DETERMINANTS OF UTILIZATION OF HEALTH RELATED DATA FOR SERVICE IMPROVEMENT: A CASE OF HEALTHCARE FACILITIES IN NYANDO SUB-COUNTY, KENYA.

BY

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DECLARATION

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

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DEDICATION

I would like to dedicate this research project report to my dear parents, colleagues, brother and sisters for their moral and material support as well as their advice encouragement that got me through my learning process.

God bless you all.

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The entire work of carrying out a research project report requires serious thought and therefore calls for combined responsibilities of many people within the institution, and outside the institution, for it is not possible to give personal recognition to all, some individuals deserve special attention.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

C&L – Culture and Language

DDDU - Data Demand and Data Use

EBA – Evidence Based Assessment

EBP - Evidence Based Practice

EMR – Electronic Medical Records

HCWs – Healthcare Workers

HIS – Health Information System

HMIS – Health Management Information System

HMN – Health Metrics Network

HRIO - Health Records and Information Officer

HV – Health Visitor

ICT – Information Communication and Technology

NATC – Nurses Attitude Towards Computers

SSA – Sub-Saharan Africa

UK – United Kingdom

USA - United States of America

ABSTRACT

Health care professionals spend a significant proportion of their working time collecting large amounts of client and patient data that is rarely analyzed and used at the point of collection. Health workers merely collect aggregate and dutifully pass over this data to the next level. This information is rarely ever used to guide local action at the level at which data is collected. The purpose of this study, therefore, was to establish determinants of utilization of health related data for service improvement in healthcare facilities within Nyando Sub-County. The objectives of this study were as follows: to investigate how demographic characteristics of staff influence utilization of health related data, to establish the level at which staff involvement influence utilization of health related data, to assess the extent at which staff attitude influence utilization of health related data and finally to examine how leadership goodwill influence utilization of health related data. This study was anchored on the *Theory of Planned Behaviour* advanced by Ajzen (1991). A descriptive survey research design was adopted to guide the study. The target population of the study was 650 HCWs offering healthcare services in health facilities within Nyando Sub-County. Using Kathuri and Palls (1993), sample determination formula, the sample was determined as 241 HCWs. This study used stratified random sampling to identify the respondents. Self-administered questionnaire was used as the primary research instruments in this study. Quantitative data obtained from close ended questions which were analyzed using descriptive statistics using SPSS and presented in such as frequencies and percentage, charts and tables. The questionnaire return rate was 99% (239) of the targeted respondents. There was a significant relationship between IT knowledge and the level of data utilization for decision making, χ^2 (2 N=237) = 14.617, p=0.001.There was no significant association between staff involvement in data discussions and their levels of utilization of health related data χ^2 (2,234) = 3.108, p = 0.211. The attitude of staff on trainings received on data management had a significant relationship with the level of utilization of health related data, χ^2 (8) = 23.85, p= 0.002.The association between the support of the leader on data utilization and the level of data utilization was significant, χ^2 (6,237) = 47.997, p<0.000.The study concluded that demographic characteristics of staff, staff attitude and leadership goodwill influence utilization of health related data. Staff involvement in data related discussions did not have significant influence on utilization of health related data. It is recommended that the IT knowledge of all HCWs be; there is need to have staff engage more in tailor made trainings and workshops on data collection, collation, processing and utilization; and, leadership support to staff should be enhanced in relation to collecting, collating, processing and utilizing the data in decision making.

CHAPTER ONE
INTRODUCTION

1.1 Background of the study

Around the world, data are collected at health facilities about the populations they serve, their health needs and the services provided to meet those needs. These data are used to populate reports that are required by the varied national health programs. Often, once these data are sent to the higher level in the health system, they are not considered or used by the facilities themselves or their district or regional management to make decisions about future service delivery (Nutley & Reynolds, 2011).

Most developed nations have made remarkable strides in strengthening data driven decisions in healthcare, though it remains a challenge across various nations globally. In Thailand, China mainland, Taiwan and Malaysia, ministry of health is responsible through its various agencies for collecting and managing health care data. Sharing and access to data is still a challenge. This is due to limited access to some data and privacy protection, fragmented health care system, poor quality of routinely collected data, unclear policies and procedures to access data and control on the freedom of publication (Ngorsuraches, Meng, Kim & Kulsomboon, 2012).

Lack of consistency in health care provision has also been observed in parts of Europe due to lack of harmonized approach by health facilities (The Times, 25 October 1997). Intense interest in increasing the value obtained from investments in health care has stimulated a broad array of efforts to develop and apply the best possible science to inform health care delivery (Clancy and Cronin, 2005). In the United Kingdom, for example, economic evaluation plays a key part in the technology appraisal process (The Times, 25 October 1997). In this process, evidence on clinical and cost effectiveness is used to make assessments of value for money and to inform the decision about whether a given technology should be adopted.

Information on disability in the U.S. population is critical to health planning and policy. Several initiatives were put in place to coordinate and standardize the measurement of disability across federal data systems.

Health, United States introduced the first detailed Trend Table using data from the National Health Interview Survey to create disability measures consistent with two of the conceptual components that have been identified in disability models and legislation: basic actions difficulty and complex activity limitation. Basic actions difficulty captures limitations or difficulties in movement and sensory, emotional, or mental functioning that are associated with a health problem (Altam, 2008).

Wilson-Stronks (2008), adds that while many hospitals already collect community- and patient-level data in the United States, few hospitals have developed systems for using them to guide service development and improvement. A thorough understanding for instance the need for culture and language (C & L) services, and the usefulness of those data to improve C & L services can all contribute to a hospital's ability to identify and monitor health disparities and provide safe, quality health care to culturally and linguistically diverse patients.

Focusing on the African experience, Peter (2007), observed that 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. Despite the expense of these systems, poor data coverage means they are rarely, if ever, used to generate reliable evidence for decision makers both at the health facility and national level. Peter, (2007) adds that the resource-constrained countries lack the evidence base for timely and effective health system decision-making, and this is exemplified by the scarcity of reliable data on health service use.

Mutale and Chintu, (2013) in a study looking at HIS for decision making in 5 African countries observed that Mozambique, Ghana, and Tanzania all focus on improving the quality and use of the existing Ministry of Health HIS, while the Zambia and Rwanda partnerships have introduced new information and communication technology systems or tools, and have adopted a flexible, interactive approach in designing and refining the development of new tools and approaches for HIS enhancement (such as routine data quality audits and automated troubleshooting), as well as improving decision making through timely feedback on health system performance (such as through summary data dashboards or routine data review meetings) and health facility levels.

Within Kenya, demand for high quality data for health sector planning, management, monitoring, and evaluation has increased steadily over recent decades. System design and strengthening activities have contributed to positive progress in this area, but in general the health information system (HIS) is not sufficiently responsive or effective. Data is generated and disseminated by the Division of HIS and other stakeholders, but deficiencies in quality, timeliness, and widespread availability hamper their use and relevance (Luoma, 2010).
In Kenya therefore HIS shall be decentralized progressively and efforts will be made to promote information use at the point of data collection. HIS should avail information to gauge the efficiency and effectiveness of the health systems and provide lessons for the next steps at all levels. This HIS policy is a positive step in the right direction for better health for Kenyans through better information (HMN, 2008).

Kenya like many Sub-Saharan African (SSA) countries has had her fair share of challenges with data use for decision making at the primary level of health care. The findings of a task force that looked into the issue observed low reporting rates (under 60% for most of the sub systems), making the data unrepresentative for management, planning and budgeting at all levels. There was also un-timeliness/ late reporting resulting in delays in data processing, analysis and utilization. Inadequate personnel and inadequate capacity for data analysis and management skills as well as lack of data repositories and data warehouse at all levels were observed as reflected in the HIS report (HIS-K, June 2008).

Nearly 2500 years ago, Hippocrates kicked off a revolution in healthcare by calling for the careful collection and recording of evidence about patients and their illnesses. This call which first introduced the goal of sharing data among physicians to provide the best care possible for patients established a foundation for the evolution of modern healthcare. Although 25 centuries have passed since Hippocrates' call, we have not yet attained the dream of true evidence-based healthcare (Horvitz, 2010).

Large quantities of data about wellness and illness continue to be dropped on the floor, rather than collected and harnessed to optimize the provision of care. We are simply not yet doing the best that we can (Horvitz, 2010).

Even though good quality and timely data from health information systems are the foundation of all health systems. Nutley and Heidi(2013) further observe that 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.

According to Pickering (2013), the work of healthcare professionals and physicians is largely a work of making decisions and solving problems. Despite great steps forward, in the United States uncertainty still plays a pivotal role in most aspects of medical decision making. This uncertainty is compounded by the information overload that characterizes modern medicine (Pickering, 2013). Today's experienced clinician needs close to 2 million pieces of information to practice medicine and doctors subscribe to an average of seven journals, representing over 2,500 new articles each year, making it almost impossible to keep abreast with the latest information about diagnosis, prognosis, therapy and related health issues (Pickering, 2013).

'Data-informed decision making' therefore entails a proactive and interactive processes that consider data during program monitoring, review, planning, and improvement; advocacy; and policy development and review. By these definitions, it is clear that data use goes beyond filling out data reporting forms at the various levels of a national health information system and the passive dissemination of reports and information products (Patton, 2008).

Data feedback loops and use for management and decision-making is variable across health system levels and across management units. The country's File Transfer Protocol (FTP) system to transmit routine service data from lower levels to the central level lacks adequate features to facilitate analysis and use of data for decision making, and the quality of data within the system requires improvement. Information products are produced and disseminated by the Division of HIS and other stakeholders, but deficiencies in quality, timeliness, and widespread availability hamper use and relevance (Luoma, 2010).

Health data is barely used by health workers for service delivery planning and decision-making. Anecdotal evidence suggests that while district level managers regularly discuss information and use routine data in the review of district implementation plans (DIP), use of information for operational plans and at source for decision-making is limited (WHO, 2008). This study therefore seeks to understand the determinants of utilization of health related data for service improvement in healthcare facilities within Nyando Sub-County.

1.2 Statement of the problem

An unfortunate feature of health care systems in many parts of the world is that decisions are taken despite the absence of information use. One critical weakness across Africa is the current lack of capacity to effectively use data to monitor patterns of service use through time so that the impacts of changes in policy and service delivery can be evaluated. In practice, decision-making in health is all too often based on political opportunism, expediency or donor demand and at times on infrequently repeated national studies like demographic health survey (DHS) which are insensitive to changes occurring over shorter time scale (Gething, 2007). This has been a challenge in improving health sector performance. The health data could be effective health assessments, health planning, detecting problems, defining priorities, identifying innovative solutions, and allocating resources for improved health outcomes (Sapirie, 2000).

According to the welfare Monitoring Survey III (1997), Nyando Sub-County is among the poorest in Kenya. Over 65.4% of population lives in absolute poverty. Achievements of many indicators in the county show low performance and the Life expectancy level which is at 51 years below the national average. This Sub-County is prone to diseases caused by poor sanitation which include malaria, diarrhea, anemia, pulmonary tuberculosis, typhoid fever and STI/HIV/AIDS. The other disease is malnutrition due to high level of poverty in the district.

However the county lacks the necessary equipment's, drugs and specialist personnel to manage and treat these common illnesses. In the health facilities the routine generated data is not used to detect drug stock outs and this leads to expensive drugs being prescribed to patients who are forced to buy them outside the facility.

Large amount of family resources is used for buying ineffective medication in shops and valuable time wasted due to facility revisits whereas the average distance that the people have to access to the nearest health facility is over 5 Km (National Coordinating Agency for Population and Development, 2005). All this contributes to inefficient and ineffective use of resources. Health data lack value unless it is used to inform decisions and resource allocation at all levels of the health system (AbouZahr & Boerma, 2005).

1.3 Purpose of the Study

The study sought to investigate determinants of utilization of health related data for service improvement focusing on healthcare facilities in Nyando Sub-County.

1.4 Study Objectives

The study was guided by the following objectives,

1. To investigate how demographic characteristics of staff influence utilization of health related data.
2. To establish the level at which staff involvement influence utilization of health related data.
3. To assess the extent at which staff attitude influence utilization of health related data.
4. To examine how leadership goodwill influence utilization of health related data.

1.5 Research Questions

This study sought to address the following research questions;

1. How do demographic characteristics of staff influence utilization of health related data?
2. To what level does staff involvement influence utilization of health related data?
3. To what extent does staff attitude influence utilization of health related data?
4. How does leadership in health facility influence utilization of health related data?

1.6 Significance of the Study

It is hoped that the study will bring to the fore the critical determinant of data utilization in decision making to the facility in charges so that that they can pay specific attention to them as to enhance data utilization for decision making at the health facilities. It is also hoped that the ministry of health of Kisumu County will be able to know the critical determinants of data utilization and come up with policies to guard against decision-making in health being based on political opportunism, expediency or donor demand but data.

It is also expected that the study will bring to the consciousness the pertinent personnel and facility issues that influence the utilization of data in decision making. They will also learn the essence of strengthening data collection, processing and utilization for more accurate and informed healthcare decision at the facility level. It is also hoped that the findings of the study will contribute to new knowledge hence providing invaluable literature to scholars who would want to conduct studies on data utilization for decision making.

