UTILIZATION OF DATA VISUALIZATION TOOLS TO INFORM DECISION-MAKING AMONG HEALTH MANAGERS IN SELECTED COUNTIES IN KENYA

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A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN HEALTH INFORMATION MANAGEMENT IN THE SCHOOL OF HEALTH SCIENCES OF KENYATTA UNIVERSITY

MAY, 2025

DECLARATION

This Thesis is my original work and has not, to the best of my knowledge, been presented to any other college, university, and institution or examination body.

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DEDICATION

This thesis is dedicated to my family for their financial and moral support in undertaking this research.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS AND ACRONYMS

AHILA	Association of Health Information Libraries in Africa
BMJ	British Medical Journal
DFID	Department for International Development
DHMT	District Health Management Team
DHIS	District Health Information Software
DHIS2	District Health Information Software version 2
HIFA	Health Information for All
HINARI	Health Inter Network Access to Research Initiative
HIS	Health Information System
HMIS	Health Management Information System
HRIO	Health Records and Information Officer
ICT	Information and Computer Technology
IT	Information Technology
INASP	International Network for the Availability of Scientific Publications
KII	Key Informant Interview
MEDLINE	Medical Literature Analysis and Retrieval System Online
MOH	Ministry of Health
WHO	World Health Organization
UHC	Universal Health Coverage
DV	Data Visualization
KPI	Key Performance Indicator
SPSS	Statistical Package for the Social Sciences
RMNCH&N	Reproductive, Maternal, New-born, Child Health and Nutrition
FGDs	Focus Group Discussions
PHIN	Public Health Information Network
ANOVA	Analysis of Variance
M&E	Monitoring and Evaluation
MDGi	Maternal and Child Health Initiative

ABSTRACT

This study investigated the factors influencing the utilization of data visualization (DV) tools among county and sub-county health managers in selected counties in Kenya. The research was motivated by the persistent underuse of health information despite substantial investments in data collection across various programs. Four specific objectives guided the inquiry: determining the effects of (i) individual characteristics, (ii) technological factors, (iii) organizational factors, and (iv) behavioural factors on the utilization of DV tools for decision-making. Additionally, the study assessed how these factors collectively impact effective evidence-based decisions in healthcare management. A mixed-methods, longitudinal case study design was adopted, combining quantitative (structured questionnaires) and qualitative (key informant interviews) approaches. Eight counties, Machakos, Isiolo, Nyeri, Kisumu, Makueni, Mombasa, Laikipia, and Garissa, were purposively selected to reflect diverse healthcare settings and varying degrees of Universal Health Coverage implementation. The target population comprised 294 county and sub-county health managers, with 160 chosen via purposive sampling. A total of 149 respondents participated, yielding a 93% response rate. Data collection included structured questionnaires focused on demographics, data utilization practices, and training; key informant interviews provided more profound insights into organizational culture, leadership support, and policy frameworks. Quantitative data were analysed using descriptive statistics, correlation analysis, and multiple regression with SPSS (v.26). Qualitative data underwent thematic and content analysis, capturing nuanced perspectives on facilitators and barriers to DV adoption. Findings indicated that all four categories of factors significantly influence DV-tool utilization. Correlation coefficients showed strong positive associations between use of DV tools and (a) individual characteristics ($r=0.504$, $p<0.05$), (b) technological factors ($r=0.784$, $p<0.001$), (c) organizational factors ($r=0.776$, $p<0.001$), and (d) behavioural factors ($r=0.404$, $p<0.001$). A combined R^2 value of 0.823 suggested that over 82% of the variation in DV-tool utilization could be attributed to these four dimensions, underscoring their collective influence on data-driven decision-making. The final regression model highlighted training, infrastructure, supportive management, and positive staff attitudes as key predictors. The study recommends that strengthening data visualization competencies among health managers, improving technology and infrastructure, and fostering an organizational culture that values evidence-based decision-making are critical for enhancing health service delivery. The study recommends targeted training on advanced analytics, continuous mentorship, and clear governance frameworks to sustain DV-tool usage, thereby optimizing healthcare outcomes and supporting Kenya's progress toward Universal Health Coverage.

CHAPTER ONE: INTRODUCTION

1.1 Background to the Study

Health Information System (HIS) refers to a set of procedures and tools used by a health program in collecting, processing, transmitting and using data to monitor, evaluate and control health system (PHIN (2011). Whereas “a health system is not a statistical phenomenon, it is an ongoing change process caused by from within and outside the system” (Vital Wave Consulting, 2019). The HIS gives underpinnings for making decisions and has 4 primary functionalities: (i) generating data, (ii) compiling, (iii) analysing and synthesising, and (iv) use and communication. The HIS gathers health data and related industry, evaluates it and makes sure the overall timeliness, relevance and quality and does its conversion to information for making health-associated decisions (WHO Health System Framework, 2016).

Data visualization is representing data and information graphically. Through using visual elements such as maps, graphs, and charts, an accessible approach of seeing and understanding patterns, outliers and trends is provided by data visualization tools. Data visualization technologies and tools are important in the world of vast data since they help in analysing big quantities of data and in making decisions that are data-driven (Measure Evaluation 2017).

Globally modern societies buzz by constantly creating new data, though it fails to give the proper tools for understanding it, this has resulted to the urge to design advanced visualization options to address the gap between abstracted data and public needs and bring clarification out of the data and give new methods to approach complex figures (Sprint Interactive, 2018) The situation is similar in the Kenyan context.

The major hurdles to data usage are lack of essential data skills among personnel, inadequate data availability and accountability, poor data quality, infrastructure constraints and financial constraints. Implementing live data visualization tools to strengthen data will probably influence positively i.e. strengthen and improve data use and management practises than the current situation. However, even as research posit that live data tools may enhance use of data potentials through improvement odd data quality, availability and access, general infrastructural and financial constraints would challenge such measures.

