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SCHOOL OF COMPUTING AND INFORMATICS

A FRAMEWORK FOR INCREASING THE TECHNICAL CAPACITY OF HEALTH WORKERS TO USE HEALTH DATA FOR DECISION MAKING AT THE LEVEL III HEALTH FACILITIES IN NAIROBI COUNTY

BY

JOSHUA NGUMBA

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Supervisor

DR. ROBERT OBOKO

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ABSTRACT

Data is often not used effectively by the individuals at the health facilities to inform policy and programmatic decision making. The objective of this study is to identify barriers to data use, to design a framework for the technical capacity of health workers to use health data for decision making at the level III health facilities in the county of Nairobi and provide recommendations for practices that will address constraints to data use and data demand. An assessment was done at the level III health facilities in Nairobi among decision makers, health facility managers, and health facility staff and health record information officers. 177 questionnaires will be analyzed using SPSS software. Findings from this study will identify constraints to data use and inform health workers on how data can be used for improved decision making.

The objective of this research is to employ a logic model to describe a pathway of how specific activities and interventions can strengthen the use of health data in decision making in order ultimately to fortify the other building blocks of the health system. The research builds on previous work in the field by making specific recommendations about interventions that are most proximate to affect the use of data in decision making. The logic model with activities and examples of their implementation provide a practical strategy for developing, monitoring, and evaluating interventions to strengthen the use of data in decision making.

This study explores how to increase the technical capacity of health workers to use health data for decision making at the level iii health facilities in Nairobi County. An exploratory and descriptive, cross-sectional study method was undertaken. Both qualitative and quantitative approaches were used. The study collected primary data through the use of a questionnaire.

Health data is barely used by health workers for service delivery planning and decision-making. Quality health data are, in and of themselves, prerequisites to improving the building blocks of the health systems. The relationship of improved information, demand for data, and continued data use creates a cycle that leads to improved health programs and policies. The ‘use’ of data is the analysis, synthesis, interpretation, and review of data as part of a decision-making processes, regardless of the source of data.

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LIST OF ABBREVATIONS

DDIU	Data Demand and Information Use
M&E	Monitor and Evaluation
MOH	Ministry of Health
HMIS	Health Management Information System
MDGs	Millennium Development Goals
ICT	Information Communication Technology
RHIS	Routine Health Information Systems

CHAPTER ONE: INTRODUCTION

1.0 Introduction

Health data and information lack value unless they are used to inform decisions. As such, interventions that increase demand for information and promote/facilitate its use data demand and information use (DDIU) are critical to improving the effectiveness and sustainability of the health system(Ed Abel., et al, 2012).

A key element in improving health system performance is the data and information base and its effective use in making routine as well as strategic decisions. Improving performance to make it more effective requires that:

1. The quality of data collected is improved and that weaknesses in data quality are identified and understood.
2. The data are actually used for making decisions (Scott M, 2009).

As the Ministry of Health decentralizes their core business, the demand for sound information and skilled workforce to manage and use the information needs to be strengthened. To this end, the Ministries will mobilize resources to improve and strengthen database management and communication technology skills in the counties in order to provide information that meets the needs of policy makers, managers and service providers. This calls for development of infrastructure and human capacity to collect, process the data and use the information for evidence-based decision making at all levels. (Ministry of Health, 2010).

Use of information technology in the healthcare sector also creates its own set of issues. These issues concern the right to privacy of individuals and the protection of this right in relation to health information and the development of suitable standards for regulating the provision of healthcare services by the use of technology. Proper regulation of the creation and use of healthcare information is imperative and is a matter of special concern to the government as well as other stakeholders in the field of healthcare (Ministry of Health, 2010).

There are a number of factors that foster or impede the use of information in decision-making. Behavioral, organizational and environmental factors greatly influence the extent to which information is used (World Health Organization, 2008).

Information and communication technology (ICT) can play a major role in the achievement of the health sector's goal. ICT is increasingly applied to the global health sector because it can significantly enhance and improve all facets of health services delivery (Samuel A., et al, 2005).

According to Samuel Akor, Information, communication and technology can also make a significant contribution to the health sector, ICTs can

1. **Increase access to health services** by expanding the scope of activities of health professionals and specialists in a way that will minimize the effect of their low numbers in the sector; by supporting the establishment of a rapid response system to enhance performance in both clinical and public health care.

2. **Improve efficiency of heath delivery by** improving both management and technical efficiency of the sector through reliable information dissemination systems; and by supporting the decision making process through the prompt availability of information for all decision-makers.

3. **Foster partnerships in improving health** through dissemination of health information and data; by providing support to overall planning.

Using ICT in the health sector will help in the improvement of infrastructure in the health sector by networking all health institutions and by providing adequate ICT tools for service delivery and management, also improve access to and management of health information by deploying a health information dissemination network and a health information management systems network and finally improve ICT knowledge, capability and utilization among health workers by providing training in ICT skills to all prospective and current health workers; by maintaining a critical group of ICTs specialists in the health sector; and by deploying ICTs to support and enhance job functions of health workers (Samuel A., et al, 2005).

1.1 Problem statement

Recently, there has been increased attention to data use in the international public health community. At the most general level the issue is that there have been, and continue to be, major investments in data collection for public health programs but there is concern that such data are not being used for health system performance to their full potential (Ministry of Health, 2012).

Too often data sits in reports, on shelves, or in databases and are not sufficiently used in program development and improvement, policy development, strategic planning, or advocacy. The output of improving the health workforce, for example, is directly related to improvements in service quality and coverage, while the output of improved information systems is higher quality and timely data. The existence of quality data is insufficient to ensure use because data use has not been adequately integrated into decision-making processes and the information needs of decision makers are often not adequately represented in data collection efforts (Lomas J, 1997). Without specific policies and interventions aimed at improving the use of data produced by health systems, the health systems will never fully be able to meet the needs of the populations they serve. To date, clear guidance on how to comprehensively improve data-informed decision making is lacking.

Issues of access and intensity of use of health services have always been of significant concern in the health sector in Kenya. The increasing levels of investments in the health sector and the need to show more precisely corresponding achievements and benefits to vulnerable groups in particular have considerably intensified these concerns. Consequently, performance measurement has become a critical management endeavor in the health sector. Performance measurement has influenced and exerted pressure on both national and global demands for information. The demand for evidence towards the achievement of the Millennium development goals (MDGs), coupled with the increasing need for both multilateral and bilateral donors to demonstrate their contribution towards health development has also created increased demand for information (Ministry of Health, 2010).

Challenges with the development of the national health management information system (HMIS) has resulted in minimal informed decision making for effective data planning, monitoring and evaluation at the level III health facilities (Ministry of Health, 2010) . Thus there are DDIU challenges that are facing the health system which include: lack of capacity of managers to use data for decision making; lack of trained monitoring and evaluation (M&E) personnel to support data management and overview monthly reports; lack of training on data analysis, data interpretation and report writing; lack of regular supportive supervision visits to the health facilities to check on data quality leading to poor quality data; (Ministry of Health, 2012).

Improving DDIU is necessary to improve the effectiveness and sustainability of a health system. Health system performance is enhanced when data and information are used in making strategic and routine decisions. Improving data use requires that those who can use data understand how it can help them in making decisions. Data users must also have confidence in the quality and veracity of the data and the data must be in a format that can be interpreted.

It is useful to distinguish data users (or decision-makers), from data producers (usually staff or researchers) since improved DDIU requires interventions with both. It is also important to understand the context in which decisions are made and how this influences not only the demand for data and the use of information but also the collection and availability of data.

1.3 Objectives

The objectives of this study are:

1. To determine the barriers associated to data demand and information use at the level III county health facilities in Nairobi County.

2. To design a framework for increasing the technical capacity of health workers to use health data for decision making at the level III health facilities in Nairobi county.

3. To validate and test the developed framework.

1.2 Hypothesis

H1 Data analysis has a direct relationship with information availability on information use and is moderated by problem solving skills

H2 Data analysis has a direct relationship with information availability on information use and is moderated by staff attitude

H3 Usability has a direct relationship with information availability on information use and is moderated by problem solving skills

H4 Usability has a direct relationship with information availability on information use and is moderated by staff attitude

H5 Interoperability has a direct relationship with information availability on information use and is moderated by problem solving skills

H6 Interoperability has a direct relationship with information availability on information use and is moderated by staff attitude

H7 IT technology has a direct relationship with information availability on information use and is moderated by problem solving skills

H8 IT technology has a direct relationship with information availability on information use and is moderated by staff attitude

H9 Data collection has a direct relationship with information availability on information use and is moderated by problem solving skills

H10 Data collection has a direct relationship with information availability on information use and is moderated by staff attitude

1.3 Significance

If information is relevant, reliable and available for decision-makers, it can influence decisions but may not necessarily do so (Chaulagai CN, et al 2005). Health data is barely used by health workers for service delivery planning and decision-making. Behavioral determinants of data use include basis for decision making, incentives and disincentives for promotion of a culture of data use, staff attitude, and training and self-efficacy (Land FF, Kennedy-McGreggor M, 2002).

If senior managers fail to promote evidence-based decision-making and the use of information for transparency and accountability then a culture of information is unlikely to be fostered. It is therefore crucial to examine the perceptions, attitudes and values of senior managers and other organization members in relation to information-related functions (Odhiambo-Otieno O, 2005).

1.4 Justification

Improving DDIU is necessary to improve the effectiveness and sustainability of a health system. Improving data use requires that those who can use data understand how it can help them in making decisions. Data users must also have confidence in the quality and veracity of the data and the data must be in a format that can be interpreted (Ekirapa A., et al, 2008).

It is useful to distinguish data users (or decision-makers), from data producers since improved DDIU requires interventions with both. It is also important to understand the context in which decisions are made and how this influences not only the demand for data and the use of information but also the collection and availability of data.

Health data are collected by people who play professional and personal roles in the health system. The technical aspects of performance are often the most difficult to identify and confront in a meaningful way. They involve users with what data they want, are the goals and objectives addressed in data terms, are the data systems functioning well, and are there any data processing constraints. Technical constraints are related to the ability to generate high-quality data and analyses. Influencing many of these technical factors will require interventions that go beyond simple training that improves knowledge and skills in data collection and use (Galimoto MS, 2007).

1.5 Assumptions

1. Systems achieve better outcomes when they operate collaboratively.

2. Better outcomes will be derived if existing resources are used more effectively.

3. The careful collection and analysis of data and information regarding the implementation of the conceptual framework will produce clear and convincing evidence to guide further advancements in the decision making process.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

DDIU is a systematic approach that applies proven, effective best practices and appropriate tools to help increase demand for health system data and ensure that the information is used in an evidence-based decision-making process (Measure Evaluation, 2008).

Efforts to improve M&E systems have been increasing however data is often not used effectively by stakeholders to inform policy and programmatic decision making. In Kenya, M&E of health programmes is based on reports from the routine Health Management Information System (HMIS). Challenges with the development of the national HMIS has resulted in informed decision making that has been widely non-existent for effective planning and M&E. Efforts to improve monitoring and evaluation systems and other data sources have increased over the past few decades to improve tracking of MDGs and respond to performance-based release of funds from donors. However in spite of these improvements data is often not used effectively by stakeholders to inform policy and to inform programmatic decision making (Nutley T, 2012).

In Kenya, M&E of health programmes has been set as a key priority in the National Health Sector Strategic Plan (NHSSP) (Ministry of Health, 2006). The M&E support system which is primarily based on reports from the routine health management information system aims to assist health managers in making informed decisions and contributing to evidence-informed planning and management (Ministry of Health, 2006). The government and other stakeholders have embarked on initiatives to develop and improve a web based national health information system (DHIS) that captures data from all health systems thus reducing the need for multiple parallel systems that are capturing data at community, district and national levels. The strengthening of the health information system will ultimately lead to building the foundation of the health system and informing decision making in each of the following areas that have been outlined in the WHO framework: health workforce, health services, health financing, governance and leadership, medical products, vaccines, and technologies and health information. (Ekirapa A., Mgomella G., and Kyobutungi C, 2012).

It is useful to distinguish data users (or decision-makers), from data producers (usually M&E staff or researchers) since improved DDIU requires interventions with both. It is also important to understand the context in which decisions are made and how this influences not only the demand for data and the use of information but also the collection and availability of data. The PRISM analytical framework of health information system performance identifies three main determinants of the use of health information: the technical aspects of data processes and tools, the behavior of individuals who produce and/or use data, and the system/organizational context that supports data collection, availability and use (LaFond A., R Field., 2003). These can be used to identify opportunities for and constraints to effective (and strategic) data collection, analysis, availability, and particularly use. Strategies to improve performance in this area can then be built along the same three parameters.

DATA VS INFORMATION

Can be used interchangeably, but:

- Data often refers to raw data, unprocessed information.
- Information usually refers to processed data, or data presented in some sort of context

2.1 Determinants of DDIU

In addition to considering decision makers and how they make their decisions, it is important to understand the context in which decisions are made and how this influences not only the demand for data and the use of information but also the collection and availability of data.

The PRISM analytical framework of health information system performance identifies three main determinants of the use of health information: the technical aspects of data processes and tools, the behavior of individuals who produce and/or use data, and the system/organizational context that supports data collection, availability and use (LaFond A., R Field., 2003). This DDIU framework proposes that sustained and effective availability and use of good-quality health information is more likely to result from a strategy that focuses on all three fronts—technical, individual, and organizational—than a strategy focusing on one front alone. These three components of the PRISM analytical framework can be used to identify opportunities for and constraints to effective data collection, analysis, availability, and particularly use.

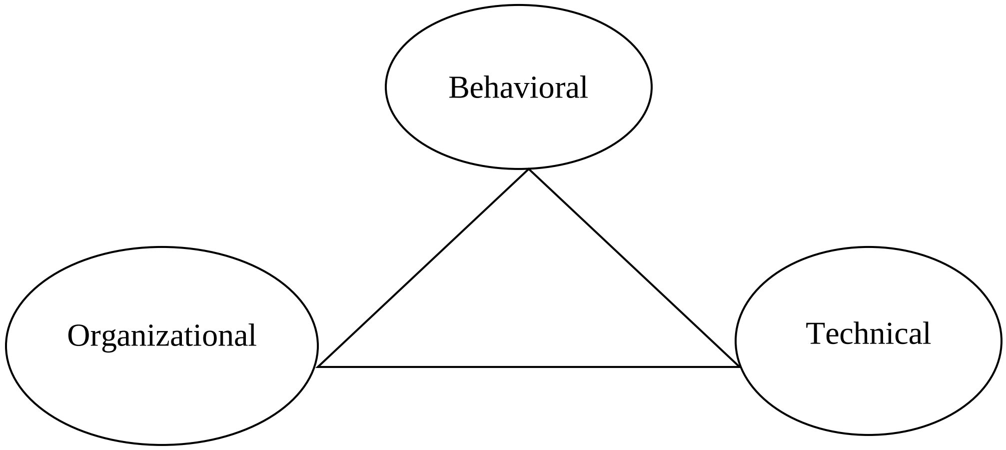

Figure. 1: Determinants of DDIU (LaFond A., R Field., 2003).