1.7 Basic Assumptions of the Study

All information required for this study would be provided by respondent within required timeframe.

Respondents would cooperate with the study team hence and would be truthful and honest in their responses to research questions. The sampled health facilities would be representative of the region in terms of data utilization and its challenges.

1.8 Limitation of Study

The study would be conducted at some health facilities within Nyando Sub-County hence the findings may not be easily generalized and may need to be applied selectively to other facilities. The study targets one high volume Sub-County hospital and some factors specific to the facilities may have subjectively affect the findings of the study.

1.9 Delimitation of Study

This study shall be conducted with health care workers who are involved in patient data capture and will miss out on the opinion of health care workers not involved in data capture. The study will be to how demographic characteristics, staff involvement, staff attitude, leadership in health facility influence utilization of health related data.

1.10 Definition of terms

In this study the following terms shall be defined as follows

Data	Refers to facts and figures collected together for reference or analysis.
Data Utilization:	Refers to putting the collected, collated and synthesized information from patients in use to appropriately inform decisions, procedures and policies to improve patient management and treatment outcomes in health care facilities.
Government Policy	Any course of action by government which intends to change a certain situation.
Leadership Goodwill	Refers to capacity of translating vision into reality in a friendly, helpful or cooperative way.
Staff Attitude	Refers to the feelings staffs have towards their supervisors, co-workers and their positions within their working area.
Staff Demographics	Refers to the category in which a staff member is classified.
Staff Involvement	Refers to regular participation of staff in deciding how their work is done, making suggestion for improvements, goal setting, planning and monitoring their performance.

1.11 Organization of the study

Chapter one presents the general background to the study, statement of the problem, research objectives, and research questions, significance of the study, limitations, delimitation, basic study assumptions and operational definitions of key terms used in the study. Chapter two presents a comprehensive literature review both empirical and theoretical, depicts the conceptual and theoretical frameworks and summarizes the literature.

Chapter three describes the research methodology adopted for the study and highlights procedures that will be carried out during the research process. It also discusses the justification of the choices made for research process. Chapter four consists of data analysis, presentation and interpretation of the study findings. Lastly, chapter five contains summary of findings, discussion, and contribution to body of knowledge, conclusions and recommendations.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

According to Mumford (2010), data provide information that guides the majority of health care decisions. This chapter seeks to point out the existing information gap from the available literature on the determinants of utilization of health related data for service improvement. This chapter comprises of the following sub themes: Demographic characteristics of staff as a determinant of utilization of health related data, Staff involvement levels as a determinant of utilization of health related data, Staff attitude as a determinant of utilization of health related data and Leadership goodwill as determinant of utilization of health related data.

2.2 Demographic characteristics of staff as a determinant of utilization of health related data

Demographic characteristics as used in this study will refer to the quantifiable statistics of a given population including gender, age, ethnicity, knowledge of languages, disabilities, mobility, home ownership, employment status, and even location. Historically, care of the patient was influenced by the experiences and opinions of those involved in providing treatment (Kania-Lachance,2006). Evidenced Based Practices (EBP) marks a shift among health care professionals from a traditional emphasis on authoritative opinions to an emphasis on data extracted from prior research and studies (Jette, 2003).Nurses are increasingly regarded as key decision makers within the healthcare team and are expected to use the best available evidence in their judgments and decisions. A meta-analysis done by Heater et al. demonstrated that nursing practice based on evidence improves patient care, as compared to traditional practices (Heater,1989). Moreover, as nurses are increasingly more involved in clinical decision making, it is becoming important for them to utilize the best evidence to make effective and justifiable decisions (Mantzoukas, 2007). A study by Kivuti observed that many accounts of failed ICT Systems have been attributed to failed mismatch between technology capabilities, needs and constraints of health care workers (Kivuti-Bitok, 2009).

A study by Gordana in Croatia that looked at the demographic characteristics of nurses and the use of Health Information Systems (HIS) established that there was no difference regarding use of HIS based on gender. With regards to age, nurses younger than 30 years were more likely to embrace the use of HIS compared to older nurses.

Nurses with a bachelor’s degree were also more likely to embrace use of HIS than nurses with a high school degree. Computer science education was also related to a higher total score, whereby nurses who attended classes of medical informatics during their formal education obtained significantly higher total score than others (Gordana Brumini, 2005). A similar study by Amanda that sought to understand why clinicians were not typically engaged in evidence-based assessment looked at clinician attitudes toward use of standardized assessment tools. The study established that Doctoral-level clinicians and psychologists expressed more positive ratings in all three domains than master’s-level clinicians and non-psychologists respectively.

A study in Miami USA by Jensen looking at clinician diagnostic practices suggest they may not align with evidence-based guidelines. The study found out that. Psychiatrists were more likely than other disciplines to value diagnosis, whereas psychologists were more likely than others to value standardized diagnostic tools. Private practitioners held less positive views in both domains than other practitioners. Both attitude scales predicted self-reported diagnostic practices, although views of diagnosis utility were more associated with diagnosing in general, whereas views of diagnostic tools were more predictive of standardized tool use (Jensen-Doss & Hawley, 2010). Kagasi in her study investigating factors influencing the quality of data for the tuberculosis control programme in Oshakati district in Namibia established that health care workers with training on program indicators were more likely to record accurate and complete data that would encourage data use. A similar study in Malawi also revealed that provision of technical support and on job training was key in good data quality capture and use.

In Kenya it was further revealed that revealed that In order to increase the success of adoption of Information, communication and Technology (ICT) for data management by nurses it is important that all measures be taken into consideration before adoption (Kivuti-Bitok, 2009).

Majority of the nurses in Kenya are females and since it has previously been urged that women in general tend to be slow in engaging with computing and there are many records of women's negative experiences with ICT this could have an effect in the nursing care fraternity's adoption of ICT since majority of the nurses in the world are women. Women have often been portrayed as passive users of ICT (Kivuti-Bitok, 2009).

From the volumes of literature reviewed, it is evident that there is need for a study to unearth more on the influence of demographic characteristics of health care workers on data driven decision making, since there is limited literature specifically addressing the same. This study seeks to shed more light on the same.

2.3 Staff Involvement Levels in Data Utilization

Employees' involvement refers to work structures and processes that allow employees to systematically give their input into decisions that affect their own work (Powell, 2011). It creates an environment in which people have an impact on decisions and actions that affect their jobs. (WebFinance, 2014)adds that it entails regular participation of employees in deciding how their work is done, making suggestions for improvement, goal setting, planning, and monitoring of their performance. Encouragement to employee involvement is based on the thinking that people involved in a process know it best, and on the observation that involved employees are more motivated to improve their performance (WebFinance, 2014).

Despite training on the HIS, health care workers and managers do not always put the data collected to best use (Naeme, 1993). This has been described as a culture of reporting rather than a culture of using the information. There is little tradition of information use for decision making at the facility level in most developing countries, even among health managers. Health care workers need to have sufficient knowledge and skills in order to have confidence to use information for decision-making.

Today's complex healthcare systems allow little to no margin for error, and health care workers throughout USA vigilantly monitor unit benchmarks to ensure delivery of quality, accessible, and cost-effective services.

As healthcare organizations rapidly develop informatics and electronic systems, data become readily available hence operational and data analysis becomes a primary skill to encourage data use for decision making by clinical team managers in constant pursuit of process improvement and quality (Sherrod, McKesson, & Mumford, 2010).

In the USA Medical and health care is one of the most dynamic human disciplines, and large amounts of money are spent annually on high-quality and sophisticated research, resulting in an exponential growth in health care literature.(Majid, et al., 2011) Regularly, new and more effective medicines, medical devices, and procedures are invented.

In the UK, for example, nurses have probably always known that their decisions have important implications for patient outcomes. Increasingly, however, they are being cast in the role of active decision makers in healthcare by policy makers and other members of the healthcare team. Recently the Chief Nursing Officer outlined 10 key tasks for nurses as part of the National Health Service's modernization agenda and the breaking down of artificial boundaries between medicine and nursing (Kania-Lachance,2006). As well, nurses are expected to access, appraise, and incorporate research evidence into their professional judgment and clinical decision making (Jette, 2003)**.**

Studies in developed world looking at employee involvement in other sectors established that in order to increase the workers commitment and humanize the workplace with the intention of improving work performance and good citizenship behavior, managers need to permit a high degree of employee involvement (Cohen, 1997). Thus, the involvement of workers in decision making is considered as a tool for inducing motivation in the workers leading to positive work attitude and high productivity (Kuye & Sulaimon, 2011).

Managers in all industries have made employee engagement a hot button issue because of growing evidence that engagement has a positive correlation with individual, group, and organizational performance in areas such as productivity, retention, turnover, customer service, and loyalty (Peltier & Andy, 2008). The health care industry is no exception to this phenomenon in human resource management theory and practice.

Around the world, data are collected at health facilities about the populations they serve, their health needs and the services provided to meet those needs. These data are used to populate reports that are required by the varied national health programs. Often, once these data are sent to the higher level in the health system, they are not considered or used by the facilities themselves or their district or regional management to make decisions about future service delivery (Nutley & Reynolds, 2011).

While providers may use data for individual patient management, health managers and providers rarely analyze the data they collect to monitor service delivery trends or to assess problems and identify new strategies for improving health services. As a result, many health systems fail to fully link evidence to decisions and suffer from a decreased ability to respond to the priority needs of the communities they serve (Nutley & Reynolds, 2011).

Clinicians involved in clinical care generate daily volumes of important data. This data is important for continuity of care, referrals to specialists and back to the patient's medical home. The same data can be used to generate alerts to improve the practice and to generate care activities to ensure that all appropriate care services are provided for the patient given their known medical histories using electronic quality (eQuality) monitoring(Elkin PL, 2010).Studies in Europe by Elkin (2010) revealed that for many years we have used patient records as a data source for human abstraction of clinical research data. With the advent of Electronic Health Record (EHR) data health workers can now make use of computable EHR data that can perform retrospective research studies more rapidly and lower the activation energy necessary to ask the next important question using electronic studies (e-Studies).

Barriers to these e-Studies include: the lack of training and involvement of health professionals to use Ontology based Informatics tools that allow the execution of this type of logic, common methods need to be developed to distribute computable best practice rules to ensure rapid dissemination of evidence, better translating research into practice (Westra,, 2008) It was further observed that Quality and low cost health care that is free of medical mistakes requires continuity of person-centric healthcare information across the life span and healthcare settings.

Interoperable clinical information systems that rely on the use of multiple standards to support health information exchange and, in particular, nurse sensitive data, information, and knowledge are key components to support information use for high quality safe care.

Studies in West Africa highlighted the importance involving health care workers- nurses at various levels revealed that nurses feeling disengaged and un-empowered in their roles in delivering patient care a similar research further revealed that Research has shown, as expected, that when employees are disengaged in their jobs they are more likely to leave because they feel unappreciated (Fukuyama,1995).

In Kenya there have been efforts to improve health care workers involvement in data driven decision making. An assessment by Health Metrics Network (HMN) identified various areas that need support to strengthen data use including among others; Lack of HIS policy guidelines and clear responsibilities of health workers at all levels; Weak linkages and data sharing; Inadequate feedback at all levels; Inadequate capacity building in data management; Inadequate health information scientists at all levels; lack of standard operating guidelines at all levels; Inadequate infrastructure at all levels i.e. email, computer services and databases; Inadequate use of HIS for planning and allocation of resources; inadequate allocation of resources to support HIS activities. Based on the recommendations from the findings efforts have been made through capacity building to upscale data driven decision making (HMN, 2008). The available literature is however scanty and is limited in focus particularly on how involving health care workers promotes data use for decision making hence the focus of this study.

2.4 Staff Attitude on Data Utilization

Staff attitude refers to a predisposition or a tendency to respond positively or negatively towards a certain idea, object, person, or situation. Attitude influences an individual's choice of action, and responses to challenges, incentives, and rewards (together called stimuli). Four major components of attitude are (1) Affective: emotions or feelings. (2) Cognitive: belief or opinions held consciously. (3) Conative: inclination for action. (4) Evaluative: positive or negative response to stimuli (WebFinance, 2014).

Hwang, et al. (2008) supported that system quality had a strong direct effect on perceived usefulness and actual use of data. In addition Park, et al. (2011) supported that system quality has a positive influence on perceived usefulness of data which would influence its utilization. Moreover Halawi, et al. (2008) supported that there is a positive relationship between system quality and user satisfaction and use. In addition Ainin, et al. (2012) supported that system quality will have a significant, positive relationship with user satisfaction level and utilization of data.

Negative attitudes among clinicians and health workers – such as "data collection is a useless activity or a waste of care-provider time" – are detrimental to data quality (Odhiambo, 2005). The efficiency with which a job is carried out may depend in part upon the technical apparatus available to do the job, and the extent to which the job provides satisfaction (Naeme, 1993).

Some of these factors may be assessed by the use of formal techniques during the design stage of an information system, but in the main information relating to value, attitudes, and power is derived from the informal system. Motivating data collectors remains a challenge despite training on data-collection registers and questionnaires (Odhiambo, 2005). Staff attitude towards health information management determines their use of the data for improvement delivery at the point of collection.

