capable staff; it extends to building institution-wide commitment to using data to inform change efforts. The study found out that capacity to analysis and interpret data needs to be improved with a focus to synthesis and communication of data into understandable actions.

Establishing and sustaining a “culture of information” is often the greatest challenge in improving the use of routine health information. The study therefore posits that changing the way information is gathered, processed, and used for decision making will require changing the way the way organizations operates, by producing and utilizing information more effectively will affect the behavior and motivation of all personnel.

Secondly, training notwithstanding, healthcare providers have an insufficient understanding of data, especially those providers at the facility level. This is aggravated by the fact that there is no feedback on the HIV data submitted from the health facility. The lack of data sharing among stakeholders from the facility, as noted in the study, can lead to incomplete data and poor understanding of the true picture of routine health data at all levels. Therefore, health facilities need to engage more with the relevant stakeholders to discuss their routine health data for purposes of planning and management.

5.5 Recommendations

The findings of this study offer opportunities for improving use of routine health data in evidence based decision making. The study therefore recommends the following;

1. The need to develop, communicate and implement data quality protocols as well as training and retraining of health professionals on data quality techniques and approaches at the facility level.
2. Health managers at the county/sub-county and facility levels need to prioritize improving the capacity of the facility staff so that they can access data, synthesize data and communicate data so as to support the use of the information in decision making in a programmatic context.
3. There is need for training in leadership and advocacy skills which will be critical to equip facility managers to leverage the funding (partners and county government) and buy-in needed to implement and sustain interventions to improve demand for and use of data.
4. Develop standard operating procedures that clearly state the role and value of data in organizational functioning and the need to specify in job descriptions, employee roles and responsibilities for routine data use.

5.6 Suggestions for further Research study

The following related areas can be researched on to add to the knowledge to this study

1. There is need to conduct further research on the cost and effectiveness of using routine health data in planning and management of health services.
2. There is need to conduct a study on the effects of engaging data users and producers to catalyze information use.
3. There is need for a study on the role of incentives as a motivator to facility, sub-county and county mangers to collect, analyze, and use information.

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APPENDICES

Appendix 1: Letter of Permission to Carry out Research Work

UNIVERSITY OF NAIROBI
COLLEGE OF EDUCATION AND EXTERNAL STUDIES
SCHOOL OF CONTINUING AND DISTANCE EDUCATION
DEPARTMENT OF EXTRA - MURAL STUDIES

Tel 051 - 2210863

P. O Box 1120, Nakuru
4th May 2015

Our Ref: *UoN/CEES/NKUEMC/1/12*

To whom it may concern:

RE: PETER MUGENDI NJOKA – L50/64465/2010

The above named is a student of the University of Nairobi at Nakuru Extra-Mural Centre Pursuing a Masters degree in Project Planning and Management.

Part of the course requirement is that students must undertake a research project during their course of study. He has now been released to undertake the same and has identified your institution for the purpose of data collection on " Factors Influencing Utilization of Routine Health Data in Evidence Based Decision Making by Public Health Facilities in Nakuru County."

The information obtained will strictly be used for the purpose of the study.

I am for that reason writing to request that you please assist him.

Yours faithfully,

NAKURU EXTRA-MURAL CENTRE
RESIDENT LECTURER
P.O. Box 1120
NAKURU
UNIVERSITY OF NAIROBI

Mumo Mueke
Ag. Resident Lecturer
Nakuru Extra-Mural Centre

Appendix 2: Research Permit

THIS IS TO CERTIFY THAT:
MR. PETER MUGENDI NJOKA
of UNIVERSITY OF NAIROBI,
13208-20100 Nakuru,has been
permitted to conduct research in
Nakuru County

on the topic: *FACTORS INFLUENCING UTILIZATION OF ROUTINE HEALTH DATA FOR EVIDENCE BASED DECISION MAKING IN HIV/AIDS SERVICES BY PUBLIC HEALTH FACILITIES IN NAKURU COUNTY*

for the period ending:
4th December,2015

Permit No : NACOSTI/P/15/5484/6456
Date Of Issue : 9th July,2015
Fee Recieved :Ksh 1,000

....
Applicant's Signature

....
Director General
National Commission for Science, Technology & Innovation

NATIONAL COMMISSION FOR SCIENCE,
TECHNOLOGY AND INNOVATION

Telephone: +254-20-2213471,
2241349, 310571, 2219420
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Email: secretary@nacosti.go.ke
Website: www.nacosti.go.ke
When replying please quote

9th Floor, Utalii House
Uhuru Highway
P.O. Box 30623-00100
NAIROBI-KENYA

Ref: No.