2.1.1 Technical determinants

A system without a sound technical design, well-trained people, and clear norms and standards cannot produce the information needed for making decisions. Consequently, the path to improving the use of health information focuses mainly on introducing or upgrading technical skills, changing the design of the data system, or revamping the technology used to improve the availability and quality of data (Foreit K., et al., 2006).

Technical rigor is clearly needed in information systems; these essential elements and skills are at the core of an effective and efficient health information system. Nevertheless, technical interventions alone cannot translate into use of data on the ground. There are many examples of information systems where the indicators are sound, data collection forms are well designed, and people are well trained, but where neither data tools nor information itself are used routinely to manage health services, design programs or make policy.

2.1.2 Behavioral determinants

Health data are collected and used by people who play professional and personal roles in the health system. Although building the capacity of these people is at the center of data and information use strengthening, behavioral aspects of capacity are often the most difficult to identify and confront in a meaningful way. Behavioral influences on data demand and use often involve intangible concepts such as motivation, attitudes, and the values that people hold related to health information, job performance, responsibilities, and hierarchy. Influencing many of these behavioral factors will require interventions that go beyond simple training that improves knowledge and skills in understanding data and using information.

Behavioral factors give crucial insight into the way in which health workers, managers and policymakers use information. For example, the primary role of health service providers revolves around their roles and responsibilities as health workers or managers of health services. They see their other duties, such as disease surveillance, stock keeping, and evidence-based planning and budgeting, as secondary to providing health care (Foreit K., et al., 2006).

2.1.3 Organizational determinants

These determinants relate to the organizational context that supports data collection, availability, and use, such as the identified procedures and the roles and responsibilities of those that collect, analyze, disseminate, and use data.

According to Foreit K., too often, data collectors and users are not motivated to use the information system, or the organizational context undermines evidence-based health action. For example, in health systems that use normative rather than strategic planning, decision makers follow traditional patterns of resource allocation based on set formulas. Even the availability of accurate and timely health data cannot guarantee that evidence becomes the basis of decision making. For data to be used consistently, the entire health system must place a high value on health information and be structured in a way that allows evidence-based decision making. Ensuring that information based on technically sound data is understood by potential users is another aspect of the technical determinants of information use. This requires the adaptation of data and information products to the organizational contexts in which they are intended to be used. Lay people, especially those not working in public health, are often unfamiliar with statistical concepts or demographic indicators.

If expectations with respect to data use are unclear to health professionals at all levels of the system, their motivation and commitment to making informed decisions can suffer. Technical, system, or individual behavioral determinants of the use of data and information in evidence-based public health policy and program design rarely act alone. They are interconnected. For example, on the technical-behavioral continuum, if policymakers feel that they have not effectively mastered the necessary skills to understand and use information effectively, then they are less likely to demand appropriate data and use information strategically. On the environmental/behavioral continuum, competency in collecting and using health information requires not just knowledge and skills but a supportive environment as well (Foreit K., et al., 2006).

2.2 Defining use and demand

Use

We take 'information use' to mean that both positive and negative findings affect the decision-making process (Marin M., et al., 2005). A definition of use must, therefore, include the two key elements of this process: those who make decisions and the decisions they make.

A decision is a choice between two or more courses of action. In practice, not all choices are made consciously: the decision maker may not be aware that he/she is making a choice or even of what the alternative courses of action might be possible. The simplest choice is to do or continue with *X* versus not to continue with *X;* for example, to continue with a particular HIV prevention program or to suspend it. For the purposes of DDIU, the definition of use includes awareness of decisions and choices. The decision maker must be explicitly aware of the decision he/she is about to make as well as at least two possible behaviors or courses of action to choose between. For example, if sales data from a program to provide insecticide-treated bed nets show that the program seems to be successfully increasing distribution of bed nets, the program manager may decide to maintain the program as it is rather than make any changes to it. Alternately, the manager may decide that based on information from similar programs elsewhere, the program could be even more successful if a new distribution mechanism were used. That would lead to a decision to try the new distribution strategy or to conduct operations research to test the new strategy compared to the existing strategy.

Two other aspects of use are also important:

1. Raw data are seldom useful for decision making and usually must be transformed into information that is usable and that relates to the issue being addressed.

2. Data collection/generation, its transformation into information, and its use in decision making may be done by the same person. However, they are more likely to be done by different people that have varying levels of understanding about each other's work (Yinger N., 2003).

Foreit K defined Information use as:

Decision makers and stakeholders explicitly consider information in one or more steps in the process of policymaking, program planning and management, or service provision, even if the final decision or actions are not based on that information.

Data Demand

In order for stakeholders and decision makers to place value on information, they should have some incentive or motivation to use it. Demand is a concept distinct from use and it reflects, at least in part, a measure of the value that the stakeholders and decision makers place on the information, independent of their use of that information. For the purposes of defining demand, stakeholders actively and openly request information.

Data demand requires both of the following criteria:

1. The stakeholders and decision makers specify what kind of information they want to inform a decision.

2. The stakeholders and decision makers proactively seek out that information.

In practice, it may be difficult to distinguish between data demand and information use, and one may choose to treat them as parts of a single process. Evidence of data demand could include managerial or policy directives to collect specific data, new or increased resource allocation for data collection and analysis (e.g., budget line items, establishing or strengthening statistical units inside ministries or programs, modifying job descriptions), and requests for special analyses (Foreit K., et al., 2006) .

2.3 Measure Evaluation

The MEASURE Evaluation project has a major focus on data demand and information use.

2.3.1 Background

Health data and information lack value unless they are used to inform decisions. Interventions that increase local demand for information and facilitate its use enhance evidence-based decision making. Activities that foster DDIU, therefore, are critical to improving health system effectiveness.

The MEASURE Evaluation DDIU conceptual framework is a cycle connecting data demand, data collection/analysis, information availability, and data and information use. This cycle is supported by collaboration, coordination, and capacity building. In this framework, there is a clear and consistent link between the use of health information and the commitment to improving the quality and availability of data. In this cyclic process, increased information use stimulates greater demand for data which, in turn, leads to more information use, leading to more demand, and so on.

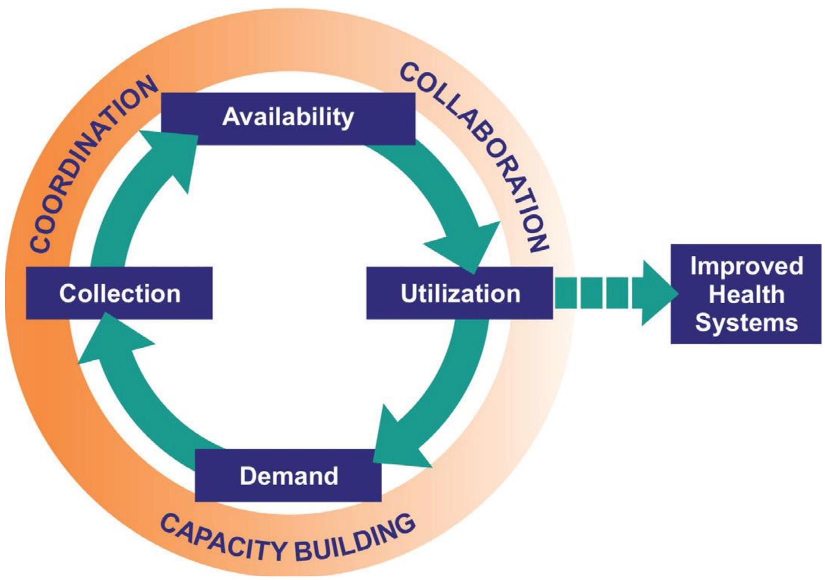

Figure 2 : Conceptual Framework for improving health systems (MEASURE Evaluation, 2008)

2.3.2 Measure Previous Studies

In a series of case studies, MEASURE Evaluation has documented instances in which their data demand and use strategies and tools have been used effectively to facilitate use of data and information for programmatic and policy decision making (MEASURE Evaluation, 2008). For example, in Ghana local partners conducted trainings on data use, communication and facilitation skills which supported the development of district-level action plans used to justify program interventions and funding requests. In Kenya, the national government made data and information from a study on contraceptive prevalence and fertility issues publicly available in a format that was understandable and useful to the user. This strategy drew attention from the public and politicians resulting in evidence-based advocacy for additional funding.

MEASURE Evaluation conducted a situational analysis in Uganda using the PRISM framework tools to assess how data were being used by health facilities and district health departments, what factors impeded information use, and to provide recommendations to strengthen the health information system. The findings revealed that information use was limited. The technical capacity to analyze, interpret and use data barely existed while organizational factors that affect data use were weak, such as a promoting a culture of information and quality supervision. The findings are consistent with the results of similar assessments in China, Mexico, Pakistan, and South Africa (Aqil A., 2008).

In another case, the government of Tanzania lacked a reliable sentinel vital registration that could be used to track malaria infections and also generate annual data to support fiscal decisions at the district level. Training workshops were conducted to increase the levels of confidence and skills among district health management teams to use vital registration data for district planning. In addition, a series of tailored data use workshops were conducted with district-level representatives on how to organize, analyze, and report their malaria mortality data in ways that helped them set priorities and inform operational decisions.

A study conducted among mid-level health managers in an unidentified developing country completed a survey assessing their competency with analyzing and using data from a health information system (Loevinsohn B., 1994). The results showed there to be a significant need to train managers in data analysis and use, and to integrate data utilization activities when information systems are installed.

2.4 Evidence-based decision making

Evidence-based decisions rely upon data and information from a variety of sources. Each source aspires to produce data that are transparent, consistent, verifiable, and understandable (AbouZahr, Boerma, 2005)

2.4.1 Background

Much has been written about using information for program decision making (Lippeveld T., et al., 2000); assessing routine health information systems and using the information they generate (Health Metrics Network, 2005); and using information to guide problem identification and policy formulation, implementation, and evaluation (Hardee K., et al., 2004).While there remain important challenges regarding the quality, timeliness and level of detail of available information, it is generally recognized that much of the data needed for decision making are already being collected on an on-going basis by national health information systems. While national health information systems vary from country to country, in their broadest sense, they include all sources of health information, encompassing vital events monitoring; service statistics and surveillance (maintained by health and other ministries); population and housing censuses; periodic surveys; national health accounts; and resource tracking (often under the auspices of other local institutions).Often these systems exist in countries with highly decentralized planning and service delivery structures; this introduces the need to address DDIU at many levels

2.4.2 Conceptual Framework for evidence-based decision making

Evidence-based decision making is enhanced by a sound demand for health information, the collection and analysis of health data, making information available to decision makers, and finally, from facilitating use of information to improve health system performance.

Figure 3 presents a framework for data demand and information use. The cycle connects demand for data to use of information through the intermediate steps of data collection and analysis and ensuring the availability of health information. This Data Demand and Use Framework (Foreit K., et al., 2006) is presented as a cycle rather than a linear process, such that increased information use in turn stimulates greater demand for data. Embedded within this cycle is the evidence-based decision-making process. The decision-making process involves decision makers and the decisions they make.

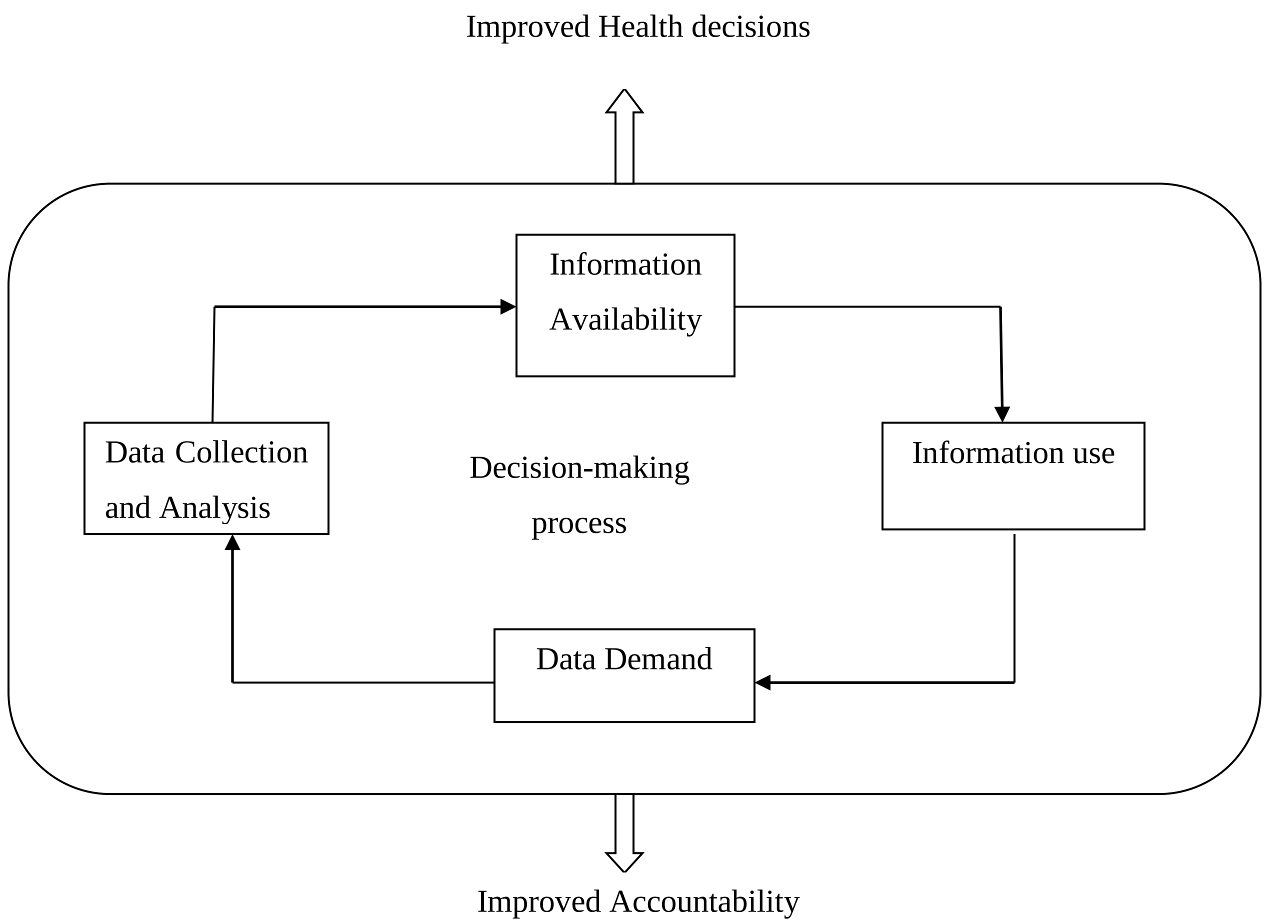

Figure 3: DDIU Framework (Foreit K., et al., 2006)

The diagram of the DDIU conceptual framework contends that evidence-based decision making is improved by:

- Generating a sound demand for health information
- Collecting and analyzing relevant health data
- Making information available to decision makers, and finally
- Using the information to improve health system performance

From above it can be noted that, the framework from MEASURE evaluation has demonstrated use of data demand and information use implementation but it lacks the evidence based decision making process as is evident from the studies that were carried out in. Thus it cannot help in the process of evidence based decision making process. Also a data use assessment conducted among a small sample of health professionals working in the Tanzanian health system found that staff in health organizations/agencies primarily lack technical and analytical skills creating a barrier to producing high-quality, reliable data and information (Harrison , Bakari, 2008).