A study conducted in the USA indicated that there are many factors involved in clinical decision making and each of the core skills has the potential to impact effective decision making. In an ideal world decisions would be made objectively, with a full set of evidence, an endless bank of resources, no time pressures, minimal interruptions, decision support tools to hand and plenty of energy to handle any decision making situation at any time of the day(Nutley & Reynolds, 2011).

However, this is not always the reality. Clinical decision making is a balance of known best practice (the evidence, the research), awareness of the current situation and environment, and knowledge of the patient. It is about 'joining the dots' to make an informed decision. Informed clinical decision making should include a variety of information and knowledge sources.

In an era of evidence-based practice, one wonders why clinicians are not typically engaged in evidence-based assessment (EBAs) and data use (Jensen-Doss & Hawley, 2010).

To begin to understand this issue, a national multidisciplinary survey was conducted in Canada to examine clinician attitudes toward standardized assessment tools. Despite the importance of EBA, much available evidence suggests that clinicians are not engaged in assessment practices consistent with EBA, including what is arguably the core component of EBA: use of standardized assessment tools with research support for their reliability and validity. It was observed that Data on clinician diagnostic practices suggest they may not align with evidence-based guidelines. (Jensen-Doss & Hawley, 2010).In a study in Turkey by Kaya (2010) looking at nurses attitudes on computer use for data management revealed that nurses, in general, had positive attitudes toward computers the present study showed a significant difference in attitudes for different categories of age, marital status, education, type of facility, job HD, computer science education, computer experience, duration of computer use, and place of use of computer (Kaya, 2011).

There is also a large and growing body of literature about aspects of health informatics related to policy, hardware, software and implementation. One of the factors identified as significant in the introduction of Information technology into healthcare practice is the attitude of staff that will be required to use it. In the UK Medix (a market research company in the health sector) surveys of the attitudes of doctors and nurses have shown increasingly negative attitudes. (Medix, 2005).He adds that earlier studies, Twenty years ago (Stronge, 1985) were studying this area in the USA with their Nurses' Attitudes Towards Computers (NATC) questionnaire and others have continued this work, using similar instruments with different findings(Sultana, 1990) found more positive attitudes than Stronge (1985). A similar study found out that students showed more positive attitudes than qualified staff(Schumache., 1997) but yet another study found no differences in attitude with nursing experience or educational level, but had found that experience with computers was 5 significant(Scarpa, 1992). In addition there were no gender differences another similar attitude study (Ward, Stevens, Brentnall, & Briddon, 2007).

Clinicians expressed practical concerns associated with the measures (e.g., paperwork burden), reservations about the relevance of the measures to their clients (e.g., ethnic minorities), and skepticism that the measures actually tell clinicians anything they could not learn from the other experiences with the family (Jensen-Doss & Hawley, 2010).A study done by Kipturgo(2011) at Kenyatta National and Agha Khan Hospitals looking at the nurses attitudes towards the use of electronic medical records (EMR) to improve data retrieval and use for decision making revealed a total attitude scores for nurses at both hospitals was 73.53 (SD = 13.15) out of a maximum possible score of 100. The range of attitude scores for this sample was 34 to 100. The non-users had a significantly higher attitude score (mean = 74.56) compared to the users (mean = 69.86, Majority of respondents (72.4%) totally rejected the suggestion that computers should be confined to non-nursing departments such as finance.

A similar majority rebuffed the idea that nurses should never use computers. The age of nurses showed a statistically significant association with attitude towards computerization ($p = 0.039$). Gender did not significantly impact on their attitude towards computerization. Professional training significantly influenced the nurses' attitudes towards computerization. Holders of bachelors' degrees (mean = 82.07) and higher diplomas (79.07) had the highest attitude scores.
The duration of exposure to computers showed a significant association with attitude towards computerization ($P = 0.025$). Nurses with longer durations of exposure to computers (at least three years) at both hospitals were likely to have more positive attitudes than those with relatively shorter durations of computer use. Conclusion: - Generally, nurses have positive attitudes towards computerization.

The findings further disclose that nurses with little or no experience in using computers in the places of work (non-users) and those from a hospital that had instituted use of computers (users) both had positive attitudes towards computerization. Interestingly, the non-users were more positive than the users. (Kipturgo, 2011).The available literature on attitude of health care workers as reflected in the studies conducted in Kenya, Africa and in other continents concentrates more on health care workers attitude towards computer use in health information system and is limited on the use of data for decision making.

This study seek to unveil and shed more light on how health care workers' (HCWs) attitude would influence data use for decision making at health facilities.

2.5 Leadership Goodwill on Data Utilization

A study by Chen & Hsiao (2012) on physicians' acceptance of hospital information systems: a case study revealed that top management support positively influences perceived usefulness and use of data. Shih & Huang (2003) observed that top management support strongly, directly and positively affects perceived usefulness and use of data. Moreover Cho (2007) supported that top management support positively affects HIS user satisfaction. In addition Urbach et al.(2011) supported that perceived adequacy of top management support has a significant impact on HIS user.

Nurses have probably always known that their decisions have important implications for patient outcomes. Increasingly, however, they are being cast in the role of *active* decision makers in healthcare by policy makers and other members of the healthcare team. In the UK, for example, the Chief Nursing Officer recently outlined 10 key tasks for nurses as part of the National Health Service's modernization agenda and the breaking down of artificial boundaries between medicine and nursing (CNO, 2002). As well, nurses are expected to access, appraise, and incorporate research evidence into their professional judgment and clinical decision making (Health Department, 1999).

Carl Thompson in his study on Nurses, information use, and clinical decision making found out that the number and types of decisions faced by nurses are related to the work environment, perceptions of their clinical role, operational autonomy, and the degree to which they see themselves as active and influential decision makers. Carl Thompson also established that nurses working on a busy medical admissions unit admitting 50 patients per day face a different set of decision challenges compared with health visitors (HVs) or public health nurses, who may see 10 patients per day. Examples of data-driven decisions that nurse managers make include assigning unit and shift staffing levels based on patient acuity rates, increasing focus on infection control measures based on patient infection figures, and a heightened concentration on service delivery based on patient satisfaction survey results.

As demand for quality care grows, it is important for health care workers leadership to develop competencies and skills that allow them to identify issues influencing delivery of care, determine what data are needed to provide further understanding, and analyze internal and/or external data for effective decision making. If the findings validate a need for change or unit improvement, you'll need to formulate a plan for how to implement the change and apply it.

Healthcare is an industry in which collecting data is extremely important for growth and change. Analyzing data resulting from your unit outcomes, discovering strategies to tackle the issue, and formulating a plan for improvement will assist you in making better clinical decisions. These administrative skills are a permanent component of the process for ensuring continuity and quality of care delivered to patients.

Keeping staff informed of metric results, benchmarks, and unit outcome measurements such as patient satisfaction scores and complaints is helpful for increasing staff buy-in to improve processes in the unit. But staff nurses also need to add data analysis and data-driven decision-making skills as part of their direct-care competencies. Complex, unique, and ever-changing patient demands require rapid response and frequent adjustments. As a unit leader, she/he is the critical link for completing the circle of using outcome data to improve patient care (Carl Thompson, 2004). Thus, information and knowledge resulting from data assist healthcare personnel to develop strategies to improve performance and patient-care quality.

Given that healthcare is ever-changing and evolving, it's the responsibility of the leadership to familiarize themselves with data analysis and data-driven decision-making processes in order to make more informed decisions (Carl Thompson, 2004).

Thought leaders as observed by Sherrod et.al have identified essential practices and principles for health data stewardship. They include transparency about use; identification of the purpose for data use; participation of individuals; security safeguards and controls; de-identification (when relevant); data quality, including integrity, accuracy, timeliness, and completeness; limits on use, disclosure, and retention; oversight of data uses; accountability; and enforcement and remedies (Sherrod, McKesson, & Mumford, 2010).

In Ghana, Nepal and South Africa, it was reported that there are enormous differences in culture of data use between and within districts, suggesting different management styles within the same organizational culture (Naeme, 1993).At the level of the district, health information enables health planners and managers to take decisions regarding the effective functioning of health facilities and of the health system as a whole. At higher levels, health information is needed for strategic policy-making and resource allocation. Perceived lack of use of information therefore is a cause of concern on quality of decisions; hence the importance of understanding factors that under-play the importance of information use (Campbell, 2003).
In Tanzania, a study by John Braawas is in agreement that good health information systems are crucial for addressing health challenges and improving health service delivery in developing countries. However, the quality of the data produced by such systems is often poor and the data are not used effectively for decision-making. Although there has been increasing international attention to the need to develop strong health information systems, it has proved difficult to do so for several reasons, including fragmentation and lack of coordination of health programs (Sherrod, McKesson, & Mumford, 2010).

In the Kenyan scenario, a lot of efforts have been made by the ministry of health and development partners in health to empower health care leadership to embrace data driven decision making. Available literature tend to focus more on use of electronic data management and training of health care workers and their bosses on capturing and reporting accurate data to allow data driven decision making. There however very limited or no literature addressing leadership goodwill and its influence on data use.

According to Oranga (2001), lack of involvement and motivation among health services personnel accounts for low quality of data collected and disseminated or discourage healthcare providers from submitting data collected. Since health services supervisors and peripheral health workers rarely receive feedbacks on data reported to higher level, they have little incentive to ensure the quality of data collected and to comply with reporting requirements.

2.6 Theoretical Framework

This study borrows from and is premised on the *Theory of Planned Behaviour* (TPB). According to this theory as propounded by Ajzen (1991), the performance of a given behavior is a function of individuals' intentions to do so and their perceived behavioral control, or their beliefs about their abilities to engage in the behavior. The TPB posits that intentions are a function of attitudes toward the behavior, perceptions of social pressure to perform the behavior, and perceived behavioral control. Meta-analyses of research related to the TPB suggest that attitudes toward a given behavior are good predictors of an individual's intention to perform the behavior and that intention are subsequently related to behavior suggesting those improving clinicians' attitudes toward standardized assessment tools could lead to increased use through the pathway of increased intention. In addition, knowing clinicians' existing attitudes would help Evidence Based Assessments (EBA) trainings to directly address clinician concerns about using standardized assessment tools to capture clients' data as well as for data use.

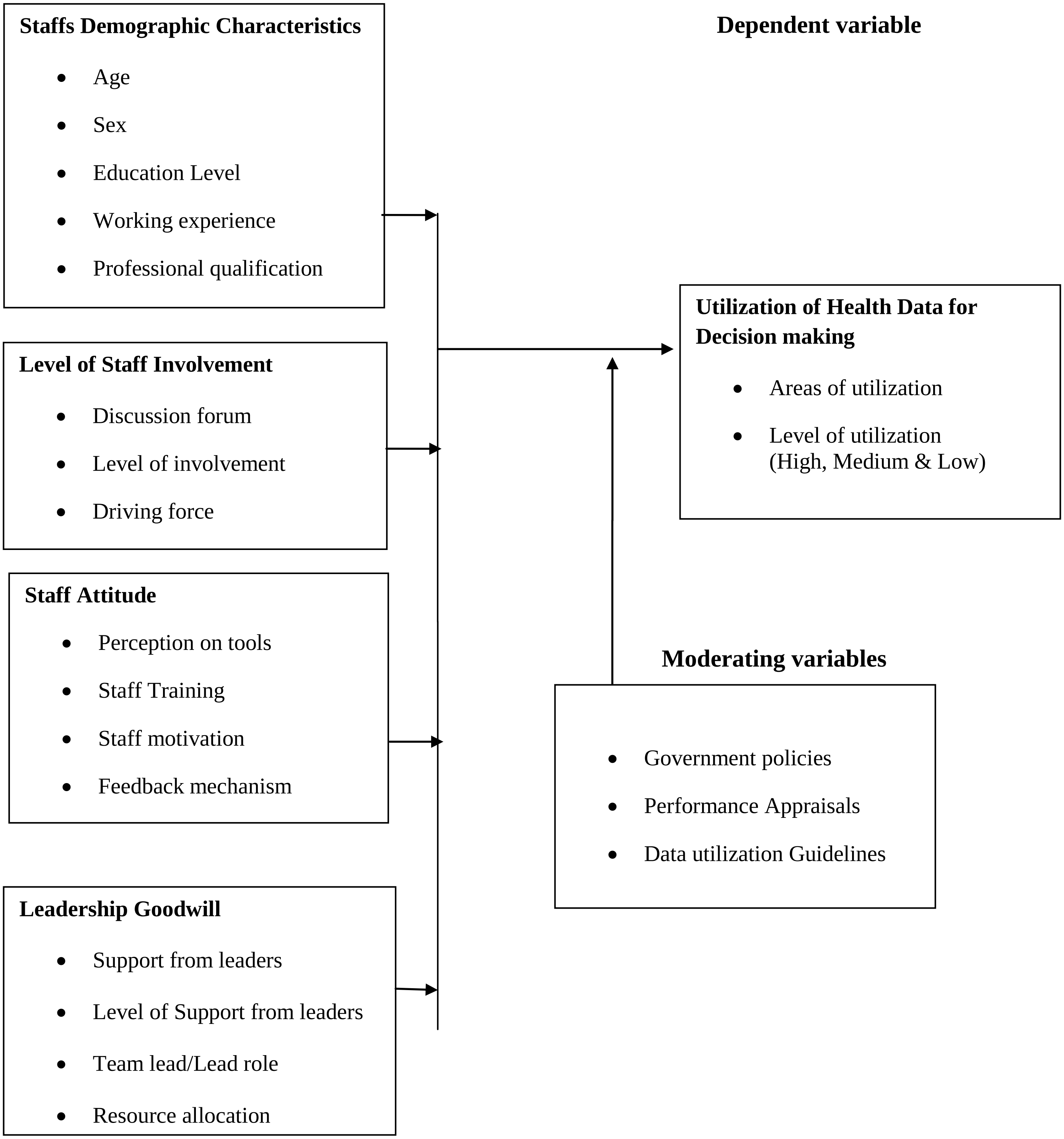
Understanding clinician characteristics predictive of positive and negative attitudes toward standardized assessment tools for data capture and use would also help EBA training efforts be more targeted to specific segments of the clinician population. It would be particularly useful to understand differences in attitudes between clinicians with different levels of training (i.e., doctoral- versus master's-level clinicians) and from different disciplinary background (i.e., psychologists, social workers, counselors, and psychiatrists).