Date:

9th July, 2015

NACOSTI/P/15/5484/6456

Peter Mugendi Njoka
University of Nairobi
P.O. Box 30197-00100
NAIROBI.

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on ***"Factors influencing utilization of routine health data for evidence based decision making in HIV/AIDS services by public health facilities in Nakuru County,"*** I am pleased to inform you that you have been authorized to undertake research in **Nakuru County** for a period ending **4th December, 2015.**

You are advised to report to **the County Commissioner, the County Director of Education and the County Coordinator of Health, Nakuru County** before embarking on the research project.

On completion of the research, you are expected to submit **two hard copies and one soft copy in pdf** of the research report/thesis to our office.

DR. S. K. LANGAT, OGW
FOR: DIRECTOR-GENERAL/CEO

Copy to:

The County Commissioner
Nakuru County.

The County Director of Education
Nakuru County.

Appendix 3: Questionnaire

Questionnaire ID No: …………………………….

Dear Respondent,

My name is Peter Njoka, a student undertaking a Master's Degree in Project Planning and Management (MAPPM) at the University of Nairobi. I am currently conducting a research study on the factors influencing utilization of routine health data in evidence based decision making by public health facilities in Nakuru County. I am kindly seeking your responses to the questionnaire below which will take not more than 30 minutes to complete. Please be assured that the information collected will be for the purposes of this study only and shall be treated with utmost confidentiality by the researcher and will not be availed to any other person. I appreciate your assistance and co-operation in completing this study.

PART ONE

SECTION 1: RESPONDENT INFORMATION

(Kindly tick your response in the appropriate box)

1. Gender: Female ☐ Male ☐
2. Name of your Sub-County: ……………………..….
3. Type of facility:

   Dispensary ☐ Health Centre ☐

   Sub-County Hospital ☐ County Hospital ☐
4. What position do you hold in the facility:

   Facility Incharge ☐ Departmental Head ☐

   HRIO ☐ Service Provider ☐
5. What is your professional background?

   Medical Officer ☐ Clinical Officer ☐

   Nurse ☐ Health Records Officer ☐
6. What is your highest level of education?

   College Certificate ☐ Diploma Certificate ☐

Undergraduate degree ☐ Master's Degree ☐

Doctorate ☐ PHD ☐

7. How long have you been employed in your current job?

Less than 1 Year ☐ between 2-3 Years ☐

Between 4-6 Yrs ☐ between 7-10 Years ☐

Above 10 Years ☐

8. What is your current age?

Below 25 Years ☐ 26-35 Years ☐

36-45 Years ☐ 46-55 Years ☐

Above 55 Years ☐

SECTION 11: DATA QUALITY (Accuracy/Completeness/Timeliness)

9. **Data Accuracy:** Please rate the performance of your facility/department on the stated data accuracy domains. Please choose your preferred response by ticking only one box per question. [Key: 1= strongly disagree, 2= Disagree, 3= Neutral, 4=Agree, 5= strongly agree]

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

10. **Data Completeness:** Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. **Key:** 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
Reported data includes all the necessary dataset reports					
Reported data is sufficiently complete for our needs					
Reported data summarizes the work of the department					
Routine health data is not relevant to my current data analysis and aggregation needs					
There is no added value due to aggregating inconsistent data					

11. **Data Timeliness:** Please rate the timeliness of routine health data from your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. **Key:** 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
Reporting from the facility is always on time (according to the set national reporting timelines)					
Corrective actions are always taken within reasonable time					
When making decisions, we always use current data					
Data is always available on time for decision making					

SECTION 111: DATA AVAILABILITY [Access/Synthesis/Communication]

12. **Access:** Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. Key: 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
It takes a lot of time to find required data to make timely decisions					
Data is stored in a way that is difficult to access					
Data is inaccessible due to technological limitations					
There is no obvious way to access the data					
I need special clearance to access routine health data					
I have limited capacity to understand the data to enable summarising into understandable formats					
Available routine health data does not support my tasks					
I do not have access to the district health information system (DHIS)					
I do not have the capacity to manipulate the DHIS to generate data reports					

13. **Data Synthesis:** On a scale of 1-5 (Key: 1-Strongly disagree, 2-Somewhat disagree, 3-Neutral, 4-Somewhat agree, 5-strongly agree), please rate the overall ability of your facility staff to synthesize available data to drive evidence based decision making?