2.5 PRISIM Conceptual framework

Performance of Routine Information System Management (PRISM), a conceptual framework developed by MEASURE Evaluation and John Snow, Inc., acknowledges the broader context in which health information systems operate. It emphasizes strengthening the health systems performance through better data quality and improved information use (Anwer A., 2007).

PRISM broadens the analysis of RHIS performance to include three key categories of determinants that affect performance: Behavioral determinants—the knowledge, skills, attitudes, values, and motivation of the people who collect and use data; Technical determinants—data collection forms, processes, systems, and methods; and Organizational determinants—information culture, structure, resources, and roles and responsibilities of key contributors at each level of the health system (Anwer A., 2007).

It is important to realize that the technical, environmental, and behavioral determinants of health information system performance rarely stand alone as the single cause of poor performance but they are often connected to one another by a continuum. For instance, "on the environmental–behavioral continuum, achieving competency in an action such as collecting and using health information requires not just knowledge and skills but a supportive environment as well"(Galimoto MS, 2007).

This framework therefore suggests that strategies for improving HIS should focus on all three groups rather than one. Information experts and public health professionals develop health information systems or tackle their problems with a technical mindset (LaFond A., R Field., 2003).

The three aspects of the analytical framework can be used to identify opportunities for and constraints to effective (and strategic) data collection, production, and use. Strategies to improve performance in this area can then be built along the same three parameters (LaFonde A, Siddiqi M,. 2003)

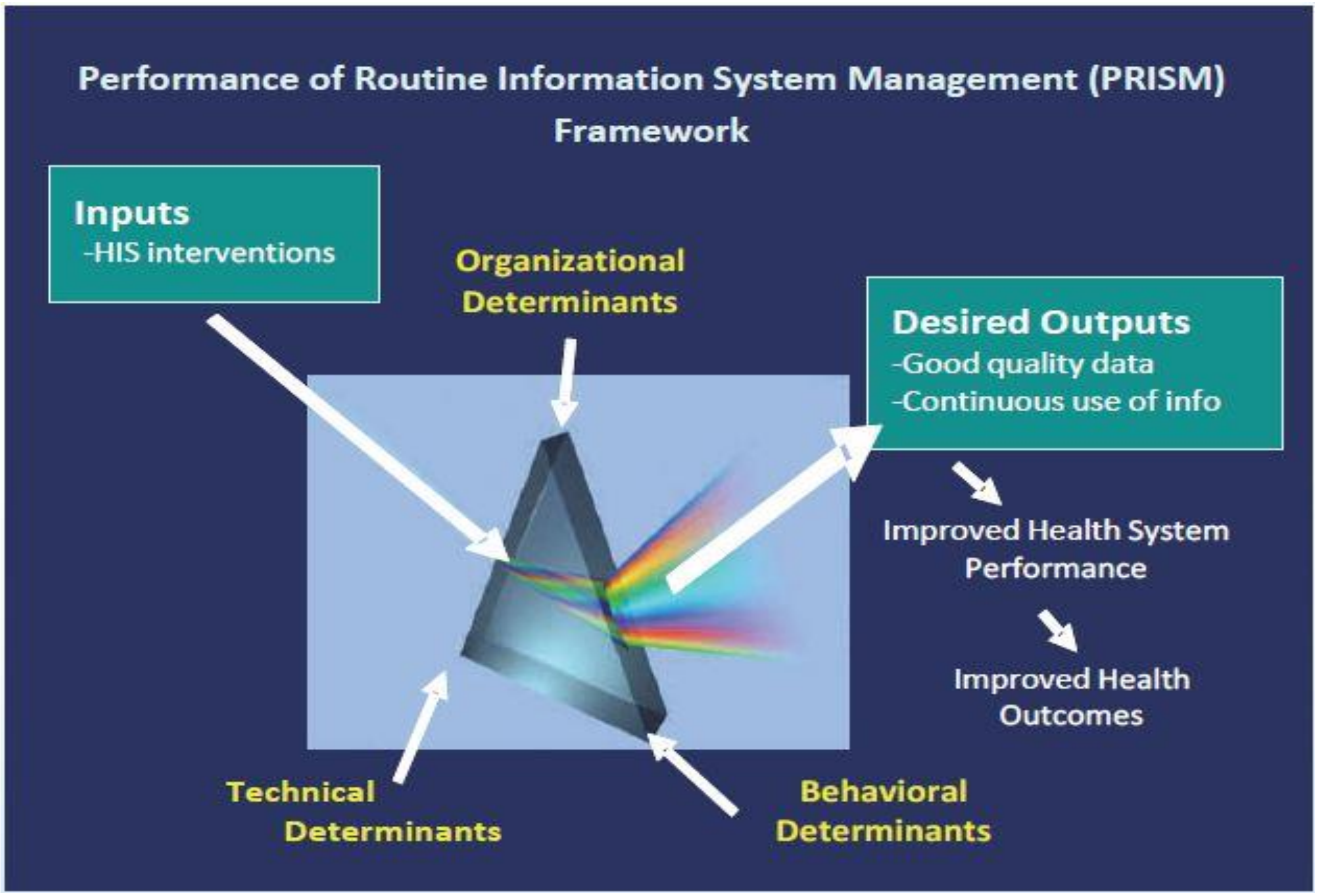

Figure 4: PRISM framework (Anwer A., 2007).

2.6 Underlying principles

Having defined data demand and data use, the following seven additional principles from the MEASURE evaluation as defined by Foreit K. will be used to underlie our approach:

1. Decisions are choices made in support of a goal. A decision as a choice that is made between two or more courses of action. But choices must be seen in the context of the goals of those

making or wishing to influence the decision. A goal is a desired outcome. For example, a goal can be to improve access to health services by an identified group or population.

2. All decisions are made on the basis of some information. Some information is always used by decision makers in reaching their decisions. The actual information that is used may and will differ between decision makers.

3. Stakeholders will want different types of information depending on the goal they are intending to achieve. This postulate underlines the fact that as goals differ so will the information that will be required to reach the supporting decisions for the goals.

4. There can be multiple and possibly contradictory goals. We also recognize that decision makers can have multiple goals, and that a decision taken to achieve one goal may have implications for another.

5. Decisions can be made by a single individual or by a group. It is also important to recognize that sometimes a decision rests with a single individual, but also that many decisions involve a range of stakeholders.

6. Individuals will have different goals or different interpretations of the same goal even if they are involved in the same decisions. Consequently they may use different information to achieve the goal. The different stakeholders involved in a decision may not have the same goals or objectives.

7. Stakeholders often differ in their views about the importance of what information is needed to make the decision. How and what information feeds into a decision depends on how the decision maker sees the decision linked to the goal.

2.7 DDIU in context of evidence-based decision

In this section, we place DDIU in the context of the development and implementation of a health intervention in which evidence-based decisions are made. Evidence-based decision making is a process by which public health decisions are informed by using data transparently, and that includes stakeholder consultation whenever possible (Foreit K., 2006). Table 2 outlines the general steps in evidence-based decision making. Each stage involves a set of discrete decisions that require data and information. It will be important to recognize these stages and the role of information in each.

Table 1DDIU in the context of evidence-based decisions and program stages (Foreit K., 2006).

Stage	**Decisions**	**Type of Data Needed**	**Stakeholders**
Problem Identification and recognition	Priority-setting Advocacy Target-setting	Situation analysis, routine/surveillance data, population-based survey	Public health officials, civil society, opinion leaders
Selection of the response	Selection of intervention Operational plan Program budgets	secondary analysis of existing data, special studies, operations and formative research, and research synthesis (if new data are needed	Public health policy officials, service providers, beneficiaries
Implementation and program monitoring	Maintain operational plan and continue funding budget Mid-course adjustments	Process monitoring and evaluation, quality assessments, outputs monitoring	Service providers and program managers, civil society
Evaluation	Scale up program Discontinue pilot and test alternative intervention	Outcome evaluation studies, surveys, routine sources and surveillance	Public health officials, civil society, opinion leaders

1. **Problem identification and recognition.** The first stage in evidence-based decision making is identifying what the issue or problem is. This may occur when data reveal some health issue that had previously not been apparent. How these issues and the information that is used to identify them come to light will differ from setting to setting and issue to issue.

2. **Selection of the response.** Once an issue has been identified, the next step is to undertake analysis of the extent and nature of the problem and to lay out alternate courses of action. This may involve looking at best practices or other sources of information on how issues have been resolved in other contexts. It may also involve identifying key target groups that may benefit from the decision. Selecting the response will also involve developing a detailed plan as to what the operational response will be.

3. **Implementation and program monitoring.** Once the response has been decided upon and implemented, policymakers and program implementers require information to monitor progress.

4. **Evaluation.** The fourth category of decision making concerns evaluating whether the original decision was the "correct" decision, whether the chosen intervention was appropriate, whether it was implemented as intended, and if the issue to be resolved has in fact been resolved. Measuring the impact of an intervention is methodologically complex and requires more information than monitoring program or policy implementation. Impact evaluation can involve a variety of study designs and so can involve different data requirements. Progressively more stringent data and resource requirements are needed as the demand for explanatory power of the evaluation increases (Habicht, V. et al. 1999).

2.8 Conceptual Framework

Sustainable production and use of good-quality health information is more likely to result from a strategy that focuses on three fronts — improving technical quality of data processes and tools, building individual capacity for understanding and using data, and strengthening the system or organizational context in support of data collection and use — than a strategy focusing on one front alone (LaFonde A, Siddiqi M,. 2003).

Health information is valuable not only to decision makers in health but to a wide range of stakeholders, such as policy-makers, public health professionals, NGOs, clients and others. When these stakeholders use this information to make evidence-based decisions, they help to improve overall health care by increasing the health system's ability to respond to health needs at all levels. Better use of population and health information also promotes transparency in the decision-making process and allows for accountability of health decision makers.

Evidence-based decision making is enhanced by creating a sound demand for population and health information; collecting and analyzing population and health data; making information available to decision makers; and, finally, facilitating the use of information to improve health system performance (Foreit et al., 2006)

To support evidence-based decision making, this research will aim at designing a conceptual framework for DDIU for decision making at the level III health care facilities at the county of Nairobi.

The conceptual framework explains the context in which decisions are made based on the information use and how this context influences the demand for data, the use of information, the use of information analysis, the dissemination of information and the collection and availability of data. The framework will put much emphasis on the technical determinants i.e. the technical aspects of data processes and tools used, but it will also consider the behavior and organizational determinants this will be important in the successful use of health information for decision making.

The DDIU cycle involves information collection and analysis, information dissemination which are methods used to communicate information, information use and data demand to support evidence-based decision making. DDIU is a concept grounded on information use by decision makers.

In the framework a clear and consistent link exists between the use of health information and the commitment to improving the quality of data upon which it is based. The more positive experiences a decision maker has in using information to support a decision, the stronger will be the commitment to improving the quality and timeliness of data collection systems.

The approach proposed here is also relevant to stakeholders at all levels of the health system- from program managers, practitioners and policymakers to members of civil society and community groups - to encourage more strategic and effective use of health data and information in decisions, whether routine or one-time, simple or complex, minor or critical.

The framework will provide a practical strategy for developing, monitoring and evaluating interventions to strengthen the use of data in decision making for the Level III health facilities at the county of Nairobi. One of the basic premises of our approach is that health data and information lack value unless they are used to inform decisions. Interventions that increase local demand for information and facilitate its use enhance evidence-based decision making. DDIU therefore, is critical to improving the effectiveness and sustainability of the health system. Unless the data are of value to the information recipient, however, they will not be used.

This research provides a framework for improving the use of information to guide policymaking, program design, management and service provision in the level III health facilities for the county of Nairobi to improve in the decision making process by observing the technical determinants. It is intended for health and information professionals who collect data and generate information to improve their understanding of the role information plays in the health decision making.

The research will try to see how the technical capacity of the decision makers is, by using health data from the health facility to make informed decision.

A conceptual framework was developed to provide a practical strategy for developing, monitoring and evaluating interventions to strengthen the use of data and information use in decision making. The model draws on the collective strengths and similarities of previous work and adds to those previous works by making specific recommendations about interventions and activities that are most proximate to affect the use of data in decision making. The model provides an organizing framework for how interventions and activities work to strengthen the systematic demand, synthesis, review, and use of data.

The objective of this research is to use a framework to describe how the technical capacity of health workers at level III health facilities in Nairobi County can increase decision making by use of health data. The framework describes the main components of an intervention and how they are intended to work together to reach measurable objectives. Use of a conceptual framework allows for critical assessment of program impact pathway theory and assumptions, appropriateness and completeness of activities.

The framework presented in this research maps out how the variables and activities are expected to influence the outputs i.e. information use and eventual the outcome of regular data use in in the decision making processes. It can help to specify the theoretical assumptions under which the intervention is intended to influence outcomes, it can help identify areas for decision making strengthening. The framework acts as a roadmap for how a set of seven interventions can affect the regular use of data in decision making and information use.

The variables that are included in the framework for increasing the technical capacity for health workers to use health data for decision making are: Data analysis, Usability, Interoperability, IT Technology, Data collection, Information availability, Information use, Problem solving skills and Staff attitude.

The framework draws on the collective strengths and similarities of the PRISIM framework and the evidence-based decision framework by Foreit, it adds to those previous works by making specific recommendations about interventions and activities that are most proximate to affect the use of data in decision making in the context of this research. The model provides a consolidating framework for how interventions and activities work to strengthen the systematic demand, synthesis, review, and use of data.