Given that these characteristics are often associated with different roles in organizations, any variability in attitudes associated with therapist degree or discipline might impact efforts to implement EBA in clinical practice settings. For example, if doctoral-level clinicians, who increasingly play roles as administrators and supervisors, have more positive attitudes than master's level-clinicians, who are becoming the most prevalent front-line service providers, this might result in EBA implementation efforts with administrative buy-in, but little cooperation from direct service providers. In terms of practice characteristics, given the resource challenges faced by many private practitioners, it is possible that these clinicians might face more challenges using standardized assessment tools than other practitioners.

2.7 Conceptual Framework

The study was guided by the following conceptual framework

Figure 2. 1: The Conceptual Framework



The diagram in figure 2.1 above reflects the determinants of utilization of health related data for service improvement in Nyando Sub-County. The diagram is a figurative representation of the interplay among the variables used in the study.
The variables which have been conceptualized as independent variables include; staff demographics, staff attitude, staff level of involvement and leadership goodwill and how they influence utilization of health related data for service improvement.

Staff demographic characteristics like educational level and working experience can have a positive impact on utilization of health related data for service improvement. Healthcare workers equipped with knowledge on data utilization are more likely to put it into practice in order to achieve a desired goal which is service improvement. Level of staff involvement plays a very important role as far as utilization of health related data is concerned. If healthcare workers have driving force towards utilization of data they produce then they are more likely to use it for service improvement. If they also take part in data discussion forum in their respective facilities then they are more likely to understand their data and use it for service improvement.

Staff attitude directly influence utilization of health related data in various ways. Staff training and mode of motivation will determine how individual staff will perceive utilization of heath data they produce. If staffs are trained on data utilization for service improvements then they are most likely to implement whatever they have been trained on hence improves service delivery. Leadership goodwill influences utilization of health related data directly in that when the level of support from health facility leaders on utilization of data is high then healthcare worker will positively embrace data and will use it for service improvement within the health facility. When leaders take lead on data utilization then their followers will try to follow their footsteps hence aide service improvement in their respective health facilities.

2.8 Literature Summary

Demographic characteristics are critical determinant of data utilization because they determine the capabilities levels.

Workers with who are younger for instance are more likely to utilize data because they have greater interests , ease and understanding of new technology especially those relating to data management. Many accounts of failed ICT Systems have been attributed to failed mismatch between technology capabilities, needs and constraints of health care workers.
Staff involvement in data management is seen as an important aspect of data utilization for decision making.

The staff involve get share their frustrations with data management systems, learn new skills and gain confidence and support from fellow colleagues on how well to utilize data and obtain better outcomes. It creates an environment in which people have an impact on decisions and actions that affect their jobs. Regular participation of employees in deciding how their work is done, making suggestions for improvement, goal setting, planning, and monitoring of their performance.

Studies unveil and shed more light on how health care workers' (HCWs) attitude would influence data use for decision making at health facilities. Staff attitudes are seen to affect data utilization differently. Staffs are seen to have different at attitudes toward data management which in turn affects data utilization: standardized assessment tools, attitudes towards computer use in data management, and, electronic medical records (EMR).

Leadership support is seen in literature as critical to ensuring that data is utilized, lack of leadership support among health services personnel accounts for low quality of data collected and disseminated or discourage healthcare providers from submitting data collected. Since health services supervisors and peripheral health workers rarely receive feedbacks on data reported to higher level, they have little incentive to ensure the quality of data collected and to comply with reporting requirements.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methodology that was used in carrying out the study. The chapter includes: Study Design, Study population, Sample and sampling procedures, Study Instruments, Reliability and Validity of study instruments, Data collection procedures, data analysis and ethical considerations.

3.2 Research Design

According to Kothari (2008), a research design is the arrangement of conditions for collection and analysis of data in a manner that combines relevance to the research purpose with a cost-cutting measure in procedure. This is the actual conceptual structure within which research is conducted. Orodho (2006) describes research design as the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose with economy and procedure.

The study adopted a descriptive survey research design. Descriptive survey research designs involves gathering data that describe events and then organizes, tabulates, depicts, and describes the data collection (Glass & Hopkins, 1984).Descriptive survey research design helped a researcher to utilize data collection and analysis techniques which yield reports concerning the measures of central tendency, variation, and correlation in a health set up.

Descriptive survey research design enabled the researcher to generalize the findings to larger population. This research design helped in identifying the relationship between utilization of health related data and service improvement in health facilities within Nyando Sub-County. Three main purposes of research are to describe, explain, and validate findings. Description emerges following creative exploration, and serves to organize the findings in order to fit them with explanations, and then test or validate those explanations (Krathwohl, 1993).

According to Orodho (2003) it is ideal when collecting information about attitude and antecedents which is relevant with the study on determinants of data utilization for decision making in health facilities within Nyando Sub-County.

3.3 Target Population

According to Kombo and Tromp (2006), a population is a group of individuals, objects or items from which samples are taken for measurement. The study target populations were healthcare workers in health facilities within Nyando Sub-County. According to Ministry of Health Annual Operation Plan (AOP) 2013/2014, Nyando Sub-County has a total population of about 650 healthcare workers.

3.4 Sample Size and Sampling Procedures

A sample design is a plan for obtaining a sample from a given population (Kothari, 2008).This section presents methods and techniques that were used for sampling and how the study sample was reached from target population. The detail on how data was obtained processed and analyzed is also discussed in this section.

3.4.1 Sample Size

The sample consisted of 241 healthcare workers selected among the healthcare facilities within Nyando Sub-County. According to Kathuri and Palls (1993), pre-determined scientific table for determining sample sizes from given populations, a population size of 650 healthcare workers was a complete representation of 241 respondents at 7% precision (See Appendix III).

3.4.2 Sampling Procedure

The study applied stratified random sampling method to select the respondents since the population is heterogeneous constituting different cadres of healthcare workers. A sample of 241 was selected from a population of 650 health workers in health facilities within Nyando Sub-County.

The following formula was used to determine the sample size in each stratum:

$\frac{\text{Population in the stata}}{\text{Total Target population}} \times$ Desired sample size,

Table 3.1: Sample size determination

	Staff Cadres	No. of Healthcare Workers	Sample size
1.	Medical Officers	8	3
2.	Public Health Officers	38	14
3.	Pharm –Tech	33	12
4.	Lab Technologist	48	18
5.	Nutritionist	20	7
6.	Physiotherapist	8	3
7.	Health Records & Information Officers	95	35
8.	Medical Engineering Technologist	10	4
9.	Administrators	8	3
10.	Clinical Officers	133	49
11.	Nurses	173	64
12.	Community Health Workers	80	30
	Total	**650**	**241**

3.5 Research Instruments

Data collection methods involve operationalizing research design into the instrument of data collection with the view to collecting data in order to meet the research objectives (Chandran, 2004). This study employed questionnaires as a research instrument. Questionnaire was used to collect primary data for the purpose of investigating the determinants of utilization of health related data for service improvement where the target population was on healthcare workers in health facilities within Nyando Sub-County, Kenya.

A questionnaire was settled upon because it enhances anonymity of respondents and uniformity of questions, thus allowing comparability. The use of closed ended questions were easier to analyze, administer and economic in terms of time and money (Mugenda and Mugenda, 1999).

The questionnaire designed for this study comprises of five sections. The first section was designed to determine fundamental issues including demographic characteristics of respondents. The second section was designed to bring out issues related to level of staff involvement in data utilization for service improvement.

The third section was designed to bring out issues related to staff attitude in relation to data utilization. The fourth section was designed to bring out issues related to leadership goodwill in relation to data utilization. The last section elicited responses on staff involvement in data utilization for service improvement.

3.5.1 Pilot testing of the instrument

The pilot testing involved the use of small number of respondent to test the appropriateness of the question and their comprehension. The instruments were waits piloted on 24 respondents from two health facilities in the neighboring Nyakach sub-County. This constituted 10% of the sample size. The pilot test involved simulating the actual data collection process on a small scale to get feedback on whether or not the instruments would collect reliable data during the actual data collection exercise. The piloting exercise helped in enhancing the clarity in eliciting information from respondents the results which was found was used to improve the research instrument.

3.5.2 Validity of the Instrument

According to Mugenda and Mugenda (1999) validity is a degree to which result obtained from data represents the phenomena under study. Ranjit and Kumar (2005) also define validity as the quality of measurement procedure that provides respectability and accuracy.

For a data collection instrument to be considered valid the content selected and included must be relevant to the need or gap established. Content of validity was be enhanced by use of results of the pilot test to gauge whether the study is measuring what it is supposed to measure. The data collected during the pilot study was entered,, analyzed and interpreted. Based on the results, the researcher concluded that the tools were able to capture information that would answer the study questions. The instruments were also subjected to appraisal and amendments by experts or supervisors whose recommendations were taken into consideration to improve the face and content validity of the data collection instruments.

3.5.3 Reliability of the Instrument

According to Mugenda and Mugenda (1999), reliability is as a measure of the degree to which a research instrument yields consistent results or data after repeated trials.

An instrument is said to be reliable when it measures a variable accurately and obtain the same results over a period of time. To measure the reliability of the study instruments, the researcher used the test-retest method which involved administering the questionnaire to 15 respondents on two different occasions within a period of three weeks. A measure of squared correlation was done between observed and true scores using SPSS to determine the Cronbach's co-efficient. The value of the alpha coefficient ranges from 0 to 1 and is used to describe the reliability of factors extracted from questions with two possible answers, a higher value greater than 0.7 shows that the questionnaire is more reliable (George and Mallery, 2003).The Cronbach value for this study was established as 0.81, this was considered adequate and signified high reliability of the instrument.

3.6 Data Collection Procedures

Permission for data collection was sought from the Ministry of Higher Education through the department of National Council for Science and Technology, a letter of transmittal was also obtained from the University of Nairobi. With the two permits, the researcher went to Sub-County Medical Officer of Health, Nyando Sub-County presented the permits, explained what the study was about and its target population. Discussions on the ethical considerations were held and the researcher was allowed to conduct the study in the Nyando Sub-County. The researcher visited the respondents explaining what the study was all about and seeking their informed consent. The questionnaires were then left with the consenting respondents and were picked two days later. All filled up questionnaires were reviewed for accuracy and completeness upon picking.

3.7 Data Analysis Techniques

Data analysis is the process of bringing orderly structure and meaning to the mass of information collected. It involves examining what has been collected and making deductions and interferences (Kombo and Tromp 2006; Mugenda and Mugenda 1999).

The questionnaires were checked for completeness, accuracy and consistency. The data were then be coded to enable the responses to be grouped in various categories. Data collected was purely quantitative and was analyzed by descriptive analysis techniques.

Data analysis was computer assisted by using SPSS. The findings were presented using tables, graphs, frequencies, percentages, cross-tabulations, and correlations.

3.8 Ethical Considerations

Permission to conduct the study was obtained from the University of Nairobi, Ministry of Higher Education through the department for National Council of Science and Technology and Sub-County Medical Officer of Health, Nyando Sub-County-County. Informed consent was sought from the respondents before the questionnaires were left for them. Confidentiality of the data collected was achieved by having the respondent not indicate their names anywhere on the questionnaire. The researcher also dropped a copy of the research project report at the Sub-County Medical Office, Nyando where the respondents are able to access and make use of the findings. The study did have any risk to the participant since the kind of questions asked were neither be personal nor sensitive.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION, INTERPRETATION AND DISCUSSION

4.1 Introduction

The chapter presented analysis, gives interpretation and discussion of the findings, this is depicted in the following thematic areas: Questionnaire response rate, Influence of demographic characteristics of staff on utilization of health related data for improved service delivery, Influence of staff involvement on utilization of health related data for improved service delivery, Influence of staff attitude on utilization of health related data for improved service delivery and, Influence of leadership goodwill and utilization of health related data.

4.2 Questionnaire return rate

The questionnaire return rate for the study was computed and the results were as shown in Table 4.1

Sample Size	Number Reached	Response Rate
241	**237**	**98.3%**

According to Mugenda and Mugenda (2003), a 60% response rate is recommended for a study. This study recorded 98.3% response rate which was considered adequate for the study. The high response rate among the respondents can be attributed to support, cooperation and diligence among the medical personnel targeted and their superiors.