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
There is a facility set of indicators with targets and annual reporting to inform annual health sector reviews and other planning cycles					
The facility/department routinely calculates performance of indicators using the catchment population					
The facility makes comparisons with sub-county/county or national set targets					
The facility makes comparisons among the different types of services coverage					
The facility make comparisons of routine health data over different times					
Facility staff are able to synthesize data into understandable and actionable narrative and graphical forms for different target audiences					

14. **Data Communication:** On a scale of 1-5 (Key: 1-Strongly disagree, 2-Somewhat disagree, 3-Neutral, 4-Somewhat agree, 5-strongly agree), please rate the overall ability of your facility to communicate routine health data to drive evidence based decision making?

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
Facility has identified HIV/AIDs performance monitoring indicators for routine monitoring					
Graphs/charts/data tables are displayed in the departments to show performance of the identified HIV/AIDs indicators?					
Facility has capacity to Identify potential target audiences or users of data (national level policymakers, advocates, technical specialists, citizen groups, etc.)					
There is systematic communication of data analysis findings through a variety of communication channels					

SECTION 1V: CAPACITY IN DATA USE COMPETENCIES

15. **Capacity on Data use and Interpretation:** On a scale of 1 to 5 please rate your capacity to conduct the following data analysis activities *(Tick against a corresponding domain for each of the question)*

	Poor [1]	**Below Par [2]**	**Average [3]**	**Good [4]**	**Exemplary [5]**
I can calculate percentages or rates correctly					
I can plot data by weeks, months or years					
I can plot data into bar charts					
I can interpret charts and their implications					

16. **Computer Use Purpose:** How frequently do you use computers to perform any of the following tasks?

	Daily	At least once a week	At least once a month	Never
Typing documents				
Data Analysis				
Presentation of Data				
Access Internet browsing				

SECTION V: ORGANISATIONAL DATA DEMAND AND USE INFRASTRUCTURE

17. **Funding for Data use activities**: On a scale of 1 to 5, please rate your facility with respect to allocation of funding for any of the following data use activities in the last 6 months? ***(Tick against a corresponding domain for each of the question)***

	Strongly Disagree (1)	Somewhat Disagree (2)	Neutral (3)	Somewhat Agree (4)	Strongly Agree (5)
The facility supports departments with airtime or internet bundles					
The facility has allocated funds for data quality assessment (DQA) activities					
The facility has funding for monthly quality improvement meetings					
The facility has funding for monthly data review meetings					
The facility has a recognition or reward system in place for good performance?					
There is dedicated resources (staff , time, money) to support data analysis and use					

18. **Data Feedback Forums**: Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. **Key:** 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
Appropriate data users and producers regularly participate in the collection, analysis, and use of data.					
An official record of management meetings is maintained?					
The facility management provides immediate written supportive supervision feedback to the staff					
The facility management seeks feedback from staff					
The facility engages stakeholders in the interpretation of analyses to extract the meaning of these data for programs and policies					

19. **Roles and Responsibilities**: Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. **Key:** 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
There designated staff responsible for reviewing aggregated data prior to submission to the next level?					
Responsibility for monthly reporting of service delivery data been clearly assigned to relevant staff?					
Facility health providers are aware of their roles and responsibilities in data management					

SECTION V1: DECISION MAKING AND USE OF INFORMATION

20. **Basis for Evidence based decision making:** Please rate the performance of your facility/department on the stated domains. Please choose your preferred response by ticking only one box per question. **Key:** 1 = strongly disagree, 2 = somewhat disagree, 3 = Neutral, 4 = somewhat agree, 5 = strongly agree

	Strongly Disagree (1)	**Somewhat Disagree (2)**	**Neutral (3)**	**Somewhat Agree (4)**	**Strongly Agree (5)**
Personal liking					
Superiors' directives					
Evidence/facts/data					
Political directives					
Experience or Gut feelings					
Donors demand					

21. **Evidence based decision making**: To what extent is the collected data used in making decisions related to the domains highlighted?

	Always use data[3]	**Sometimes use data [2]**	**Never Use data [1]**
Day-to-day program management			
Medical supply & drug management			
Formulating plans			
Review financial statement and Budget preparation			
Deciding budget reallocation			
Human resources management			
Monitoring key objectives			