The activities to improve the use of data are informed by previous work; building primarily on two major works in the field:

1. Aqil, 2008 developed the Performance of Routine Information System Management (PRISM) framework to improve routine health information systems and data use. The

framework is innovative in that it puts emphasis on RHIS performance and the three interrelated determinants of that performance: technical, behavioral, and organizational determinants. The technical refers to systems such as data collection processes, systems, and methods. The behavioral refers to the behaviors of data users and how data are used for problem solving and program improvement. The organizational refers to the structure and processes of the organizations that use the resulting information. PRISM emphasizes that specific technical, behavioral, and organizational activities need to be implemented to improve demand for, analysis, review, and use of routine health data in decision making.

2. The evidence-based decision making framework is enhanced by a sound demand for health information, the collection and analysis of health data, making information available to decision makers, and finally, from facilitating use of information to improve health system performance. The frameworks is a cycle that connects demand for data to use of information through the intermediate steps of data collection and analysis and ensuring the availability of health information.

Each author addresses data use from their own ‘data perspective’. PRISM addresses data use from routine health information systems which include any data collection conducted regularly with an interval of less than 1 year in health facilities and their extension in the community (Aqil, 2008).

While all of these authors have substantially contributed to the field of improving data use in decision making, it is challenging for the end practitioner to pull out the ‘how to’ when each author approaches the topic from different data perspectives and different levels of detail. This research builds on these previous works by drawing on their collective strengths and similarities and proposes specific interventions that are most proximate to affect the use of data in decision making.

The conceptual framework figure 6, provides a framework for implementing, monitoring and evaluating to achieve the regular demand, analysis, synthesis, review, and use of data in the decision-making processes. The framework will look at how to increase the technical capacity of the health workers to use health data for making decision.

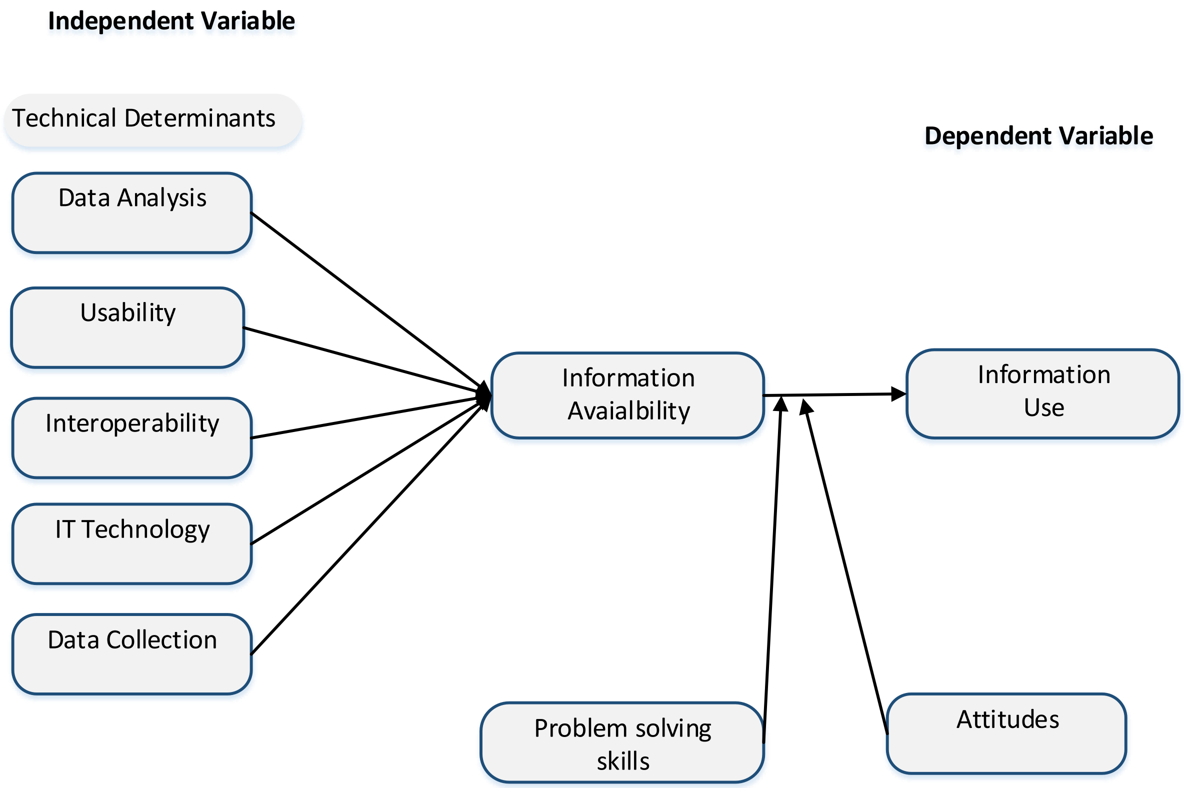

Figure 5 Conceptual framework for DDIU evidence based decision making.

Data analysis

It is the process of inspecting, cleaning, transforming, and modeling data with the goal of discovering useful information, suggesting conclusions, and supporting decision making.

Usability

It's a measure of the degree of staff to use the health data they have to make evidence based decisions. It is an indication of how often the decision makers use the information to make decisions.

Interoperability

How health systems provide dynamic interactive information and data exchange to the health users. Indicates the user experience in using health data in making decisions

IT Technology

This involves the application of computers and telecommunications equipment to store, retrieve, transmit and manipulate health data at the health level III health facilities.

Data collection

It is the process of gathering and measuring information on variables of interest, in our case being the health data at the level III health facilities.

Information availability

How available the information is to the persons involved in the decision making process. Ability to obtain and apply new information to respond to changes and to promote innovation.

Information use

The technical capacity to analyze, interpret and use data to make informed decision by use of the health data at the level III health facilities.

Problem solving skills

This are the necessary skills needed to solve a problem of make an informed decision using the health data that is provided at the health facilities.

Attitude

It is basically the attitudes and values of the users of the information system. How an individual feels about the utility or outcomes of a task or his confidence in performing that task as well as the complexity of the task, this will in turn affect the likelihood of that task being performed.

2.9 Operationalization of Variables

This section explains how the variables have been defined into measurable factors, thus allowing them to be measured, empirically and quantitatively

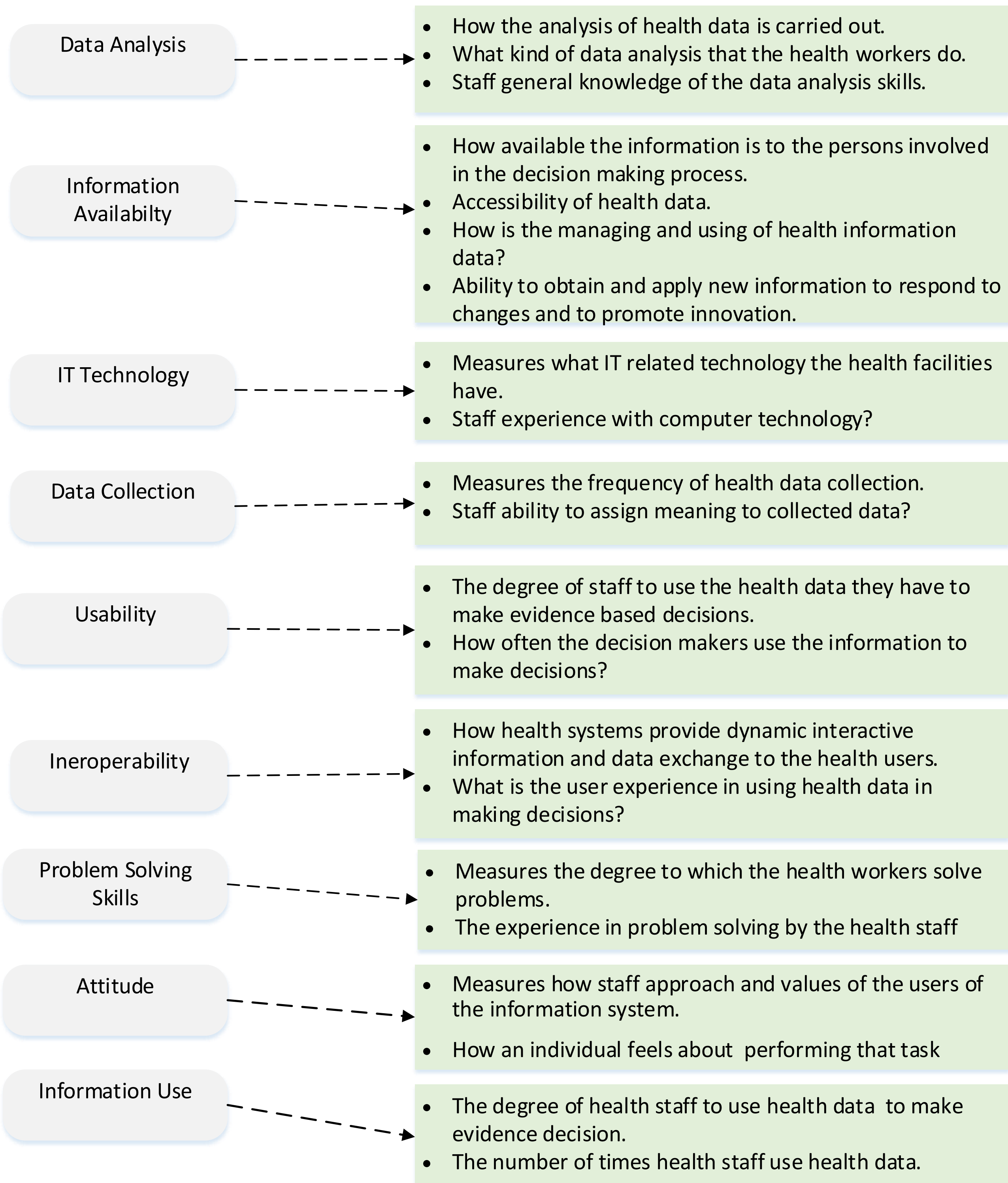

Figure 6: Operationalization of Variables

2.10 Use of Health Information in Decision Making

Several models have been used to describe decision-making. The knowledge-driven model of decision-making by Van Lohuizen and the classical model of decision-making by Lasswell represent decision making as a process consisting of linear distinct steps. However, in the real world decisions are not made in a linear logical fashion but rather in an iterative way because the phases overlap.

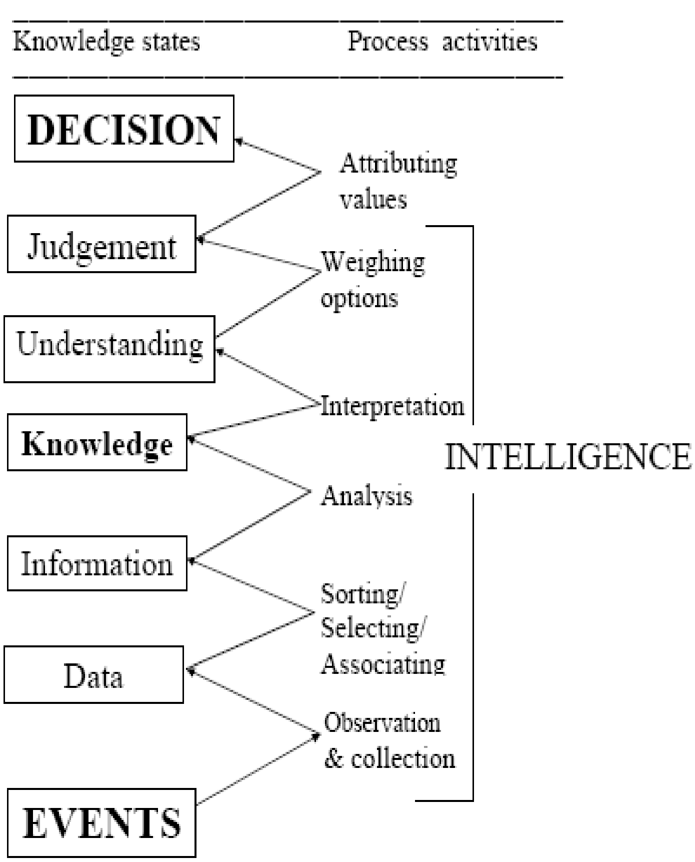

Figure 7 Knowledge-Driven Model for Decision Making: (Galimoto MS, 2007. Adapted from Van Lohuizen)

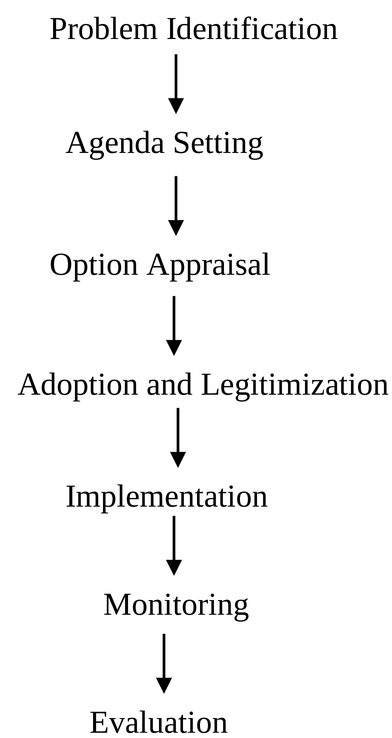

Figure 8 Lasswell's Classic Model for Decision Making (Galimoto MS, 2007).

The most frequent problem that hinders use of information for decision making is the lack of feedback to local districts and health care workers (Land FF, Kennedy-McGreggor M, 2002) It is only when those providing the data begin to receive meaningful and useful feedback that they will begin to appreciate the value of data and will therefore take appropriate steps to improve the use of the data they provide (Naeme R, Boelen C, 1993).

Studies done in Ghana, Nepal, and South Africa indicated that although most districts have reasonably accurate data and a good proportion are actively analyzing data and making routine reports for feedback to management and facilities, this was not yet achieving the culture of information use (Naeme R, Boelen C, 1993). 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 R, Boelen C, 1993). At the level of individuals and communities, information is needed for effective clinical management and for assessing the extent to which services are meeting the needs and demands of communities. 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 (Campbell B, 2003) 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.

2.11 Basis for Decision-Making

Even the availability of accurate and timely health data cannot guarantee that evidence becomes the basis of decision-making (Odhiambo-Otieno O., 2005). Decision-making in health is all too often based on political opportunism, expediency or donor demand. There is a growing awareness that this leads to inefficient and ineffective use of resources (Gething PW et al, 2007).