4.3 Influence of demographic characteristics of staff on utilization of health related data

This section addresses the first objective of the study; it presents findings, interpretations and gives discussions on the extent to which demographic characteristics of staff influence the utilization of health related data for improved service delivery.

4.3.1 Sex of the respondent and level of data utilization for decision making

The respondents were asked to indicate their sex; this was cross-tabulated with their response on the level of data utilization for decision making. The results were as shown in Table 4.2.

Table 4.2: Sex of the respondents and data utilization for decision making

		Sex		Total
		Male	**Female**	
Rate for level of data utilization for decision making	High	32(13.5%)	44(18.6%)	76(32.1%)
	Medium	70(29.5%)	78(32.9%)	148(62.4%)
	Low	8(3.4%)	5(2.1%)	13(5.5%)
Total		**110(46.4%)**	**127(53.6%)**	**237(100.0%)**

Majority of the respondents at 127 (53.6%) were female, out of these 78(32.9%) reported medium level data utilization, 44(18.6%) reported high level data utilization for decision making while 5(2.1%) reported low level of data utilization for decision making. A minority of the respondents were male at 110(46.4%), among these 70(29.5%) reported medium level data utilization for decision making, 32(13.5%) reported high level data utilization for decision making while 8(3.4%) of the men reported low level of data utilization for decision making. The chi-square analysis revealed that that the sex of the respondent did not have a significant association with the level of data utilization for decision making, chi-square (2,237) = 1.809, p = 0.405.Gordana (2005) in his study on demographic characteristics of nurses and the use of Health Information Systems (HIS) in Croatia also established that there was no difference regarding use of HIS based on gender.

4.3.2 Professional qualifications and level of data utilization for decision making

The respondents were asked to indicate their professional qualifications; this was cross tabulated with their response on level of data utilization for decision making. The results are as shown in Table 4.3

Table 4.3: Professional qualifications and data utilization for decision making

		Rate for level of data utilization			Total
		High	**Medium**	**Low**	
Professional qualification	Medical Doctor	2(0.8%)	1(0.4%)	0(0.0%)	3(1.3%)
	Clinical Officer	15(6.3%)	32(13.5%)	1(0.4%)	48(20.3%)
	Nurse	16(6.8%)	40(16.9%)	5(2.1%)	61(25.7%)
	Public Health Officer	5(2.1%)	9(3.8%)	1(0.4%)	15(6.3%)
	Pharm Tech	4(1.7%)	6(2.5%)	1(0.4%)	11(4.6%)
	Lab Tech	6(2.5%)	12(5.1%)	1(0.4%)	19(8.0%)
	Nutritionist	2(0.8%)	5(2.1%)	1(0.4%)	8(3.4%)
	Physiotherapist	0(0.0%)	3(1.3%)	0(0.0%)	3(1.3%)
	HRIO	18(7.6%)	15(6.3%)	1(0.4%)	34(14.3%)
	Administrator	2(0.8%)	1(0.4%)	0(0.0%)	3(1.3%)
	Medical Engineer	1(0.4%)	3(1.3%)	0(0.0%)	4(1.7%)
	CHEW	4(1.7%)	19(8.0%)	2(0.8%)	25(0.8%)
	Pharmacist	0(0.0%)	2(0.8%)	0(0.0%)	2(0.8%)
	Counselor	1(0.4%)	0(0.0%)	0(0.0%)	1(0.4%)
Total		**76(32.1%)**	**148(62.4%)**	**13(5.5%)**	**237(100.0%)**

Majority of the respondents were nurses constituting 61(25.7%) doctors were 3(1.3%) the, clinical officers 48(20.3%) and HRIOs were 34(14.3%), Administrators were 3(1.3%),Medical engineers were 4(1.7%),CHEWS were 25(10.5%),pharmacist were 2(0.08%),Counselor was 1(0.4%),Phisiotherapists were 3(1.3%),Nutritionists were 8(3.4%),Lab Techs were 19(8.0%) Pham Techs were 8(4.6) while Public Health Officers were 15(16.3%).

Though pronounced among public health officers, pharmacy technicians, laboratory technicians and nutritionists, the low rates of data utilization for decision making were significantly low across board. These findings converge with those of Mantzoukas, (2007) who observed that utilization of data varies across the health professions; that nurses were increasingly more involved in utilization of health related data in clinical decision making. The study findings indicated of the importance of data in every department of the health facilities especially in the making of decisions. Nonetheless, it was established that there is no significant association between the professional qualification and the level of data utilization for decision making, chi-square (26,237) = 22.840, p = 0.642 indicating an approximately similar response on the rating for the level of data utilization for decision making across the different professional qualifications.

4.3.3 Age of the respondents and the level of data utilization for decision making

The respondents were asked to indicate their ages, this was cross-tabulated with their response on the level of data utilization for decision making. The results are as shown in Table 4.4

Table 4.4: Age of the respondents and data utilization for decision making

	Age						Total
	20 - 25 years old	**26 - 30 years old**	**31 - 35 years old**	**36 - 40 years old**	**41 - 45 years old**	**46 - 50 years old**	
High	12(5.1%)	36(15.2%)	13(5.5%)	6(2.5%)	3(1.3%)	1(0.4%)	76(32.1%)
Medium	24(10.1%)	50(21.1%)	34(14.3%)	24(10.1%)	4(1.7%)	3(1.3%)	148(62.4%)
Low	3(1.3%)	3(1.3%)	1(0.4%)	4(1.7%)	0(0.0%)	1(0.4%)	13(5.5%)
	39(16.5%)	89(37.6%)	48(20.3%)	34(14.3%)	7(3.0%)	5(2.1%)	237(100%)

The chi-square analysis revealed that there is no significant relationship between the age of the HCP and the level of data utilization for decision making, chi-square (12,237)=13.424, p = 0.339 meaning that the age of the HCP does not vary with the level of data utilization for decision making at the health facility.

The findings of the study diverges with those of a study by Gordana (2005) on demographic characteristics of nurses and the use of Health Information Systems (HIS) in Croatia that established that there was a difference the age of the staff and use of HIS data; nurses younger than 30 years were more likely to embrace the use of HIS compared to older nurses.

4.3.4 Level of Education and level of data utilization

The respondents were asked to state their highest level of education; this was cross-tabulated with their responses on the level of data utilization for decision making. The results are as shown in Table 4.5

Table 4.5: Level of education and data utilization

		Highest level of education			**Total**
		Secondary level	**College level**	**University level**	
Rate for level of data utilization for decision making	High	4(1.7%)	56(23.6%)	16(6.8%)	76(32.1%)
	Medium	8(3.4%)	106(44.7%	34(14.3%)	148(62.4%)
	Low	1(0.4%)	12(5.1%)	0(0.0%)	13(5.5%)
Total		**13(5.5%)**	**174(73.4%)**	**50(21.1%)**	**237(100.0%)**

Majority of the respondents at 174(73.4%) had college level of education among these 106(44.7%)indicated medium level of data utilization, 56(23.6%) indicated high while 12(5.1%) indicated low level data utilization with ,50 (21.1%) of all the respondents had university level of education, among them 34(14.3%) indicated medium level of data utilization and 16(6.8%) indicated high level data utilization .Of all the respondents 13(15.5%) had secondary level of education, among them,8(3.4%) indicated medium rate of data utilization for decision making,4(1.7%) indicated high while 1(0.4%) mentioned low level of data utilization for decision making. In addition, the chi-square test revealed that there was no significant relationship between the highest level of education and the level of data utilization for decision making, chi-square(4,237) = 0.432, p = 3.811.

The findings of this study also finds a point of divergence with a study done by Gordana (2005) on demographic characteristics of nurses and the use of Health Information Systems (HIS) in Croatia, the study established nurses with a bachelor's degree were also more likely to embrace use of HIS than nurses with a high school degree.

4.3.5 Year of service and the level of data utilization for decision making

The respondents were asked to state their year of service; this was cross-tabulated with the level of data utilization for decision making. The results are as shown in Table 4.6.

Table 4.6: Year of service and data utilization for decision making

		Rate for level of data utilization for decision making			**Total**
		High	**Medium**	**Low**	
Years of service	0 - 5 years	52(21.9%)	104(43.9%)	10(4.2%)	166(70.0%)
	6 - 10 years	17(7.2%)	18(7.6%)	0(0.0%)	35(14.8%)
	11 - 15 years	1(0.4%)	8(3.4%)	2(0.8%)	11(4.6%)
	16 - 20 years	1(0.4%)	7(3.0%)	0(0.0%)	8(3.4%)
	Over 20 years	5(2.1%)	11(4.6%)	1(0.4%)	17(7.2%)
Total		**76(32.1%)**	**148(62.4%)**	**13(5.5%)**	**237(100.0%)**

Majority of the respondents at 166(70.0%) were between ages 0-5 years, among these, 104(43.9%) mentioned medium rate of data utilization for decision making, 52(21.9%) mentioned high while 10(4.2%) mentioned low rate of data utilization in decision making. Those with 6-10 years were 35(14.8%), among these 18(7.6%) mentioned medium rate of data utilization in decision making,17(7.2%) mentioned high. Those who had over 20 years were 17(7.2%),among there 11(4.6%) mentioned medium rate of data utilization,5(2.1%) mentioned high,1(0.4%) mentioned low level data utilization in decision making. The respondents 16-20 years constituted 8(3.4%) among them 7(3.0%) mentioned medium rate of data utilization,1(0.4%) mentioned high level of data utilization. The study also sought to establish whether the years of service have any association with the level of data utilization for decision making.

The chi-square test revealed that there was no significant association between the years of service and the level of data utilization, chi-square (8,237) = 13.175, p = 0.106 which meant that the level of data utilization for decision making was not varying with the experience of the HCP.

4.4 Influence of level at which staff involvement on utilization of health related data

This section addresses the second objective of the study; it presents findings, interpretations and gives discussions on the extent to which staff involvement influence the utilization of health related data for improved service delivery.

4.4.1 Involvement in data utilization in the facility and level of data utilization for decision making

The respondent was asked whether they are involved in data discussions in the facility, this was cross-tabulated with their opinion on the level of data utilization for decision making. The results are as shown in Table 4.7

Table 4.7: Involvement in data utilization and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	Medium	Low	
Involved in Data discussion in the facility	Yes	69(29.1%)	123(51.9%)	10(4.2%)	202(85.2%)
	No	7(3.0%)	25(10.5%)	3(1.3%)	35(14.8%)
	Total	**76(32.1%)**	**148(62.4%)**	**13(5.5%)**	**237(100.0%)**

Majority of the respondents said at 202(85.2%) mentioned that they have been involved in data discussion in the facility, among them 123(51.9%) rated data utilization as medium,69 (29.1%) rated it at high while 10(4.2%) rated the level of data utilization for decision making as low. Those who said that they have not been involved in data discussions in the facility were 35(14.8%), among them 25(10.5%) rated data utilization for decision making as medium,7(3.0%) rated it as high while 3(1.3%) rated data utilization for decision making as low. A chi-square test was done on the relation between involvement in data discussions in the facility and the level of data utilization for decision making, the value was (237,2) =3.103 p >0.211.

This meant that their involvement of staff in discussion in the facility was not important in explaining data utilization for decision making at those facilities. This finding diverges with those of Oranga (2001) who found that lack of involvement and motivation among health services personnel accounts for low quality of data collected and disseminated or discourage healthcare providers from submitting data collected.

4.4.2 Influences to involvement in data utilization

The respondents were asked to state their influences in data utilization; the results are as shown in Table 4.8

Table 4.8: Influences to involvement in data utilization

	Frequency	**Percent**
Monetary influence	18	7.5
Influence from facility in charge	16	6.7
Influence from other HCW	31	12.9
Zeal to learn more on Data utilization	146	60.8
None of the above	26	12.1
Total	**237**	**97.9**

The respondents indicated some of the hindrances to involvement to data utilization at the health facility. Majority of the respondents at 146(60.8%) said that they influenced by the zeal to learn more on data utilization,31(12.9%) mentioned that they get influence from other HCW,26(12.1%) did not have any form of influence to involvement in data utilization,18(7.5%) had monetary influence while 16(6.7%) said that they get the influence from the facility in charge. This findings is supported by those of Oranga (2001) that lack of motivation;which could also be monetary, among health services personnel accounts for low quality of data collected and disseminated or discourage healthcare providers from submitting data collected.

4.4.3 Forums that the staff is involved

The respondents were asked to state the forums that they are involved in, the responses were as shown in Table 4.9

Table 4.9: Forums that the staff is involved

	Frequency	Percent
Seminar	51	21.3
Workshops	24	10.0
CME	44	18.3
Facility based data review forum	86	35.8
Total	205	85.4
None	33	14.6
Total	**237**	**100.0**

The respondents indicated the forums in which they were involved, majority of the respondents at 86(35.8) mentioned that they are involved at facility based data review forums,51 (21.3%) were involved in seminars,44(18.3%) were involved in CME,24(10.0%) were involved in workshops,33(14.6) of the respondents said that are not involved at all in the forums. It is clear that the respondents valued the forums because of the knowledge that they gained in respects to data processing and utilization, such forums also served as platforms for decision making. It is therefore important that the all the staff are involved as much as possible in the different forums. Such forums are important for learning and Carl Thompson (2004) observed that given that healthcare is ever-changing and evolving, it's the responsibility of the leadership to familiarize themselves with data analysis and data-driven decision-making processes in order to make more informed decisions.

4.4.4 Hindrances to involvement in data utilization

The respondents were asked to state the hindrances in data utilization at the facility; the results were as shown in Table 4.10

Table 4.10: Hindrances to involvement in data utilization

	Frequency	Percent
Not trained in Data management	36	15.0
No time for data discussions	5	2.1
I have no interest	2	.8
Total	43	17.9
N/A	194	82.1
Total	**237**	**100.0**

The respondents were able indicate some of the hindrance that they faced in the course of utilizing data at the health facilities, majority of the respondents at 197(82.1%) did not cite any hindrance,43 (17.9%) cited hindrances, among them 36(15.0%) had not been trained on data management,5(2.1%) had no time for data discussion while 2(0.8%) did not have interest.

4.5 Influence of staff attitude on utilization of health related data

This section addresses the third objective of the study; it presents findings, interpretations and gives discussions on the extent to which staff attitude influence the utilization of health related data for improved service delivery.

4.5.1 Perception on tools and the level of data utilization for decision making

The respondents were asked give their perception on whether they have the right tools and registers to do their job, this was cross-tabulated with the level of data utilization for decision making. The results are as shown in Table 4.11

Table 4.11: Perception on tools and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
I have the right tools and registers to do my job	Strongly Disagree	1(0.4%)	5(2.1%)	1(0.4%)	7(3.0%)
	Disagree	2(0.8%)	15(6.4%)	4(1.7%)	2(8.9%)
	Neutral	1(0.4%)	18(7.6%)	3(1.3%)	22(9.3%)
	Agree	34(14.4%)	65(27.5%)	2(0.8%)	101(42.8%)
	Strongly Agree	38(16.1%)	45(19.1%)	2(0.8%)	85(36.0%)
Total		**76(32.2%)**	**148(62.7%)**	**12(5.1%)**	**236(100.0%)**

Asked if they had the right tools and registers to do their job, majority of the respondents at 101(42.8%) agreed, among them 65(27.5%) rated data utilization for decision making as medium,34 (14.4%) rated it as high while 2(0.8%) rated it as low. The respondents who strongly agreed were 85(36.0%), among them 38(16.1%) rated data utilization for decision making as high,45(19.1%) rated it as medium while 2(0.8%) rated it as low. Those who were neutral were 22(9.3%),out of these 18(7.6%) rated the level of data utilization for decision making as medium,3(1.3%) rated it as low while 1(0.4%) rated the data utilization for decision making as high. The respondents who disagreed were 21(8.9%) among them 15(6.4%) rated the level of data utilization for decision making as medium,4(1.7%) rated it as low while 2(0.8%) rated the data utilization for decision making as high. The respondents who strongly disagreed were 7(8.9%) among them 5(2.1%) rated the level of data utilization for decision making as medium,1(0.4%) rated it as low and another 1(0.4%) rated the data utilization for decision making as high. Since tools form part of the system, this finding is supported by those of Hwang, et al. (2008) that system quality had a strong direct effect on perceived usefulness and actual use of data. In addition Park, et al. (2011) supported that system quality has a positive influence on perceived usefulness of data which would influence its utilization.

4.5.2 Perception staff training and level of data utilization for decision making

The respondents were asked to their perception on staff training; this was cross-tabulated for date utilization .The results are as shown in Table 4.12

Table 4.12: Perception staff training and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
I received training on data management when I asked for it	Strongly Disagree	5(2.2%)	27(11.7%)	4(1.7%)	36(15.6%)
	Disagree	21(9.1%)	55(23.8%)	7(3.0%)	83(35.9%)
	Neutral	19(8.2%)	39(16.9%)	1(0.4%)	59(25.5%)
	Agree	20(8.7%)	23(10.0%)	1(0.4%)	44(19.0%)
	Strongly Agree	7(3.0%)	2(0.9%)	0(0.0%)	9(3.9%)
Total		**72(31.2%)**	**146(63.2%)**	**13(5.6%)**	**231(100.0%)**

Asked if they received training on data management when I asked for it, majority of the respondents at 83(35.9%) disagreed, among them 55(23.8%) rated data utilization for decision making as medium,21 (9.1%) rated it as high while 7(3.0%) rated it as low. The respondents who were neutral were 59(25.5%),among them 39(16.9%) rated data utilization for decision making as medium,19(8.2%) rated it as high while 1(0.4%) rated it as low**.** Those who agreed were 44(19.0%), out of these 20(8.7%) rated the level of data utilization for decision making as high,23(10.0%) rated it as medium while 1(0.4%) rated the data utilization for decision making as low. The respondents who strongly disagreed were 36(15.6%) among them 27(11.7%) rated the level of data utilization for decision making as medium,4(1.7%) rated it as low while 5(2.2%) rated the data utilization for decision making as high.

The respondents who strongly agreed were 9(3.9%) among them 5(3.0%) rated the level of data utilization for decision making as high while 2(0.9%) rated it as medium.

The perception of the HCP that they could receive a training on data management whenever they ask for it has a significant relationship with the level of data utilization for decision making, χ^2 (8) = 23.85, p= 0.002 implying that refresher trainings on data management go a great length in determining the level of data utilization at the facility. This finding is divergent from that of Naeme (1993) that despite training on the HIS, health care workers and managers do not always put the data collected to best.

4.5.3 Perception on supportive feedback and level of data utilization for decision making

The respondents were asked to give their perception on whether they get supportive feedback on the work that they do, this was cross-tabulated with the level of data utilization for decision making. The responses were as shown in Table 4.13

Table 4.13: Perception on supportive feedback and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
I am given supportive feedback on the work that I do	Strongly Disagree	0(0.0%)	6(2.6%)	0(0.0%)	6(2.6%)
	Disagree	3(1.3%)	12(5.1%)	5(2.1%)	20(8.5%)
	Neutral	4(1.7%)	22(9.4%)	3(1.3%)	29(12.3%)
	Agree	36(15.3%)	75(31.9%)	3(1.3%)	114(48.5%)
	Strongly agree	33(14.0%)	31(13.2%)	2(0.9%)	66(28.1%)
Total		**76(32.3%)**	**146(62.1%)**	**13(5.5%)**	**235(100.0%)**

Asked if they are given supportive feedback on the work that they do**,** majority of the respondents at 114(48.5%) agreed, among them 75(31.9 %) rated data utilization for decision making as medium, 36 (15.3%) rated it as high while 3(1.3%) rated it as low. The respondents who strongly agreed were 66(28.1 %), among them 33(14.0%) rated data utilization for decision making as high, 31(13.2%) rated it as medium while 2(0.9%) rated it as low.

Those who were neutral were 29(12.3%), out of these 22(9.4%) rated the level of data utilization for decision making as medium, 3(1.3%) rated it as low while 4(1.7%) rated the data utilization for decision making as high.

The respondents who disagreed were 20(8.5%) among them 12(5.1%) rated the level of data utilization for decision making as medium, 5(2.1%) rated it as low while 3(1.3%) rated the data utilization for decision making as high. The respondents who strongly disagreed were 6(2.6%) all of them rated the level of data utilization for decision making as medium. Supportive feedback given on the work done also had a significant relationship with the level of data utilization for decision making at the facility, χ^2 (8) = 35.966, p= 0.000. Through this, the persons involved in utilization of the data at the facility are able to better understand the areas that need to be worked on to ensure effective delivery of services at the facility given that at the department, there are clearly defined quality goals that have a significant relationship with the level of data utilization at the facility, χ^2 (8) = 31.78, p= 0.000. This finding converges with that of Hwang, et al. (2008) who noted that system quality had a strong direct effect on perceived usefulness and utilization of data. Park, et al. (2011) findings also supported that system quality has a positive influence on perceived usefulness of data. Oranga (2001) also established that since health services supervisors and peripheral health workers rarely receive feedbacks on data reported to higher level, they have little incentive to ensure the quality of data collected and to comply with reporting requirements.

3.5.4 Reward for my performance and responsibilities and level of data utilization for decision making

The respondents were asked to give their opinion on whether they are adequately rewarded for their performance and responsibilities; this was cross-tabulated with their response on the level of data utilization for decision making. The results are as shown in Table 4.14

Table 4.14: Reward and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
I am adequately rewarded for my performance and responsibilities	Strongly Disagree	1(0.4%)	26(11.1%)	1(0.4%)	28(12.0%)
	Disagree	10(4.3%)	48(20.5%)	5(2.1%)	63(26.9%)
	Neutral	20(8.5%)	35(15.0%)	4(1.7%)	59(25.2%)
	Agree	29(12.4%)	30(12.8%)	2(0.9%)	61(26.1%)
	Strongly Agree	16(6.8%)	7(3.0%)	0(0.0%)	23(9.8%)
Total		**76(32.5%)**	**146(62.4%)**	**12(5.1%)**	**234(100.0%)**

Asked if they are adequately rewarded for my performance and responsibilities, majority of the respondents at 63(26.9%) disagreed, among them 48(20.5%) rated data utilization for decision making as medium,10 (4.3%) rated it as high while 5(2.1%) rated it as low. Those who agreed were 61(26.1%), out of these 30(12.8%) rated the level of data utilization for decision making as medium,29 (12.4%) rated it as high while 2(0.9%) rated the data utilization for decision making as low. The respondents who were neutral were 59(25.5%), among them 35(15.0%) rated data utilization for decision making as medium,20(8.5%) rated it as high while 4(1.7%) rated it as low. The respondents who strongly disagreed were 28(15.6%) among them 26(11.1%) rated the level of data utilization for decision making as medium,1 (0.4%) rated it as low while another 1(0.4%) rated the data utilization for decision making as high. The respondents who strongly agreed were 23(9.8%) among them 16(6.8%) rated the level of data utilization for decision making as high while 7(3.0%) rated it as medium.

4.6 Influence of leadership goodwill on utilization of health related data

This section addresses the fourth objective of the study; it presents findings, interpretations and discusses the extent to which leadership goodwill influences the utilization of health related data for improved service delivery.

4.6.1 Support from Leaders and level of data utilization for decision making

The respondents were asked to rate the support that they were getting from the leader on data utilization, this was cross-tabulated with their response on the level of data utilization for decision making at the facility. The results are as shown in Table 4.15

Table 4.15: Support from Leaders and data utilization for decision making

		Rate for level of data utilization for decision making			**Total**
		High	**Medium**	**Low**	
Rate about the support from leader on Data utilization	Poor	0(0.0%	2(0.8%)	2(0.8%)	4(1.7%)
	Fair	3(1.3%)	46(19.4%)	4(1.7%)	53(22.4%)
	Good	53(22.4%)	88(37.1%)	7(3.0%)	148(62.4%)
	Excellent	20(8.4%)	12(5.1%)	0(0.0%)	32(13.5%)
		76(32.1%)	**148(62.4%)**	**13(5.5%)**	**237(100.0%)**

Majority of the respondents said that the support from leaders was good 148(62.4%) among these 88(37.1%) said the level of data utilization for decision making was medium,53 (22.4%) said high,7(3%) said low. Those who said the support from the leaders on data utilization was fair were 53(22.4%) among them 46(19.4%) said the level of data utilization for decision making was medium,4(1.7%) of the respondents said low while 3(1.3%) of the respondents said the level of data utilization for decision making was high. Some respondents at 32(13.5%) rated leadership support on data utilization as excellent, among them 20(8.4%) said the level of data utilization for decision making was high, while 12(5.1%) rated it at medium. The respondents who rated the support of leadership on data utilization as poor were 4(1.7%) among them 2(0.8%) said the level of data utilization for decision making was medium while 2(0.8%) rated it at low. The chi-square analysis revealed that the association between the support of the leader on data utilization and the level of data utilization was significant, chi-square (6,237) = 47.997, $p<0.000$ indicating the important role that the leader played in improving the level of data utilization at the facility especially in terms of offering support. This finding converges with that of Chen & Hsiao (2012) who said that top management support positively influences perceived usefulness and use of data which enhances its utilization for decision making.

4.6.2 Frequency of leadership support and the level of data utilization for decision making

The respondents were asked to state the frequency of leadership support; this was cross-tabulated with their response on the level of data utilization for decision making. The results are as shown in Table 4.16

Table 4.16: Frequency of leadership support and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
Frequency of support for data utilization	Weekly	26(14.1%)	21(11.4%)	0(0.0%)	47(25.4%)
	Monthly	29(15.7%)	59(31.9%)	6(3.2%)	94(50.8%)
	Quarterly	16(8.6%)	27(14.6%)	0(0.0%)	43(23.2%)
	Yearly	0(0.0%)	0(0.0%)	1(0.5%	1(0.5%)
Total		**71(38.4%)**	**107(57.8%)**	**7(3.8%)**	**185(100.0%)**

The respondents were able to indicate the frequency of leadership support for data utilization which was cross-tabulated with the level of data utilization for decision making. Majority of the respondents at 94(50.8%) mentioned that they get support monthly, among them 59(31.9%) rated data utilization for decision making as medium, 29 (15.7%) rated data utilization as high, while 6(3.2%) rated the data utilization for decision making as low. Respondents getting weekly support were 47(25.4%), among them 26(14.1%) rated data utilization as high while 21(11.4%) rated it at medium. Those getting support on a quarterly basis were 43(23.2%), among them 27(14.6%) rated data utilization for decision making at medium while 16(8.6%) rated it at high. Those who got leadership support once a year were a minority at 1(0.5%) rating data utilization for decision making at low. The chi-square analysis revealed that the association between frequency of support of the leader on data utilization and the level of data utilization was significant, chi-square (6,237) = 37.414, p<0.000 indicating the important role that the frequency of leadership support played in improving the level of data utilization at the facility especially in terms of offering support. This finding concurs with the views of Shih & Huang (2003) that top management support strongly, directly and positively affects perceived usefulness and use of data.