Information is just one of the many inputs of the decision making process and thus it is not surprising that decisions are made even in the absence of reliable information because in practice, decision-making in health is mostly based on political opportunism, expediency or donor demand (Campbell B, 2003).The pattern and norms which form part of the memory of how things should be done and which are often used is a completely subjective and informal way to evaluate and judge. Such information is rarely made explicit but exits in the mind of the decision makers. Some of these norms are associated with values

(Naeme R, Boelen C, 1993). Much of the information that is gathered and communicated by individuals and organizations has little decision relevance.

Much of the information that is used to justify a decision is collected and interpreted after the decision has been made, or substantially made. Much of the information gathered in response to requests for information is not considered in making the decisions for which it was requested. Regardless of the information available at the time a decision is first considered, more information is requested (Odhiambo-Otieno O., 2005). Decisions are made based not primarily on information, but rather on opportunism, expediency, donor demand, political and other pragmatic factors.

2.12 Incentives and Disincentives for Promoting Information Use

Feedback is one mechanism to promote and ensure that actions are taken based on the information and so provision of feedback is considered evidence of use of information (Land FF, Kennedy-McGreggor M, 2002) .This feedback can be in written form ranging from simple tables of the data that was reported to reports containing graphs showing and comparing indicator performance by facility, district or even country. It can also be verbal feedback given during meetings or supervision.

Zheng defines information culture as “the general capability, views, norms and rules of behavior with regard to accessing, understanding and using information in a social collectivity” (Zheng Y, 2005). Campbell explains that a “culture of information use” begins to evolve when the elements of an integrated health information system become normative practice, where the elements include data collection, self-assessment and peer review, and health information system informed decision making, feedback and reporting (Campbell B, 2003).

2.13 Steps in Facilitating DDIU

In line with the use of the proposed framework, these steps which are adopted from Foreit (2006) are going to be used in order to for the approach to be successful. Thus the outlined steps are going to be carried out to achieve the objectives of the study.

There are four distinct steps in facilitating data demand and information use for evidence based decision making. These are shown in the figure below. Step 1 is to perform a DDIU assessment using a tool described in the next section. Step 2 is to use the information from Step 1 to identify and define strategic opportunities in terms of the entry point of DDIU activity, beneficiaries and stakeholders, and anticipated results. The third step is to select the DDIU tools and approaches to be applied and, finally, the fourth step is to use those tools and approaches and to document the impact of the DDIU activities in terms of the anticipated results from Step 2

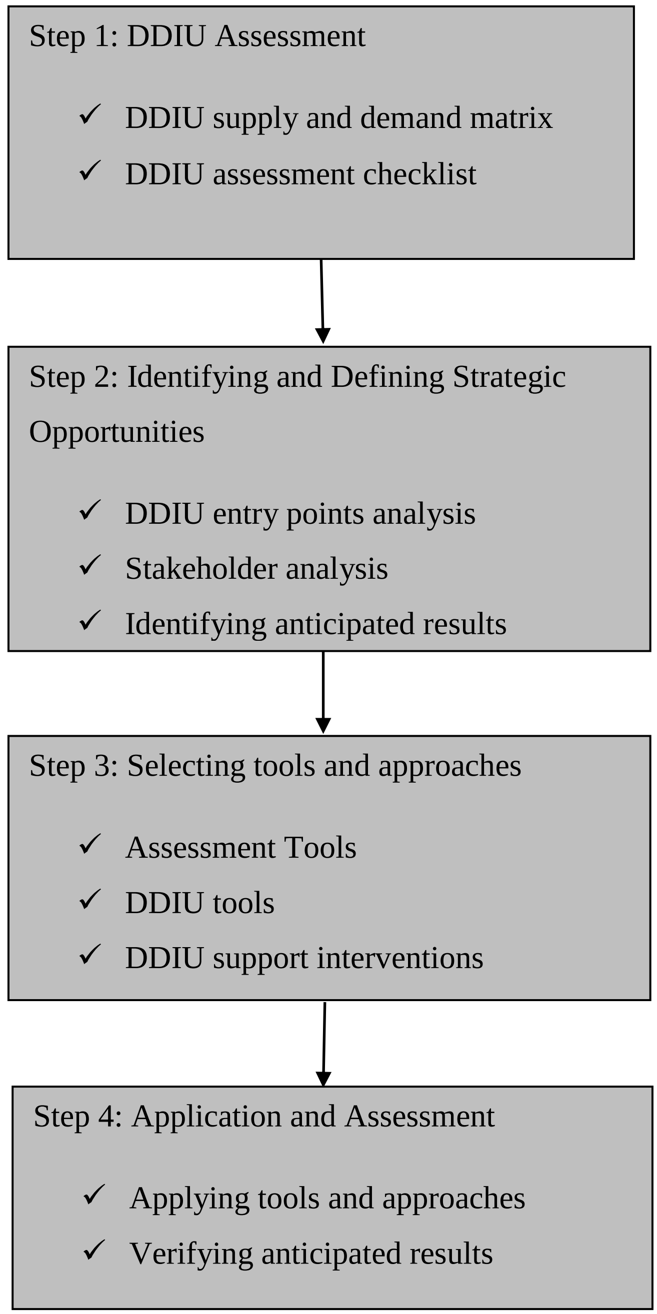

Figure 9: Steps in the DDIU process (Foreit K, et al., 2006. Data demand and information use in the health sector, MEASURE evaluation 2006).

Step 1: Assessment – Diagnosing what areas need attention

In order to begin developing a DDIU strategy and identifying supporting interventions, it is useful to assess the current situation.

Step 2: Defining strategic opportunities for DDIU

Since DDIU involves facilitating evidence-based decision making, it must also be determined what decisions, what data and what stakeholders are involved. What the DDIU approach will be in a particular context will largely depend on the initial situation and a broadly defined scope. Is the activity focused on routine health information systems or on enhancing use of a specific type of monitoring and evaluation data set or research finding?

Step 3: Developing a strategy

Once the DDIU Assessment has been carried out and the point of entry, the domain, and the anticipated results have been identified, a DDIU intervention strategy can be developed. Since the strategy involves information from steps 1 and 2, the most important remaining task is selection of the DDIU tools and approaches that will be used. Hence, the strategy will consist of deciding the entry point and domain, the beneficiaries and stakeholders, the DDIU tools and approaches to take, and the expected results. It should be emphasized that in most cases the DDIU strategy will be an ongoing process that involves several interventions.

Step 4: Use of tools/approaches and assessment of results

It involves use of the tools and approaches outlined in the strategy. Once the DDIU activity is underway, it is important, as with any intervention, to track the impact of the DDIU approach. The most important part of this assessment will be to determine if the expected results were achieved. Since the results of DDIU will normally be the creation of some report, policy, or plan of action, assessment will consist of determining if such products were achieved and if they are attributable to the DDIU activity.

Checklist

The table below presents a checklist for DDIU rapid appraisal of where a particular situation may fall. More importantly, the checklist will help with targeting which DDIU determinants area may require the most attention. The responses to these questions will also help with deciding which DDIU tool to use. Hence, if the technical demand quadrant is judged to be weak, then capacity development and technical assistance in use of data and information would be important. If the organizational supply side is weak, then efforts should be directed to addressing the weak points in that area. (Foreit K, et al.,2006).

Possible constraints	**Data Demand and Use**	**Data Collection and Availability**
Technical	Do users understand data analysis?	Are data collection systems functioning well?
	Do users know what data they want?	Is there human resource capacity to analyze data?
	Are goals and objectives articulated in data terms?	Are there any data processing constraints?
Organizational	Are organizational goals linked to quantifiable results?	Are there communications constraints to acquiring data in a timely fashion?
	Are there overarching political considerations that impede the use of information by public health decision makers?	Are there adequate communications channels for data dissemination?
	Are all stakeholders allowed access to data?	Are data quality norms established and enforced?
	Are there clear roles and responsibilities defined for information use?	Are data flow channels clear and followed?
	Do budgets include funding for M&E activities?	Are there organizational conflicts that impede data collection or sharing?
Behavioral	Do stakeholders value data and information when making decisions?	Do public health staffs have adequate time available to collect and/or analyze data and

		information?
	Are public health staffs motivated to use data and information? Are there disincentives for such use?	Are public health staffs adequately trained in data collection and analysis?
	Do stakeholders appreciate the value of information in identifying problems?	Will information sharing lead to lack of promotion or job loss?

Table 2: Checklist of DDIU Assessment (Foreit K, et al.,2006).

CHAPTER THREE: RESEARCH METHODOLOGY

3.0 Introduction

This section constitutes the road map for the collection, measurement and analysis of data. It includes research design, target population, sample design, data collection methods/instruments and data analysis.

With increased attention on strengthening health information systems, the result has been higher quality and more timely data. However, rarely is this valuable data used to make needed changes in health services. The challenge is to make the review of data integral to health program decision-making. This organizational culture change requires leadership and team building skills (Futures group, 2013).

According to the futures group, building leadership for data demand and use within health organizations requires strategic analysis of the data use opportunities, practical skills in both leadership and management, and the ability to inspire others on the value of health information in creating effective health systems.

Why improve data-informed decision-making? The pressing need to develop health policies, strategies, and interventions

Data use – Using data in the decision making process;

- Monitor a program
- Create or revise a program or strategic plan
- Develop or revise a policy
- Advocate for a policy or program
- Allocate resources

Data Demand- decision makers specify what kind of information they want and seek it out.

3.1 Research Design

A descriptive, cross-sectional study method will be undertaken to determine factors affecting information use in decision making using the technical determinants. The survey research method is going to be adopted in this research design this will enable the researcher to capture a representative image of the attitude and opinions of a large population. This method is conducted by collecting information by asking questions to the target population. The questions will be asked by use of questionnaires. This will help in providing for the answers to such questions as who makes decisions and what are the kinds of decisions made, what are the perceived data use constraints, what are the major data processing challenges, do health staff have adequate data analysis skills etc.

3.2 Population

This study was carried out in level III health facilities in the county of Nairobi. According to the Kenya open data website, the county of Nairobi has 54 level III health facilities. The selection of which facility the respondent that is going to be interviewed will be selected randomly.

The research is aiming to conduct interviews via questionnaires to assess the technical determinants at the county of Nairobi and at level III of the health sector. The respondents from the county will be drawn from an array of health facilities. The selection of respondents will assume a mix of senior-level policy decision makers and middle and junior-level health staff at all levels. It will entail collecting of data from the following health staff; health facility managers, district medical health officers, district public health officers, district public health nurses and health record information officer.

3.3 Sample Design

Stratified sampling technique was used to split the population to strata. In addition, the study will adopt simple random sampling to pick specific representation from each category of the population. The population was divided into 5 strata. The sample size was determined by the following formula recommended by Nassiuma (2000) for determining sample size.

$n = NC^2/ C^2 + (N-1)E^2$

Where n = Sample size, N = Population Size C = Coefficient of variation E = margin of Error. Nassiuma (2000) recommends a margin error ranging between 2%-5% and coefficient of variation ranging between 20%-30%. The table 3 below shows a summary of the sample size.

Target Group	**Population**	**Margin of error %**	**Coefficient of variation %**	**Sample size**
Health facilities managers	50	0.02	20	34
District medical health officers	100	0.02	20	50
District public health officers	80	0.02	20	45
District public health nurses	120	0.02	20	55
Health record information officer	70	0.02	20	41
Total	420			225

Table 3: Summary of Sample Selected for the study.

3.4 Data Collection

Data to be collected included decisions that were made about policy, technical constraints to generating quality data, individual capacity to collect, analyze and report data, organizational constraints to promoting data use, barriers to information use and the quality of data. Data collection is going to take place in Nairobi County .The methods that will be used to collect the data are; Questionnaires, Interviews and focus group interviews. The questionnaire will consist of open-ended and close-ended questions aimed at achieving the objective of the research.

3.5 Data analysis and Presentation

This research used descriptive statistics to carry out analysis of the data. With the help of statistical Package for Social Sciences software (SPSS) package and Microsoft Excel. Statistical measure will be used to summarize descriptive survey data, the measure of central tendency, means, frequencies etc. Findings from this study will identify constraints to data use and information use to inform the level III health programmes on how data can be improved for evidence-based decision making process.

3.6 Project Timeline

Proposed timeline for the research project

Task	**Week 1**	**Week 2**	**Week 3**	**Week 4**	**Week 5**	**Week 6**	**Week 7**	**Week 8**	**Week 9**	**Week 10**	**Week 11**	**Week 12**
Literature review												
Research methodology												
Conceptual Framework												
Data Collection												
Data analysis												
Data presentation												

CHAPTER FOUR: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

This chapter presents descriptive statistics and principal component results, hypothesis testing and the discussion of the results obtained. The purpose of going to collect data was to test the reliability and validity of the conceptual framework. In this chapter the research findings were collected by using questionnaires. The findings are mainly presented using parametric statistical method.

Before going to the field and collecting the data a sample data was collected so as to measure the reliability of the questionnaire. Cronbach's alpha was used to measure the internal consistency of the questionnaire. A reliability of 0.7 or higher is required for the pilot study before the use of the instrument. I used a sample size of 20 and the Cronbach alpha was 0.85.

4.1 Data preparation

The first step was to examine all the questionnaire's and clean the data, preparing it for analysis. A combination of qualitative and quantitative analysis was adopted depending upon the type of questions asked as illustrated in the table below.

Data type	Processing	Analysis	Software
Closed Multiple Type questions	Numerical coding	Quantitative	SPSS Spreadsheet
Open-Ended questions	Literature study to form themes	Qualitative	SPSS Spreadsheet Text Analysis

The questionnaire had a set of multiple choices to select from. These options were thus coded numerically and analyzed using SPSS and spreadsheet software. Open-ended were used to give the opinions of the respondent.

While data processing involved cleaning, editing and coding of raw data, classification and tabulation of this data comprised the next stage of data analysis in order to get patterns or relationship among data groups.

4.2 Interpretation of Results

The purpose of this interpretation phase is to transform the data collected into credible evidence about the development of the intervention and its performance. In conducting the research I managed to interview a total of 177 respondents this represents 79% of the target population.

4.2.1 Analysis of respondent by gender

The bar graph below shows the distribution of the respondents by gender it shows that 32% of the respondents were male and 67.8% were female.

In conducting the research a total of 177 respondents were interviewed.