4.6.3 Adequacy of leadership support and level of data utilization for decision making

The respondents were asked to state whether the felt that the support from the leadership was adequate, this was cross-tabulated with the data utilization for decision making. The results are as shown in the Table 4.17

Table 4.17: Adequacy of leadership support and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	**Medium**	**Low**	
Is the feeling about support from leader adequate	Yes	69(29.1%)	95(40.1%)	4(1.7%)	168(70.9%)
	No	7(3.0%)	53(22.4%)	9(3.8%)	69(29.1%)
Total		**76(32.1%)**	**148(62.4%)**	**13(5.5%)**	**237(100.0%)**

The respondents were able to indicate whether they felt that leadership support was adequate or not, this was cross-tabulated with level of data utilization for decision making. Majority of the respondents at 168(70.9%) said the leadership support was adequate, among them 95(40.1%) rated data utilization for decision making as medium,69 (29.1%) rated it as high while 4(1.7%) rated. Those who said that the support of the leader was inadequate were 69(29.1%),among them 53(22.4%) rated data utilization for decision making at medium, 9(3.8%) rated it as low while 7(3.0%) rated data utilization for decision making as high. The chi-square analysis revealed that the association between the feeling about the adequacy of support by the leader and the level of data utilization was significant, chi-square (2,237) = 27.942, $p<0.000$ indicating the important role that the feeling of adequacy of support from leaders played in improving the level of data utilization at the facility. This finding converges with those of Urbach et al.(2011) supported that perceived adequacy of top management support has a significant impact on HIS user.

4.6.4 Lead role in data utilization and level of data utilization for decision making

The respondents were asked to state the person who spearheads data utilization at the health facility; this was cross-tabulated with their response on data utilization on decision making. The results are as shown in Table 4.18

Table 4.18: Lead role in data utilization and data utilization for decision making

		Rate for level of data utilization for decision making			Total
		High	Medium	Low	
Who spearheads data utilization	Facility in charge	23(9.8%)	51(21.7%)	3(1.3%	77(32.8%)
	Facility HRIO	36(15.3%)	56(23.8%)	6(2.6%)	98(41.7%)
	CCC in charge	6(2.6%)	8(3.4%)	0(0.0%)	14(6.0%)
	Data Clerk	6(2.6%)	8(3.4%)	1(0.4%)	15(6.4%)
	Peer Educators	0(0.0%)	2(0.9%)	0(0.0%)	2(0.9%)
	Partners	5(2.1%)	21(8.9%)	3(1.3%)	29(12.3%)
Total		**76(32.3%)**	**146(62.1%)**	**13(5.5%)**	**235(100.0%)**

The respondents were able to indicate the person who spearheaded data utilization, this was cross-tabulated with the level of data utilization for decision making. Majority of the respondents at 77(32.8%) mentioned that it is the facility in charge, among them 51(21.7%) rated data utilization for decision making as medium, 23(9.8%) rated it as high, while 3(1.3%) rated data utilization for decision making as low. Facility HRIO was mentioned by 98 (41.7%) of the respondents, among them 56(23.8%) rated data utilization for decision making as medium,36(15.3%) rated it as high, while 6(2.6%) rated data utilization for decision making as low. Partners were mentioned by 29 (12.3%) of the respondents, among them 21(8.9%) rated data utilization for decision making as medium,5(2.1%) rated it as high, while 3(1.3%) rated data utilization for decision making as low. Data clerks were mentioned by 15 (6.4%) of the respondents, among them 8(3.4%) rated data utilization for decision making as medium,6(2.6%) rated it as high, while 1(0.4%) rated data utilization for decision making as low. CCC in charge were mentioned by 14(6.0%) of the respondents, among them 8(3.4%) rated data utilization for decision making as medium,6(2.6%) rated data utilization for decision making as high. Peer educators were mentioned by 2(0.9%) of the respondents who also rated data utilization for decision making as medium. The chi-square analysis revealed that the association between who spearheads data utilization for decision making and the level of data utilization was significant, chi-square (6,237) = 8.540, $p > 0.576$ indicating the important role that who spearheads data utilization for decision making played in improving the level of data utilization at the facility.

This finding supports those of Carl Thompson (2004) that lead role plays significance in data use,he established that a unit leader is the critical link for completing the circle of using outcome data to improve patient care Thus, information and knowledge resulting from data assist healthcare personnel to develop strategies to improve performance and patient-care quality.

4.6.5 Resource allocation and level of data utilization for decision making

The respondents were asked to state the resources that have been committed by the support data utilization at the facility, this was cross-tabulated with their response on the level of data utilization for decision making. The results are as shown in table 4.19

Table 4.19: Resource allocation and level of data utilization for decision making

		Rate for level of data utilization for decision making			**Total**
		High	**Medium**	**Low**	
Resource put in to support data utilization at facility	Manpower	26(11.1%)	51(21.7%)	2(0.9%)	79(33.6%)
	Procurement of Tools	14(6.0%)	22(9.4%)	2(0.9%)	38(16.2%)
	Trainings	22(9.4%)	36(15.3%)	3(1.3%)	61(26.0%)
	Mentorship by NGOs	14(6.0%)	39(16.6%)	4(1.7%)	57(24.3%)
Total		**76(32.3%)**	**148(63.0%)**	**11(4.7%)**	**235(100.0%)**

The respondents were able to indicate the resources that were put to support data utilization at facility; this was cross-tabulated with the level of data utilization for decision making. Majority of the respondents at 79(33.6%) mentioned manpower, among them 51(21.7%) rated data utilization for decision making as medium, 26(11.1%) rated it as high, while 2(0.9%) rated it as low. Those who mentioned trainings were 61(26.0%), among them 36(15.3%) rated data utilization for decision making as medium, 22(9.4%) rated it as high while 3(1.3%) rated it as low. Procurement of tools was mentioned by 38(16.2%) of the respondents, among them 22(9.5%) rated data utilization for decision making as medium, 14(6.0%) rated it as high while 2(0.9%) rated data utilization for decision making as low.

Mentorship by NGOs was mentioned by 57(24.3%), among them 39(16.6%) rated data utilization for decision making as medium,14(6.0%) rated it as high while 4(1.7%) rated data utilization for decision making as low. The chi-square analysis revealed that the association between resource put in to support data utilization at facility and the level of data utilization was significant, chi-square (6,235) = 3.661, $p > 0.722$ indicating the important role that resource put in to support data utilization played in improving the level of data utilization at the facility.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This section entails the summary of findings, conclusions and recommendations, contribution to body of knowledge and suggestions for further research.

5.2 Summary of findings

The first study objective was to investigate how demographic characteristics of staff influence utilization of health related data. The study revealed that there was no significant association between the professional qualification of staff and the level of data utilization for decision making, χ^2 (26, N=237) = 22.840, p = 0.642; the level of data utilization was similar across the different professional qualifications. The study also revealed that there is significant relationship between the kind of IT knowledge; basic or advanced and the level of data utilization for decision making at the health facilities, χ^2 (2 N=237) = 14.617, p=0.001.Moreover, it was also established that that there was no significant relationship, between the level of facility and level of utilization of information in decision making χ^2 (6, N=239) = 4.136, p=0.658.

The second objective was to establish the level at which staff involvement influence utilization of health related data. The findings revealed that there was no significant association between whether the staff was involved in data discussions in the facility and their levels of utilization of health related data for decision making χ^2 (2,234) = 3.108, p = 0.211. It was also found out that there was no significant association between what influenced involvement in data utilization and the rate of level of data utilization for decision making, χ^2 (8,234) = 8.393, p = 0.396.The influences to involvement in data utilization were: monetary influence, influence from facility in charge, influence from other HCW and the zeal to learn more on data utilization.

The third objective was to assess the extent at which staff attitude influence utilization of health related data. The study results revealed the perception among staff on the importance of data collection at facility did not significantly influence the level of utilization of health related data for decision making, χ^2 (8) = 1.032, p= 0.984.

The perception that decision making at the health facility did not require data also did not have significant influence on the utilization of health related data for decision making, χ^2 (8) = 3.621, p= 0.89.

The attitude of staff that they can receive trainings received on data management whenever they need it had a significant relationship with the level of utilization of health related data for decision making, χ^2 (8) = 23.85, p= 0.002.It was also found that there was a significant relationship between the perception of staff of having the right tools and registers and the level of utilization of health related data for decision making at the facility, χ^2 (8) = 31.971, p= 0.000. The opinion of the respondents that they are involved in important decisions that affect their department was found to have a significant influence on the utilization of health related data in decision making the facilities, χ^2 (8) = 19.947, p= 0.011. The respondents' perception that they are given supportive feedback on the work that they do had a significant influence on the level of utilization of health related data for decision making by staff at the facility, χ^2 (8) = 35.966, p= 0.000. The perception that the respondents were able to generate monthly reports for their departments had a significant relationship with the level of utilization of health related data for decision making, χ^2 (8) = 22.591, p= 0.004.

The forth objective was to examine how leadership goodwill influences utilization of health related data. The study revealed that on average, the support from the leader on data utilization at the facility was good as indicated by 62.4% (148) of the respondents. The frequency of support was mainly on a monthly basis, 94 (50.8%) while others were on a weekly and quarterly basis with the support mainly being spearheaded by the facility HRIO, 98 (41.7%) and the facility in-charge, 77 (32.8%). The chi-square analysis revealed that the association between the support of the leader on data utilization and the level of data utilization was significant, χ^2 (6,237) = 47.997, $p<0.000$.

5.3 Conclusions

The study concluded that demographic characteristics of staff influence utilization of health related data especially in relation to the kind of IT knowledge; basic or advanced of the staff. Nonetheless, age, academic qualifications and the number of years a staff had worked did not have significant influence on the level of utilization of health related data at the health facilities.

The study also concludes that the level at which staff involvement in data related discussions did not have significant influence on utilization of health related data. It is also concluded that monetary, facility in charge, HCW and the zeal to learn more on data utilization do not significantly influence utilization of heath related data at the facilities.

The study concluded that staff attitude largely influence utilization of health related data, this was seen especially in relation to staff attitude on whether or not they can receive training on data management whenever they need it, staff perception of having the right tools and registers, the perception that they are involved in important decisions that affect their department and the perception that they were able to generate monthly reports for their departments.

The study concludes that leadership goodwill influences utilization of health related data; the leaders played in improving the level of data utilization was very important at the facility and especially in terms of offering support. The more frequent the leadership supports the higher the level of utilization of health related data in decision making.

5.4 Recommendations

The following recommendations have been drawn based on the findings of the study:

1. The health facilities should undertake to have the IT knowledge of all HCWs their strengthened through trainings as this will enhance data utilization for decision making.
2. There is need to have staff engage more in tailor made trainings and workshops on data collection, collation, processing and utilization however this should not be forced, zeal needs to be inspired in them to have them participate.
3. There is need to create a perception among staff that they have been given the necessary skills for collecting, collating, processing and utilizing the data in decision making in an enabling and supportive work environment.
4. The facilities need to strengthen leadership support to staff in relation to collecting, collating, processing and utilizing the data in decision making by enhancing the frequency, extent of such support and also leading by example.

5.5 Contribution to body of knowledge

The contribution to the body of knowledge is summarized as follows:

Objective	**Contribution to body of knowledge**
To investigate how demographic characteristics of staff influence utilization of health related data	Instead of concentrating on the overall professional qualifications of the health personnel, focus should be placed on strengthening the IT knowledge as this will directly influence the level of data utilization for decision making at the health facilities.
To establish the level at which staff involvement influence utilization of health related data	For better data utilization outcomes at the facility level, the leaders inspire the zeal to learn more on data utilization among staff than to giving them directives to engage in data utilization or entice them with monetary incentives.
To assess the extent at which staff attitude influence utilization of health related data	Positive attitudes of self-efficacy and supportive systems and work environment are key to enhancing effective data utilization at the health facilities.
To examine how leadership goodwill influence utilization of health related data	Leadership support is not sufficient to have the health personnel utilize data in decision making, of importance is the frequency, extent of such support and leadership by example in data utilization.

5.6 Suggestions for further research

There is need to investigate the moderating effect of data quality in the relationship between data utilization and the provision of quality health services. This was because the perception of the data quality was found to enhance the level of utilization of health related data, nonetheless whether utilization of such basis influences delivery of quality services remains unknown.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

INTRODUCTION

The purpose of this questionnaire is to solicit the perceptions, views, opinions and experience of Healthcare workers on Determinants of Utilization of Health Related Data for Service Improvement: A Case of Healthcare Facilities in Nyando Sub-County.