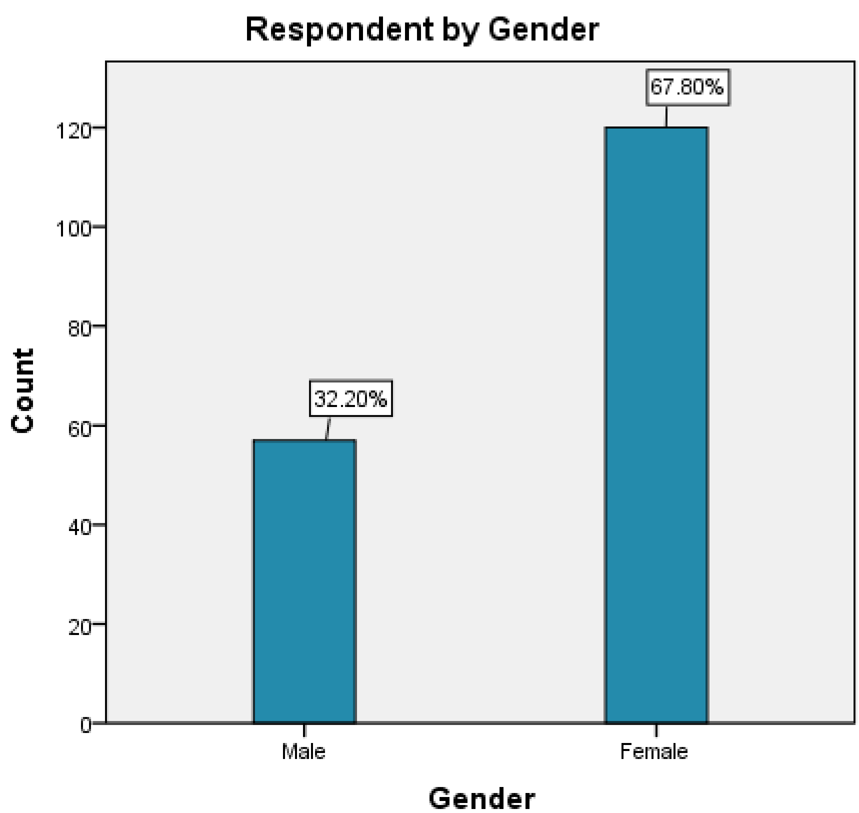

Figure 10 Respondent by gender

4.2.2 Respondent by age group

The chart below shows the distribution of the age groups of the respondents who were interviewed.

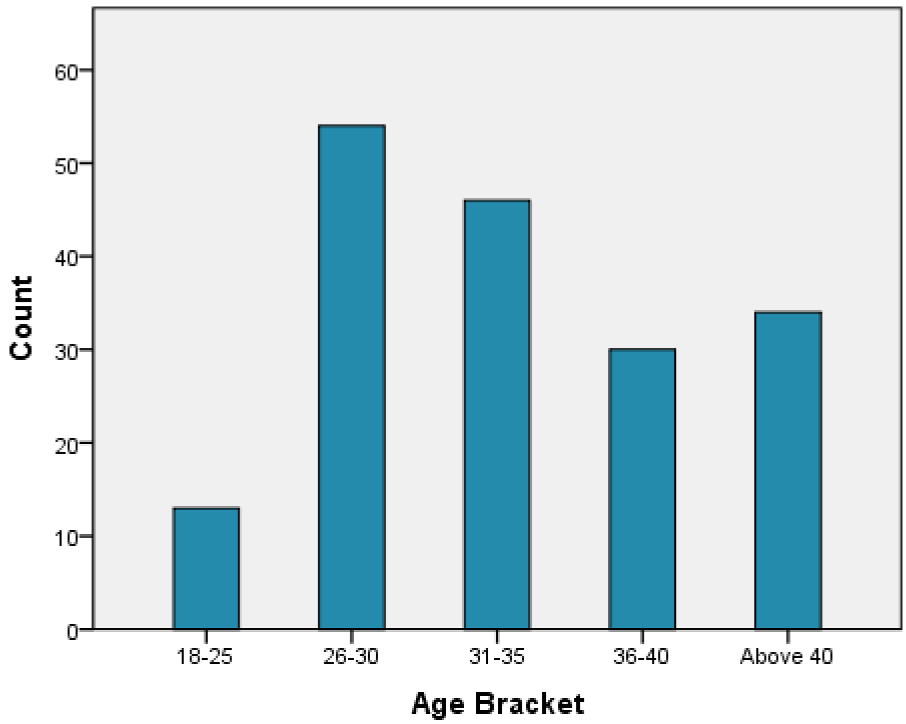

Figure 11 Respondents by age group

4.2.3 Respondents Background Characteristics

The portion of respondents by the years they have worked on their current position is shown in the table below. A majority of the respondents who have worked in their position for 6 to 10 years represent 49.2 % of the total respondents and those who have worked in their current positions for 30 years and above represent 3.4 %.

Years in current position	N	Percent
0-5	50	28.2
6-10	87	49.2
11-20	21	11.9

21-30	13	7.3
30+	6	3.4
Total	177	100

Table 4: Respondents' year in current position

Based on the results of the table below it can be inferred that 73% of the respondents do supervise staff at the health facility where they work.

Supervise Staff At Health Facility

		Supervise Staff				Total	
		Yes		No			
		Count	% within Supervise Staff	Count	% within Supervise Staff	Count	% within Supervise Staff
Gender	Male	41	31.8%	16	33.3%	57	32.2%
	Female	88	68.2%	32	66.7%	120	67.8%
Total		129	100.0%	48	100.0%	177	100.0%

Table 5 Supervise Staff at health facility

4.2.4 Information use for decision making

The DDIU framework emphasizes that data is a key element in decision making, however, we first need to look at who makes decisions and the types of decisions they make. We asked respondents if they were involved in any or influenced any kinds of decisions in the health sector. As seen in the table below, a majority of the respondents do make decisions across all the categories.

Decisions pertaining to the monitoring of key objectives were made by a large percentage of all respondents. In addition, staff working in facilities mostly made decisions regarding staffing decisions and service improvements. Decision makers at the level III health facilities found that they had to make decisions of staffing, and resource allocation.

The majority of decision makers felt that they did not have the necessary skills to use data for decision making. The primary decisions made by health facility managers were to influence budget preparation, inform medical supply and drug management, plan clinical service, making staffing decisions and promoting service improvement.

Information use for decision making	**N**	**Percent**
Budget preparation/allocation	145	81.9
Staffing decisions	161	91.0
Medical supply and drug management	113	63.8
Planning clinical services	145	81.9
Service improvement (counseling practices, outreach, adding services)	159	89.8

Table 6: Percentage of respondents who make decisions by category

The following table show the statistics of how respondents make decision by category where n = 177.

Statistics

	Budget Preparation/allocation	Staffing Decisions	Medical Supply and Drug Management	Planning Clinical Services	Service Improvement (Counseling Practices, Outreach, Adding Services)
Mean	1.18	1.09	1.36	1.18	1.00
Median	1.00	1.00	1.00	1.00	1.00
Std. Deviation	.386	.288	.482	.386	.000

Table 7: Mean, Median and Std. Deviation of respondents who make decisions by category.

4.2.5 Perceived data use constraints

As previously discussed in the Conceptual Framework section, the issue of data use is widespread in other parts of the world. We wanted to get an idea of what respondents thought were some of the most pressing issues in data use and in health decision making. The table below shows the ranking of perceived data constraint issues. 91% perceived that incomplete data was the major issue while 54.9% said that poor quality data was a constraint to data use, 82 % said that the data was not produced or if it was it was produced late, 58.8% perceived that data was not being well presented.

The main barriers to data use faced by the health facility were having incomplete data or cases where data was not produced or reported from the health facilities and also poorly presented data was a barrier to data use. Health facility managers also faced challenges with the low technical capacity of staff that had little knowledge of data collection processes and use of tools thus resulting in the collection of poor quality of data.

Constraint to data use	**N**	**Percent**
Incomplete data	161	91
Poor quality data	97	54.9
Data was produced late or not at all	145	82
Data/information was not well presented	104	58.8

Table 8: Percentage of respondents on data use constraints

During the data collection process, we also asked the respondents if they had provided feedback about the above constraints to data use to the management team. The response results of this were that all the respondents said that they had provided the feedback to the management.

Over 80% of the health facility managers also reported that they provide feedback to their records team and it is addressed. Further they felt they had the necessary skills to make decisions using data. Data producers reported that (28%) of the staff lack data analysis and interpretation skills. The majority of data producers strongly agreed that supervisors promote a culture of data use.

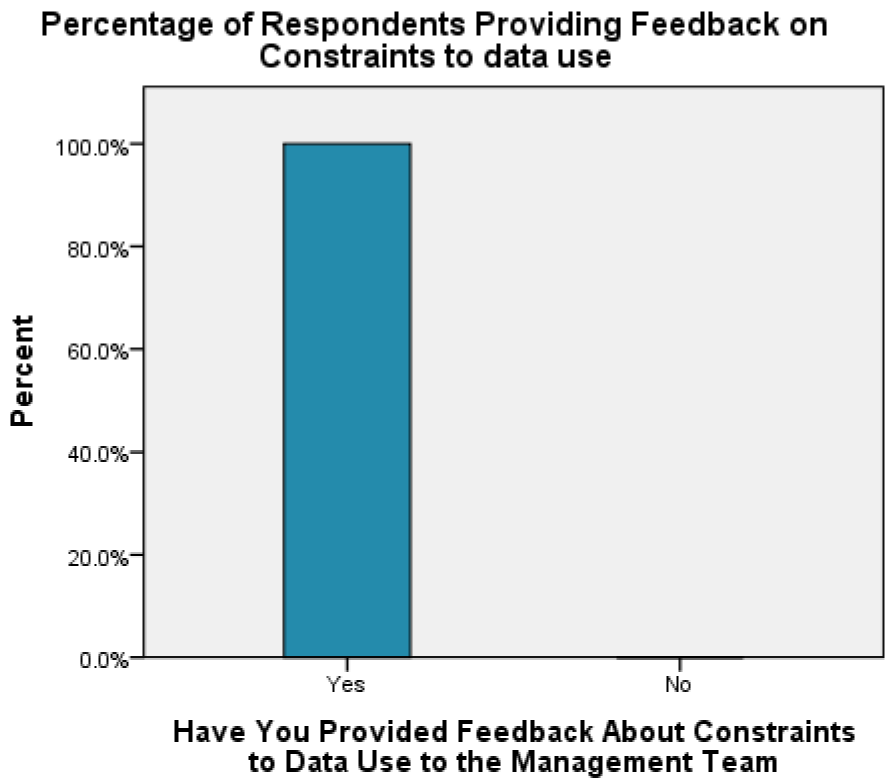

Figure 12: Percentage of respondents providing feedback on constraints to data use.

From the above we see that all the respondents did provide feedback about the constraints. The following bar graph shows if the feedback was addressed. 82% percent of the respondents said that the issue of data constraint was addressed by the management.

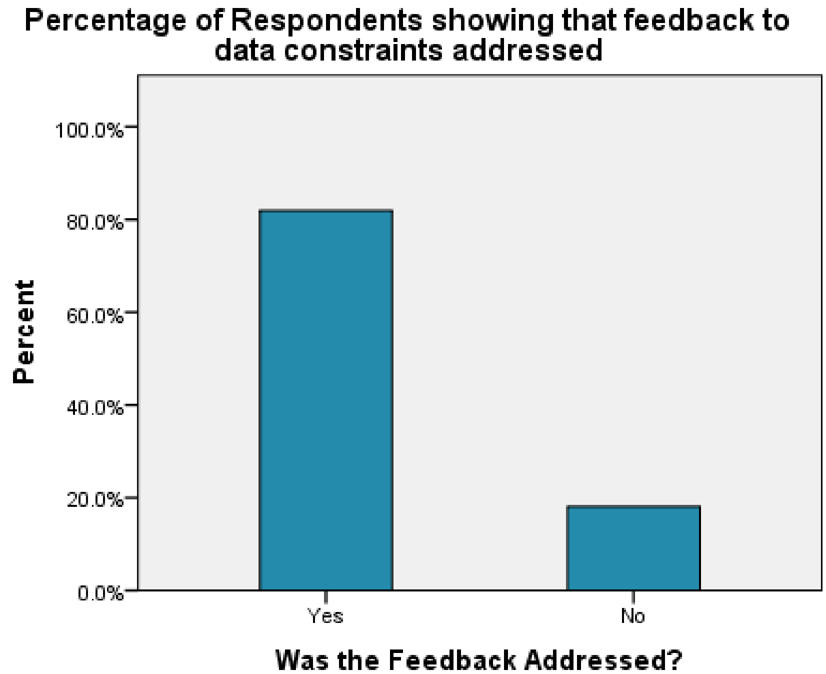

Figure 13: Percentage of respondents showing that feedback to data constraints was addressed

The questionnaire went ahead and asked if they feel that they have the necessary data skills to use to make the kinds of decisions in which they are involved in.

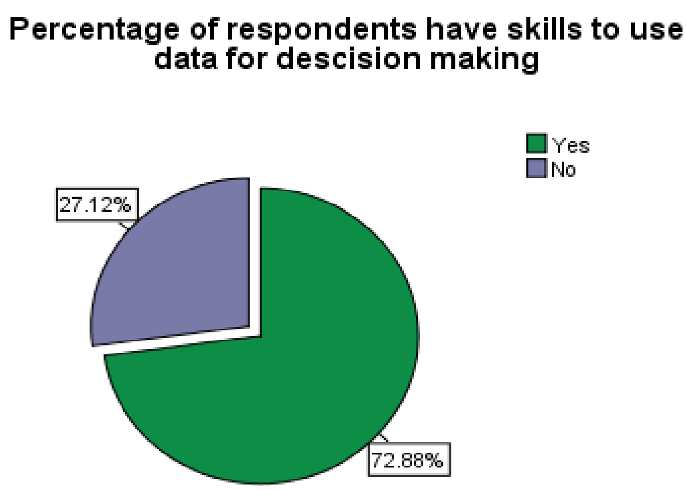

Figure 14: Percentage of respondents has data skills for decision making

4.2.6 Data analysis skills

In the DDIU approach, we recognize three broad areas that can influence decisions, technical, individual and organizational. As shown in previous studies, one of the more important technical areas is the technical capacity of which this research narrowed down to. We, therefore, asked a series of questions regarding data analysis skills, including the types of skills for which respondents thought they needed training on.

Would You Like Training in Data Collection?

		Gender				Total
		Male		Female		
		Count	% within Would You Like Training in Data Collection?	Count	% within Would You Like Training in Data Collection?	Count
Would You Like Training in Data Collection?	Yes	55	32.4%	115	67.6%	170
	No	2	28.6%	5	71.4%	7
Total		57	32.2%	120	67.8%	177

Table 9 Staff Who would like training in data collection

From the above results we see that a total of 170 respondents would like to have training in data collection this shows that a majority if the staff does need the necessary training so as to be able to handle collect the data.

Would You Like Training in Data Analysis?