INSTRUCTIONS

i. Please answer all the questions honestly.

ii. You are humbly requested to tick (√) in the appropriate bracket or give brief opinion where necessary.

SECTION ONE:

1. Sex Male [ ] Female [ ]

2. What is your age?

[ ] Under 20 years old [ ] 20 - 25 years old
[ ] 26 - 30 years old [ ] 31 - 35 years old
[ ] 36 - 40 years old [ ] 41 - 45 years old
[ ] 46 - 50 years old [ ] Over 50 years old

3. What is your highest level of education?

Primary Level [ ] Secondary Level [ ]

College Level [ ] University Level [ ]

4. How many years have you worked for the Ministry?
[ ] 0 - 5 years [ ] 6 - 10 years
[ ] 11 - 15 years [ ] 16 - 20 years
[ ] Over 20 years

5. What kind of information technology knowledge have you acquired?

Basic [ ] Advanced [ ]

6. What level of facility do you work in?

Level 1 [ ] Level 2 [ ] Level 3 [ ] Level 4 [ ]

7. What is your professional qualification?

Medical Doctor	[ ]	Clinical Officer	[ ]
Nurse	[ ]	Public Health Officer	[ ]
Pharm Tech	[ ]	Lab Tech	[ ]
Nutritionist	[ ]	Physiotherapist	[ ]
HRIO	[ ]	Administrator	[ ]
Medical Engineer	[ ]	CHEW	[ ]

SECTION TWO:

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

Yes [ ] No [ ]

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

A. Seminars [ ]

B. Workshops [ ]

C. Continuous Medical Examination [ ]

D. Facility based data review forum [ ]

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

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

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

C. I have no interest [ ]

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

A. Monetary Influence [ ]

B. Influence from facility in charge [ ]

C. Influence from other healthcare workers [ ]

D. Zeal to learn more on data utilization [ ]

E. None of the above [ ]

SECTION THREE:

5-Strongly Agree (SA) 4-Agree (A) 3-Neutral (N) 2-Disagree (D) 1-Strongly Disagree (SD)

Please tick the following factors regarding satisfaction:

		SA	A	N	D	SD
1	Collecting data is not important in your health facility					
2	It is important to collect data in your facility					
3	I always like to be guided by data to make decisions					
4	Decision making in the facility doesn't necessarily need data					
5	The trainings I receive don't support me in data management.					
6	I received training on data management when I asked for it.					
7	I have the right tools and registers to do my job.					
8	I have outdated tools and registers to do my job					
9	I am involved in important decisions that affect my department					
10	Decisions in all departments are made by the top most authority					
11	I am adequately rewarded for my performance and responsibilities					
12	I have never been rewarded for my performance and responsibilities					
13	I am given supportive feedback on the work I do					
14	I do my work as a routine without feedback					
15	On my department, I have clearly defined quality goals.					
16	My department doesn't have standard operation procedures on data use					
17	I am able to generate monthly report for my department					
18	I need assistance to generate monthly report for my department					
19	I always conduct data quality audit in my department					
20	I have never conducted data quality audit in my department					

SECTION FOUR:

1. In your own opinion, how do you rate the support you get from your leader on data management and utilization?

Poor [ ] Fair [ ]

Good [ ] Excellent [ ]

2. Do you feel the support you get from your leader on data Utilization is adequate?

Yes [ ] No [ ]

a). If the answer in question 2 above is yes, How often does he give support on data utilization?

Weekly [ ] Monthly [ ] Quarterly [ ] Yearly [ ]

3. Who spearhead data utilization meetings or forums in your facility?

Facility In – charge [ ] Facility HRIO [ ]

CCC In - charge [ ] Data Clerk [ ]

Peer Educators [ ] Partners [ ]

4. How much resources have been put to support data utilization in your facility?

Manpower [ ]

Procurement of Tools [ ]

Trainings [ ]

Mentorship by NGOs [ ]

SECTION FIVE:

1. Kindly rate the level of data utilization for decision making in your facility?

   High [ ]

   Medium [ ]

   Low [ ]

2. In which sector within the facility did you utilize health related data for decision making?

   Purchasing equipment [ ]

   Planning [ ]

   Ordering drugs [ ]

   Motivation [ ]

APPENDIX II – SAMPLE SIZE FOR FINITE POPULATION TABLE

N		S	N		S	N		S	N		S
10	-	10	150	-	108	480	-	214	2400	-	331
15	-	14	160	-	113	500	-	217	2600	-	335
20	-	19	170	-	118	550	-	226	2800	-	338
25	-	24	180	-	123	600	-	234	3000	-	341
30	-	28	190	-	127	650	-	241	3500	-	346
35	-	32	210	-	136	700	-	248	4000	-	351
40	-	36	220	-	140	750	-	254	4500	-	354
45	-	40	230	-	144	800	-	260	5000	-	357
50	-	44	240	-	148	850	-	265	6000	-	361
55	-	48	250	-	152	900	-	269	7000	-	364
60	-	52	260	-	155	950	-	274	8000	-	367
65	-	56	270	-	159	1000	-	278	9000	-	368
70	-	59	280	-	162	1100	-	285	10,000	-	370
75	-	63	290	-	165	1200	-	291	20,000	-	377
80	-	66	300	-	169	1300	-	297	30,000	-	379
85	-	70	320	-	175	1400	-	302	40,000	-	380
90	-	73	340	-	181	1500	-	306	50,000	-	381
95	-	76	360	-	186	1600	-	310	75,000	-	382
100	-	80	380	-	191	1700	-	313	100,000	-	384
110	-	86	400	-	196	1800	-	317			
120	-	92	420	-	201	1900	-	320			
130	-	97	440	-	205	2000	-	322			
140	-	103	460	-	210	2200	-	327			

Table

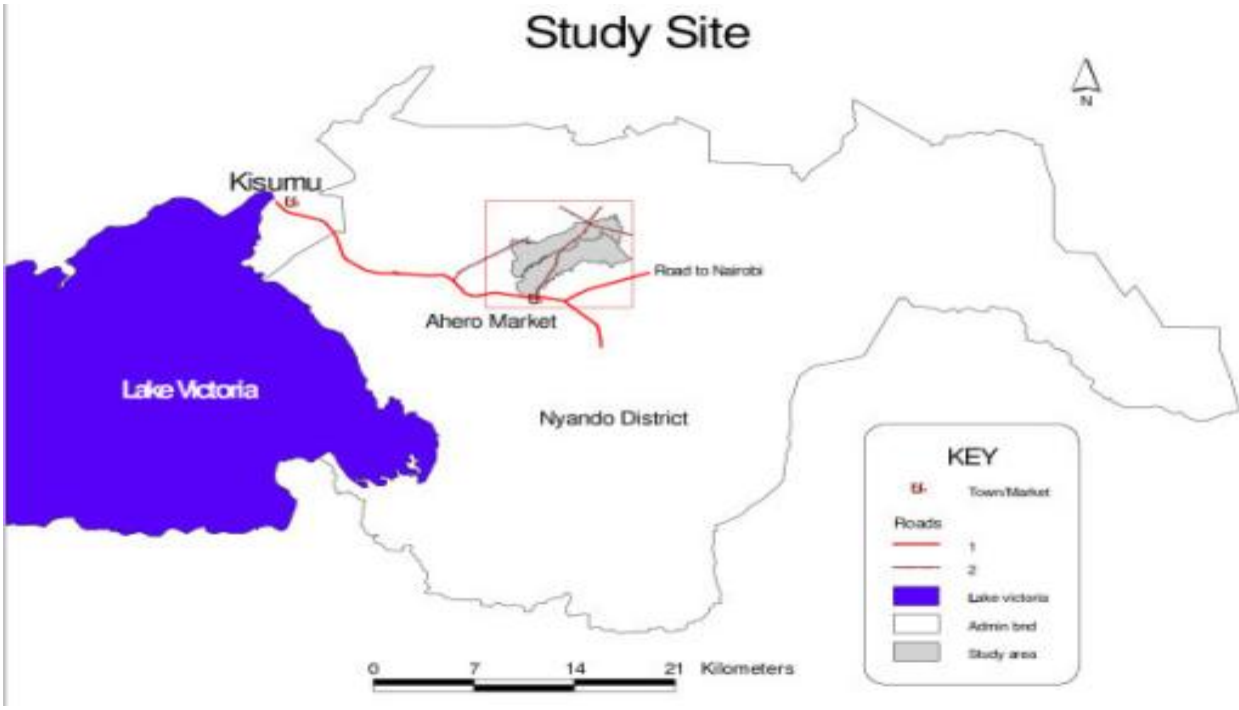
N= Population size

S=Sample size

Adapted: Kathuri and Palls (1993).

The table above is used to determine the sizes of randomly selected samples from a given finite population such that the sample population will be within +/- 0.05 of the population with a 95% level of confidence. If the number chosen fall between two numbers, the higher sample is always selected.

APPENDIX III: MAP OF THE STUDY AREA



APPENDIX IV: LETTER OF TRANSMITTAL

UNIVERSITY OF NAIROBI
COLLEGE OF EDUCATION AND EXTERNAL STUDIES
SCHOOL OF CONTINUING AND DISTANCE EDUCATION
KISUMU CAMPUS

Our Ref: UON/CEES/KSM/4/13

Your Ref:

Telephone: 057-2021534 Ext. 28626

University of Nairobi Plaza
Oginga Odinga Street,
P.O. Box 825,
KISUMU, Kenya.

25th September, 2014

TO WHOM IT MAY CONCERN

RE: TOM OTIENO OJUOK- REG NO: L50/82209/2012

This is to confirm to you that the above named **Tom Otieno Ojuok** is a student of the University of Nairobi, College of Education and External Studies, School of Continuing and Distance Education undertaking Masters in Project Planning and Management in Kisumu Campus and she has successfully completed her course work and examinations as required.

In partial fulfilment of the requirements for the Masters in Project Planning and Management, Tom is undertaking research for his Masters Project. We therefore request you to allow him access the data/information he may need for the purpose of his study. Any assistance, information or data collected is needed for academic purposes only and will therefore be treated in strict confidence.

We would appreciate any assistance that may be given to him to enable him carry out the study.

Thank you.

UNIVERSITY OF NAIROBI
26 SEP 2014
KISUMU CAMPUS

Dr. Raphael O. Nyonje, PhD
RESIDENT LECTURER
KISUMU CAMPUS

ISO 9001: 2008 CERTIFIED
The Fountain of Knowledge Providing Leadership in Academic Excellence

APPENDIX V:RESEARCH AUTHORIZATION

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY AND INNOVATION

Telephone: +254-20-2213471, 2241349, 310571, 2219420
Fax: +254-20-318245, 318249
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:

13th November, 2014

NACOSTI/P/14/8777/3967

Tom Otieno Ojuok
University of Nairobi
P.O. Box 30197-00100
NAIROBI.

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on ***"Determinants of utilization of Health Related Data for service improvement: A case of Healthcare Facilities in Nyando Sub County, Kenya,"*** I am pleased to inform you that you have been authorized to undertake research in **Kisumu County** for a period ending **5th December, 2014.**

You are advised to report to **the County Commissioner, the County Director of Education and the County Coordinator of Health, Kisumu 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: SECRETARY/CEO

Copy to:

The County Commissioner
Kisumu County.

The County Director of Education
Kisumu County.

National Commission for Science, Technology and Innovation is ISO 9001: 2008 Certified

APPENDIX VI: RESEARCH CLEARANCE PERMIT

CONDITIONS

1. You must report to the County Commissioner and the County Education Officer of the area before embarking on your research. Failure to do that may lead to the cancellation of your permit
2. Government Officers will not be interviewed without prior appointment.
3. No questionnaire will be used unless it has been approved.
4. Excavation, filming and collection of biological specimens are subject to further permission from the relevant Government Ministries.
5. You are required to submit at least two(2) hard copies and one(1) soft copy of your final report.
6. The Government of Kenya reserves the right to modify the conditions of this permit including its cancellation without notice

REPUBLIC OF KENYA

NACOSTI

National Commission for Science, Technology and Innovation

RESEARCH CLEARANCE PERMIT

Serial No. A 3629

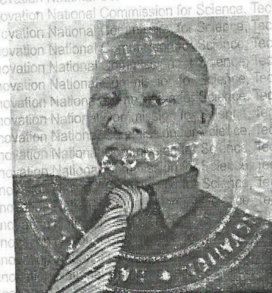
CONDITIONS: see back page

THIS IS TO CERTIFY THAT:
MR. TOM OTIENO OJUOK
of UNIVERSITY OF NAIROBI, 0-40107 MUHORONI,has been permitted to conduct research in ***Kisumu County***

on the topic: ***DETERMINANTS OF UTILIZATION OF HEALTH RELATED DATA FOR SERVICE IMPROVEMENT: A CASE OF HEALTHCARE FACILITIES IN NYANDO SUB-COUNTY, KENYA***

for the period ending:
5th December,2014

Permit No : NACOSTI/P/14/8777/3967
Date Of Issue : 13th November,2014
Fee Recieved :Ksh 1,000



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Applicant's Signature

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Secretary
National Commission for Science, Technology & Innovation