		Gender				Total
		Male		Female		
		Count	% within Would You Like Training in Data Analysis?	Count	% within Would You Like Training in Data Analysis?	Count
Would You Like Training in Data Analysis?	Yes	51	31.5%	111	68.5%	162
	No	6	40.0%	9	60.0%	15
Total		57	32.2%	120	67.8%	177

Table 10: Staff who would like training in data analysis

94% of the respondents require training in data analysis this is important because it helps the decision makers at the health facility be able use the data that they have and analysis it in a profound way as to be able to make evidence based decisions.

Would You Like Training in Data Presentation?

		Gender				Total
		Male		Female		
		Count	% within Would You Like Training in Data Presentation?	Count	% within Would You Like Training in Data Presentation?	Count
Would You Like Training in Data Presentation?	Yes	54	32.1%	114	67.9%	168
	No	3	33.3%	6	66.7%	9
Total		57	32.2%	120	67.8%	177

Table 11: Training in Data Presentation

Would You Like Training in Data Use? (Planning, Quality Improvement)

	Gender				Total
	Male		Female		
	Count	% within Would You Like Training in Data Use? (Planning, Quality Improvement)	Count	% within Would You Like Training in Data Use? (Planning, Quality Improvement)	Count
Would You Like Training in Data Use? (Planning, Quality Improvement) Yes	57	32.2%	120	67.8%	177
Total	57	32.2%	120	67.8%	177

Table 12: Training in Data Use

4.2.7 Perceptions about data use

The research also went ahead and asked the respondents about the perception to data use, based on the following categories: How decision are based on the facility, involvement of superiors in decision making, involvement of staff and finally the personal liking.

At this facility, decisions are based on	Strongly Disagree	Somewhat Disagree	Neither Agree nor	Somewhat Agree	Strongly Agree
Personal liking	82%	9%			9%
Superiors' directives					100%
Evidence/facts			9%	9%	82%
Political interference	73%	9%			18%
Cost considerations	18%			11%	71%

Table 13: Percentage of respondents showing how decisions are made at the facility

The results indicate that most of the decisions that are made in the facility are as a result of the superiors directives. And that personal liking shows that it does not influence the decisions which are made at the health facility.

In your health facility, superiors	Strongly Disagree	Somewhat Disagree	Neither Agree nor	Somewhat Agree	Strongly Agree
Seek feedback from staff	27%				73%
Emphasize data quality in regular reports	45%	1%	1%	4%	50%
Promote a culture of data use	18%				82%
Explain what they expect from staff	4%			4%	92%
Share data with other facilities	65%	2%	1%	4%	28%

Table 14: Percentage of respondents indicating how superiors are involved in decision making

In your health facility, staff	Strongly Disagree	Somewhat Disagree	Neither Agree nor	Somewhat Agree	Strongly Agree
Are aware of their responsibilities	18%				82%
Are appropriately trained to use data	9%				91%
Rely on data for planning and monitoring set targets	2%			3%	95%

Table 15: Percent of staff involvement in decision making

Personal	Strongly Disagree	Somewhat Disagree	Neither Agree nor	Somewhat Agree	Strongly Agree
Collecting data makes me feel bored	9%	65%		14%	12%
Collecting data is meaningful to me				5%	95%
Collecting data gives me the feeling that it is needed for monitoring and facility performance	9%				91%

Table 16: Percent of involvement of personal in decision making

The data and results presented in this report can inform the health facilities about appropriate interventions that can encourage and improve the use of data for health decisions.

4.3 Correlation of variables

A correlation was used to measure the strength of a relationship between the variables using the correlation coefficient. The correlation coefficient can range from –1 to 1, where –1 or 1 indicates a perfect relationship. Positive coefficients indicate a direct relationship, that is, when one variable increases, the other increases. Negative coefficients indicate an inverse relationship, that is, when one variable increases, the other one decreases. Thus a Pearson product-moment correlation coefficient was computed to assess the relationship between the hypothesized variables.

Hypothesis	Pearson correlation Result
Data analysis has a direct relationship with information availability on information use and is moderated by problem solving skills	There was a positive correlation between the variables, r = 0.620, n = 177.
Data analysis has a direct relationship with information availability on information use and is moderated by staff attitude.	There was a positive correlation between the variables, r = 0.510, n = 177.
Usability has a direct relationship with information availability on information use and is moderated by problem solving skills.	There was a positive correlation between the variables, r = 0.451, n = 177.
Usability has a direct relationship with information availability on information use and is moderated by staff attitude.	There was a positive correlation between the variables, r = 0.688, n = 177.
Interoperability has a direct relationship with information availability on information use and is moderated by problem solving skills.	There was a positive correlation between the variables, r = 0.508, n = 177.
Interoperability has a direct relationship with information availability on information use and is moderated by staff attitude.	There was a positive correlation between the variables, r = 0.543, n =177.
IT technology has a direct relationship with information availability on information use and is moderated by problem solving skills.	There was a positive correlation between the variables, r = 0.698, n = 177.
IT technology has a direct relationship with information availability on information use and is moderated by staff attitude.	There was a positive correlation between the variables, r = 0.758, n = 177.
Data collection has a direct relationship with	There was a positive correlation between the

information availability on information use and is moderated by problem solving skills.	variables, r = 0.579, n = 177.
Data collection has a direct relationship with information availability on information use and is moderated by staff attitude	There was a positive correlation between the variables, r = 0.456, n = 177.

Table 17 Pearson Correlation Result

There was a large positive correlations between data analysis and information availability on information use and is moderated by attitude (r = .510, p = 0.000). This would indicate that the staff at the health facility have high availability of information and thus tend to have a high use of information. There was a positive correlation between IT technology has a direct relationship with information availability on information use and is moderated by skills. (r = 0.698, p= 0.001) this indicates that the use of IT Technology at the health facilities is high thus implying that information use is also high at the health facilities. There is a positive correlation between Interoperability and information availability on information use and is moderated by attitude. (r = 0.543, p= 0.001) indicating that as the interoperability increase so does the need for information use.

Usability use has a positive correlation with information availability on information use and is moderated by attitude (r = 0.688, p= 0.001), as usability use tends to be high so does the use of information gets high at the health facility. Data collection has a positive correlation with information availability on information use and is moderated by skills (r = 0.579, p= 0.001), as data collection increases so does information use increase. Data analysis has a positive correlation with information availability on information use and is moderated by skills (r = 0.620, p = 0.002), indicating that as the rate at which the data analysis increases so does the need for information use.

4.4 The coefficient of determination

The coefficient of determination R2 (or sometimes r^2) is a measure used in statistical model analysis to assess how well a model is explained. It is indicative of the level of explained variability in the model. The coefficient, also commonly known as R-square, is used as a guideline to measure the accuracy of the model. One use of the coefficient of determination is to test the goodness of fit of the model. It is expressed as a value between zero and one. A value of one indicates a perfect fit, and therefore, a very reliable model. A value of zero, on the other hand, would indicate that the model fails to accurately model the dataset.

With the information form table 17, we can therefore now determine the coefficient of determination, the table below summaries the results.

Pearson result (r)	**Coefficient of determination ($r^{2)}$**	**Percentage of r^2**
0.620	0.384	38.4
0.510	0.260	26
0.451	0.203	20.3
0.688	0.473	47.3
0.508	0.258	25.8
0.543	0.294	29.4
0.698	0.487	48.7
0.758	0.575	57.5
0.579	0.335	33.5
0.456	0.207	20.7

Table 18: Coefficient of determination

So, looking at the above table, we can infer that only 38.4 per cent of the variance in data analysis is related to information use moderated by skills. We should therefore conclude that data analysis ratings are related to how the information is used but this only accounts for 38.4 per cent of the variance. We can see that data analysis only accounted for 26 per cent of the variance in how the information is used at the health facility for decision making and moderated by staff attitude. On the other hand 20.3 per cent of the variance in usability use is related to information use at the health facilities being moderated by skills, thus the ratings usability are related to information use.

47.3 per cent of the variance in usability is related to information use and moderated by attitude, thus the ratings are related to how the information is used at the health facility this accounts for 47.3 per cent of the variance. Interoperability accounted for 25.8 percent of the variance in information use at the health facility. IT technology on the other hand accounted for 48.7 per cent of the variance in relation to the use of information aspect at the health facility. 33.5 per cent of the variance in data collection was related to the demand for information use at the health facility.

4.5 Hypothesis test

In conducting the research, hypothesis testing using linear regression was done, we used the linear regression algebraic formula for the regression line, which states the mathematical relationship between the independent and the dependent variable. The stronger the relationship between the independent and dependent variables, the closer these estimates will come to the actual score that each case had on the dependent variable.

The standard form for the regression equation or formula is:

$$Y = a + bX + e$$

Where;

Y is the value of the Dependent variable (Y), what is being predicted or explained

a or Alpha, a constant; equals the value of Y when the value of X=0

b or Beta, the coefficient of X; the slope of the regression line; how much Y changes for each one-unit change in X.

X is the value of the Independent variable (X), what is predicting or explaining the value of Y

e is the error term; the error in predicting the value of Y, given the value of X (it is not displayed in most regression equations).

Hypothesis testing was carried out by using a p-value which helps to determine the significance of the results. Hypothesis tests are used to test the validity of a claim that is made about a population. All hypothesis tests ultimately use a p-value to weigh the strength of the evidence (what the data are telling you about the population). Thus, the lower the p-value the more certain that we can be that there is a statistically significant difference between the observed and hypothesized mean. Most disciplines use an alpha value of 0.05; that is, if the p-value is less than 0.05 then the difference is regarded as statistically significant.

Hypothesis	**p-value**
H1 Data analysis has a direct relationship with information availability on information use and is moderated by skills.	0.018
H2 Data analysis has a direct relationship with information availability on information use and is moderated by attitude.	0.024
H3 Usability has a direct relationship with information availability on information use and is moderated by skills.	0.001
H4 Usability has a direct relationship with information availability on information use and is moderated by attitude.	0.011
H5 Interoperability has a direct relationship with information availability on information use and is moderated by skills.	0.032
H6 Interoperability has a direct relationship with information availability on information use and is moderated by attitude.	0.043
H7 IT technology has a direct relationship with information availability on information use and is moderated by skills.	0.064
H8 IT technology has a direct relationship with information	0.010

availability on information use and is moderated by attitude.	
H9 Data collection has a direct relationship with information availability on information use and is moderated by skills.	0.005
H10 Data collection has a direct relationship with information availability on information use and is moderated by attitude.	0.002

Table 19 Hypothesis test P-Value table

From the above table we see that hypothesis H7 had a p-value which was greater than 0.05 which means that there is no sufficient evidence to conclude that there is a significant association between IT Technology on information use.

H1 Data analysis has a direct relationship with information availability on information use and is moderated by skills.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.707	1	11.707	20.579	.018[b]
	Residual	34.243	175	.196		
	Total	45.950	176			

Based on the ANOVA table above for the linear regression (F (177) = 20.579, p<0.018), there was a relationship between data analysis with information availability on information use and moderated by skills. Since the probability of the F statistic (p<0.018) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between data analysis with information availability on information use and moderated by skills.

The research hypothesis that there was a relationship between data analysis with information availability on information use and moderated by skills was supported.

H2 Data analysis has a direct relationship with information availability on information use and is moderated by attitude.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32.700	1	32.70	25.250	.024[b]
	Residual	34.104	174	.196		
	Total	66.804	175			

Based on the ANOVA table above for the linear regression (F (177) = 25.250, p<0.024), there was a relationship between data analysis with information availability on information use and moderated by attitude. Since the probability of the F statistic (p<0.024) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between data analysis with information availability on information use and moderated by attitude

Thus the research hypothesis that there was a relationship between data analysis with information availability on information use and moderated by attitude was supported.

H3 Usability has a direct relationship with information availability on information use and is moderated by skills.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.740	1	.740	3.780	.001[b]
	Residual	34.083	175	.196		
	Total	35.703	176			

Based on the ANOVA table above for the linear regression (F (177) = 3.780, p<0.001), there was a relationship between usability with information availability on information use and is moderated by skills. Since the probability of the F statistic (p<0.001) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between usability with information availability on information use and is moderated by skills

The research hypothesis that there was a relationship between usability with information availability on information use and is moderated by skills was supported.

H4 Usability has a direct relationship with information availability on information use and is moderated by attitude.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.204	1	23.204	13.117	.011[b]
	Residual	176.05	175	1.006		
	Total	199.254	176			

Based on the ANOVA table above for the linear regression (F (177) = 13.117, p<0.011), there was a relationship between usability and information availability on information use and is moderated by attitude**.** Since the probability of the F statistic (p<0.011) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between usability with information availability on information use and is moderated by attitude

The research hypothesis that there was a relationship between usability with information availability on information use and is moderated by attitude was supported.

H5 Interoperability has a direct relationship with information availability on information use and is moderated by skills.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	88.096	2	44.048	9.780	.032[b]
	Residual	165.996	174	.954		
	Total	254.092	176			

Based on the ANOVA table above for the linear regression (F (177) = 9.780, p<0.032), there was a relationship between interoperability with information availability on information use and is moderated by skills. Since the probability of the F statistic (p<0.032) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between interoperability with information availability on information use and is moderated by skills.

The research hypothesis that there was a relationship between interoperability with information availability on information use and is moderated by skills was supported.

H6 Interoperability has a direct relationship with information availability on information use and is moderated by attitude.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.976	2	7.458	36.048	.043
	Residual	227.418	174	1.307		
	Total	242.394	176			

Based on the ANOVA table above for the linear regression (F (177) =36.048, p<0.043), there was a relationship between interoperability with information availability on information use and is moderated by attitude. Since the probability of the F statistic ($p<0.043$) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between interoperability with information availability on information use and is moderated by attitude.

The research hypothesis that there was a relationship between interoperability with information availability on information use and is moderated by attitude was supported.

H7 IT technology has a direct relationship with information availability on information use and is moderated by skills.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30.065	1	30.065	44.089	.064
	Residual	217.525	175	1.243		
	Total	247.59	176			

Based on the ANOVA table above for the linear regression ($F(177) = 44.089$, $p<0.064$), there was no relationship between IT technology with information availability on information use and is moderated by skills. Since the probability of the F statistic ($p<0.064$) was greater than the level of significance (0.05).

Since the p-value of the test statistic is greater than 0.05, there is sufficient evidence to conclude that there is no significant association between IT technology with information availability on information use and is moderated by skills.

The research hypothesis that there was a relationship between IT technology with information availability on information use and is moderated by skills was not supported.

H8 IT technology has a direct relationship with information availability on information use and is moderated by attitude.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.044	1	24.044	35.044	.010
	Residual	7.04	175	.040		
	Total	31.084	176			

Based on the ANOVA table above for the linear regression ($F (177) = 35.044$, $p<0.010$), there was a relationship between IT technology with information availability on information use and moderated by attitude. Since the probability of the F statistic ($p<0.010$) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between IT technology with information availability on information use and is moderated by attitude.

The research hypothesis that there was a relationship between IT technology with information availability on information use and is moderated by attitude was supported.

H9 Data collection has a direct relationship with information availability on information use and is moderated by skills.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.002	2	7.001	29.048	.005
	Residual	5.568	174	.032		
	Total	19.57	176			

Based on the ANOVA table above for the linear regression ($F (177) = 29.048$, $p<0.005$), there was a relationship between data collection with information availability on information use and is moderated by skills. Since the probability of the F statistic (p<0.005) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between data collection with information availability on information use and is moderated by skills.

The research hypothesis that there was a relationship between data collection with information availability on information use and is moderated by skills was supported.

H10 Data collection has a direct relationship with information availability on information use and is moderated by attitude.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.869	1	34.869	44.779	.002
	Residual	31.680	175	.180		
	Total	66.549	176			

Based on the ANOVA table above for the linear regression (F (177) = 44.779, p<0.002), there was a relationship between data collection with information availability on information use and is moderated by attitude. Since the probability of the F statistic (p<0.002) was less than or equal to the level of significance (0.05).

Since the p-value of the test statistic is less than 0.05, there is sufficient evidence to conclude that there is a significant association between data collection with information availability on information use and is moderated by attitude.

The research hypothesis that there was a relationship between data collection with information availability on information use and is moderated by attitude was supported.

4.6 Discussion

4.6.1 Technical Capacity for Data Use

Although the data producers strongly agree that their supervisors promote a culture of data use, they did not seem to be actively using data for decision making, considering that often times they reported submitting data (results show 96% submission).

Several decision makers perceived their organizations as having the technical capacity to ensure access and availability of reliable data. Decision makers indicated that their organizations support having the necessary information to make decisions by providing technical assistance to health records officers and workers involved in data collection.

They mentioned provision of support by training the health records officers to provide high quality data, support supervision to ensure proper reporting, provision of feedback to improve data quality, as well as data analysis for health facility staff. Most of the staff (73%) felt that have the skills necessary to use data to make the kinds of decisions in which they are involved. They listed a wide range of skills that they use for decision making such as data collection and management, data interpretation and data use, data analysis, and data presentation skills. At the same time, skills to use data for decision making at the facility level were reported as lacking by some respondents:

4.6.2 Constraints to data use

Incomplete data was reported by all decision makers as one of the major technical constraints for information use. Main issues with quality of data related to data accuracy, data completeness and timeliness were noted: Some of the decision makers reported experiencing problems with data disparity while using multiple sources of information or statistics for issues of importance to them. The introduction of new data collection tools and changes in the annual work plans were mentioned as factors that make data less reliable: To improve data quality, decision makers reported making follow ups with people providing data, especially when there is a lack of or contradicting information. Also, they conduct trainings and monthly meetings to provide feedback and emphasize the importance of data quality: Several individual constraints for data use were listed by respondents: lack of technical skills, lack of staff motivation, lack of knowledge of the benefit to using data for policy change and program management. Among technical skills, computer skills as well as data collection skills were especially lacking. As a result, lower level health facility managers or staff cannot make decisions without prior consent from their superiors.

Constraints to data use exist, respondents in our study considered insufficient technical skills as the primary impediment to data utilization. Furthermore, a substantial proportion of junior and middle level staff expressed the need for technical skills training. Another technical constraint appears to be limited amount of computer use for data processing, particularly at lower levels of the health system. These findings suggest the need to improve the technical capacity of staff working at this health facilities. If staff feel capable of using computers and analyzing and interpreting data they may be more likely to use it for decision making.

In linking the results to the conceptual framework that we had in chapter two, the results present us with a much more elaborate framework where by, the technical determinant factors that influence information use i.e. data analysis, usability, interoperability, IT technology and data collection which were measured by use of a questionnaire, the result reveal that though most of the staff do promote a culture of information use not all the decision makers use the data that they have to make decisions.

4.6.3 Information use

The study included respondents from level III health facilities at Nairobi. They included senior-level policy decision makers as well as middle and junior-level staff with the aim of understanding how health data is used for decision making and the perceived impediments to data utilization. Understanding how data and information are used for decision making in the level III health sector requires knowing what types of decisions are made or influenced not only by those working in the health sector.

In this study, the most common types of decisions reportedly made by respondents are those related to program management, planning and budgets. The types of decisions (e.g., related to medical and drug supply, and epidemiologic issues) made by staff working in health clinics probably reflect their role as service providers.

There is no evidence of performance-based resource allocation and no essay competitions and other rewards for best evidence-based decision making. There is also no practice-based training at health facilities where people would go through the process of recording, analyzing and using information in the real world; as such, staff competencies are very low as shown in this study.

Management styles in the facilities under study do not encourage information use. Lack of full commitment by management at many levels has been a major obstacle to implementation of health information systems. There is very little feedback, both written and oral, on reports sent from the facilities under study. This is further compounded by senior managers failure to promote evidence-based decision-making and the use of information for transparency and accountability, and the formal structures of hierarchy which favor a top down decision making, and bottom-up data flows.

Use of information is affected by the limited information feedback to facilities. Feedback does not occur on a routine basis. There is also limited feedback given to facilities about the constraints to data use

4.6.4 Technical Determinants

The PRISM tools identify many technical issues which can affect health information performance. The technical issues include: the user-friendliness of the procedure manual, data collection forms, software, management of information technology, software integrating information from other information systems, providing a comprehensive picture of a health system performance and use of information technology to create access to information for senior managers. Most facilities did not have computers and their accessories.

Training is limited to data collection and manual data entry. There are no institutionalized mechanisms for planned training and training usually occurs on an ad hoc needs basis, curtailing opportunities for continuous improvement.

The framework provides specific and comprehensive guidance to improve data demand and information use. It can be used to design, monitor and evaluate interventions, and to improve demand for, and use of, data in decision making. As more interventions are implemented to improve use of health data, those efforts need to be evaluated.

The lack of demand for and information use of data limits the health system's ability to respond to priority needs throughout its many levels. The failure to consider empirical evidence regularly before making program and policy decisions is due primarily to the complex causal pathway between data collection, use of data, and improvement in health outcomes. Furthermore, specific and comprehensive guidance to improve data demand and use is lacking

CHAPTER FIVE: CONCLUSION AND RECCOMENDATIONS

5.1 Conclusion

The findings from this study have identified several actions that are needed to address the technical capacity for health workers in using data for decision making and also identified the constraints to data use and the strengthening of data used to make decision. The findings reveal that a majority of the health facility staff lack data analysis skills which are vital for decision making process. In general, it was clear that there is a big gap in the Data Demand and Information Use (DDIU) but it is showing great improvements. Health personnel across the spectrum are showing great interest in the use of data for making decisions. With increased capacity building in data demand and use of information for decision making there is high likelihood that data use will increase.

A higher number of respondents also reported on barriers to data use this may have been as a result of leadership at the at the health facilities that promotes a culture of strengthening data.

There is no evidence of performance-based resource allocation and no essay competitions and other rewards for best evidence-based decision making. There is also no practice-based training at health facilities where people would go through the process of recording, analyzing and using information in the real world; as such, staff competencies are very low as shown in this study.

5.2 Limitation

The limitation of the research is that it will only be done in a select health facility and thus will limit the research to be covered in a large area, also by comparing the study findings to findings from other similar studies, as well as comparing quantitative to qualitative findings from them.

5.3 Recommendations

The research, has shown that there is a serious need to focus on improving staffs' technical skills to analyze and interpret data and to build capacity for using data and information to guide decision making. A first step to improving use of data for the health sector decision making is to sensitize staff working at all levels to the potential benefits to their health program. Support from policy makers, health administrators, program managers, and service providers is essential when building a culture of data and information use, particularly because all of these stakeholders often make or influence decisions. In addition, respondents highly ranked "training health care providers in the importance of data collection, analysis, and use” and “encouraging evidence based decision making” as possible strategies to improving data use.

Conducting a comprehensive information technology needs assessment would further highlight data processing challenges and inform the development of practical solutions.

Providing training on data analysis, interpretation and presentation, particularly among middle and junior level staff, would address the expressed need for improved technical skills. Building lower level staffs’ capacity to use computers in combination with improved data analysis and interpretation skills may further stimulate their use of data for decision making.

The following recommendations have been derived from the study findings:

The need to eliminate paper-based data collection in the health facilities; to train and re-train staff on data analysis skills to produce information and using this information in decision making; to urgently address data use constraints such as staff shortage, inadequacy of staff, lack of delegation for managerial staff to make decisions and heavy workloads among data producers; to improve quality of data (i.e., accuracy, completeness, timeliness); to make efforts at the organizational level to improve motivation and appreciation for data use at all levels of the health system including data producers.

Improve skills in data interpretation, use of information and problem solving, and performance improvement tools (such as cause and effect analysis, flow chart, priority matrix, control chart etc.). Activities may include training of master trainers and conduct training of two staff per facility and all health area management team members.

Improve the feedback/supervision system, focusing on checking use of information and comparison among facilities on health services indicators. Activities may include preparing feedback guidelines for health area, develop a supervisory checklist for checking information use, and train all health area supervisors on checklist use and activities.

Improve sharing the use of information and role modelling (promoting a culture of information use). Activities may include selecting existing channels of communication for sharing success stories on the use of information. Examples include providing a feedback report, sending directives, producing newsletters, etc. Create mechanisms to publish at least one story every month or every second month in official publications or other means.

5.4 further work

The determine was carried out to determine the use of health information to make evidence based decision making thus the proposal of further work to develop a Health Area HIS to integrate various health service related information systems at the level III health facilities at the county of Nairobi. This recommendation for further work needs to be implemented in the near future and requires considerable investment in terms of time and money.

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APPENDICES

Appendix 1-Questionnaire

READ: Dear Respondent, My name is Joshua Ngumba, a student at The University of Nairobi undertaking. I am conducting a research titled "**a framework for increasing the technical capacity of health workers to use health data for decision making at the level III health facilities in Nairobi county".** In health information systems, the ultimate purpose of collecting and analyzing data is to improve programs by enabling more informed decisions based on facts. However, information is not always available to make decisions—or if it is available, it is not always used. This study is designed to find out what barriers and constraints are causing these conditions, and how to resolve them. Your participation is requested to provide your insights about constraints and barriers to data use. Your participation is very important to this research. Your responses will be treated as confidential.

Respondent Background Information					
Name of health facility					
What is your gender		☐Male		☐Female	
What is your age bracket	☐18-25	☐26-30	☐31-35	☐36-40	☐Above 40
What is your job title?					
How long have you been in your current position?					
Do you supervise any staff at this facility?	☐ Yes		☐No		

Section 1: Information use for decision making		
1. Do you make or influence the following:		
a) Budget preparation/allocation	☐ Yes	☐No

b) Staffing decisions	☐ Yes	☐No
c) Medical supply and drug management	☐ Yes	☐No
d) Planning clinical services	☐ Yes	☐No
e) Service improvement (counseling practices, outreach, adding services)	☐ Yes	☐No
f) Other		

2. What type of data or information do you use for:	
a) Budget preparation/allocation	
b) Staffing decisions	
c) Medical supply and drug management	
d) Planning clinical services	
e) Service improvement (counseling practices, outreach, adding services)	
f) Other	

3. With the most recent decisions, please describe how you used data in the decision-making process.
a)
b)

Section 2: Technical barriers to information use		
4. In general, do you face any challenges when trying to use facility data for decision making? Please explain.		
5. Over the past 6 months, have you encountered any of the following barriers when trying to use health data or information?		
a) Incomplete data	☐ Yes	☐No
b) Poor quality data	☐ Yes	☐No
c) Data was produced late or not at all	☐ Yes	☐No
d) Data/information was not well presented	☐ Yes	☐No
e) Other:		
If "no" to Q5a–e, skip to Q7.		

6. Have you provided feedback about these barriers to the management team?	☐ Yes	☐No
a. If yes, was the feedback addressed?	☐ Yes	☐No
7. Do you feel you have the skills necessary to use data to make the kinds of decisions in which you are involved?	☐ Yes	☐No
8. Would you like training in?		
a) data collection	☐ Yes	☐No
b) data analysis	☐ Yes	☐No
c) data presentation	☐ Yes	☐No
d) data use (planning, quality improvement)	☐ Yes	☐No

Section 3 : Behavioral factors to information use					
At this facility, decisions are based on	**Strongly Disagree**	**Somewhat Disagree**	**Neither Agree nor**	**Somewhat Agree**	**Strongly Agree**
14. Personal liking	1	2	3	4	5
15. Superiors' directives	1	2	3	4	5
16. Evidence/facts	1	2	3	4	5
17. Political interference	1	2	3	4	5
18. Cost considerations	1	2	3	4	5
In your health facility, superiors					
19. Seek feedback from staff	1	2	3	4	5
20. Emphasize data quality in regular reports	1	2	3	4	5
21. Promote a culture of data use	1	2	3	4	5
22. Explain what they expect from	1	2	3	4	5
23. Share data with other facilities	1	2	3	4	5
In your health facility, staff					

24. Are aware of their responsibilities	1	2	3	4	5
25. Are appropriately trained to use data	1	2	3	4	5
26. Rely on data for planning and monitoring set targets	1	\2	3	4	5
Personal					
27. Collecting data makes me feel bored	1	2	3	4	5
28. Collecting data is meaningful to me	1	2	3	4	5
29. Collecting data gives me the feeling that it is needed for monitoring and facility performance	1	2	3	4	5
Perceived Data Use Issues					
30. There is little usability of data and information use	1	2	3	4	5
31. Do the health systems provide data interoperability?	1	2	3	4	5
32. There are no set criteria for data collection and analysis	1	2	3	4	5
33. There is an unwillingness to accept shortcomings in data	1	2	3	4	5
34. There is a general lack of skills to analyze and use data collected	1	2	3	4	5
35. There is use of IT Technology in the health facilities.	1	2	3	4	5
36. Information is available at the health facilities?	1	2	3	4	5
37. Health staff have problem solving skills	1	2	3	4	5
38. There is information use at the health facilities	1	2	3	4	5

Section 4: Open-ended questions	
39.	What was the last major decision related to policies or programs that you made?
40.	What information did you use to make this decision?
41.	How did you use information to make this decision?
42.	Was there any information you needed but did not have in order to make this decision?
43.	According to you how does use of data help in the health sector?
44.	Who are the primary stakeholders in the use of information?
45.	What recommendations would you offer to address barriers in data demand?