This study thus intended to investigate the data visualization tools utilization in informing decision-making health service delivery in the HIS using case study sites at National and County Health Programs in Kenya. The purpose of this research is to determine and ascertain the use of available data to inform policy and guidelines development, utilization of data visualization tools like dashboards in decision making; the benefits, and the challenges for implementing and maintaining data use at National programs and counties of the HIS in Kenya.

1.2 Statement of the Problem

Significant resources have been put into data collection on communities, facilities and populations. It is unfortunate that key stakeholders do not use this information in electively informing programmatic and policy decision-making process (Nutley, 2017). The ability of health systems in responding to urgent needs through its levels is hindered by the failure in considering all empirical evidence prior to making decisions (MEASURE Evaluation, 2018).

While emphasizing the importance of incorporating health information to guide health decision-making is a key focus within the National Health Sector Strategic Plan (NHSSP 2012-2017) aimed at helping health managers in making informed decisions and facilitating evidence-informed management and planning, data continues to be underused in informing programmatic and policy decision-making processes (MOH, 2018). In the Health Sector, there is scanty information on data visualizations tools in evidence-based decision making. Previous assessment on HIS Strengthening failed to assess the data visualization tools role in decision making (Health Metrics Network, 2017). Review of previous studies unveils that there is scarcity of information for evidence in real world use. As reported by Measure (2018), 42% of health managers in Kenya utilize data to impact the budgetary process and clinical services' planning. Unfortunately, administrative or managerial decisions are often not data-driven (Walshe and Rundall, 2017; Pappaioanou *et al*, 2016).

The rationale behind the approach to improve use of information is based on many current circumstances: Firstly, the issue of inadequate and low data quality and inadequate data use in policy and guideline formulation, which is applying to HIS's routine service reporting component. Secondly, according to Sauerborn & Lippeveld

(2018), routine services reporting is the sole approach of generating data decisions on program management like interventions, including policy and guidelines directions.

However, despite available theoretical information and literature on data visualization tools and decision making, the researcher did not find a recent study done on the factors that influence data visualization tools' utilization in informing decision-making processes in the healthcare sector. This research therefore to bridge this gap by assessing the relationship between utilization of data visualization tools on decision making capability of health managers in the selected Counties in Kenya that included Machakos, Kisumu, Nyeri, Isiolo, Makueni, Laikipia, Garissa, Mombasa and bridge the gap. The study presented crucial insights on effective strategies and actions aimed at enhancing the utilization of visualization tools to facilitate decision-making across various health service delivery systems.

1.3 Justification

The study addresses a critical gap in understanding how data visualization tools can enhance evidence-based decision-making in low-resource health settings. Despite an abundance of research on data visualization globally, few studies have systematically examined the interplay of individual, technological, organizational, and behavioural factors within the context of Kenyan health systems. By focusing on selected counties with varying levels of Universal Health Coverage (UHC) implementation, this research enables a nuanced comparison of diverse healthcare environments.

County and sub-county health managers were chosen as the target population because they are pivotal in shaping health service delivery and resource allocation. Their direct involvement in decision making means that even incremental improvements in data interpretation and utilization can lead to significant system-wide benefits. This study's innovative contribution lies in its mixed-methods interventional design, which combines a robust baseline assessment with targeted capacity-building initiatives. Such an approach not only quantifies the current state of data visualization utilization but also evaluates the impact of strategic training interventions on enhancing decision-making capabilities.

Ultimately, the key findings which have established predictive factors, are expected to provide actionable insights for policymakers and health administrators, offering a practical framework that can be adapted to similar low-resource settings to improve health outcomes.

1.4 Research Questions

i. What are the individual characteristics influencing the utilization of data visualization tools in decision-making among health managers in selected counties in Kenya?
ii. What are the technological factors influencing the utilization of data visualization tools in decision-making among health managers in selected counties in Kenya?
iii. What are the organizational factors influencing the utilization of data visualization tools in decision-making among health managers in selected counties in Kenya?
iv. What are the behavioural factors influencing the utilization of data visualization tools in decision-making among health managers in selected counties in Kenya?
v. What are the effects of utilizing data visualization tools on decision-making in the selected counties in Kenya?

1.5 Hypothesis

i. Individual characteristics do not influence the utilization of data visualization tools in decision-making among health managers.
ii. Technological factors do not influence the utilization of data visualization tools in decision-making among health managers.
iii. Organizational factors do not influence the utilization of data visualization tools in decision-making among health managers.
iv. Behavioural factors do not influence the utilization of data visualization tools in decision-making among health managers.1.6 Research Objectives

1.6 Objectives

1.6.1 General objective

I. To investigate factors influencing the utilization of data visualization tools among health managers in selected Counties, in Kenya.

1.6.2 Specific objectives

i. To determine individual characteristics influencing utilization of data visualization tools among health managers in selected Counties, in Kenya
ii. To determine technological factors influencing utilization of data visualization tools among health managers in selected Counties, in Kenya.
iii. To determine organizational factors influencing utilization of data visualization tools among health managers in selected Counties, in Kenya
iv. To determine the behavioral factors influencing data visualization tools among health managers in selected Counties, in Kenya.
v. To determine the effects of utilization data visualization tools among health managers in selected Counties, in Kenya.

1.7 Limitation and Delimitation

1.7.1. Limitation

Several factors may affect the desired output of the study, particularly in relation to adhering to the planned timeline, ensuring data quality, and addressing potential data-related challenges. One major limitation is the difficulty in accessing data from the counties, as administrative delays or data privacy concerns can hinder timely data collection. This can be mitigated by obtaining formal authorization letters in advance, engaging county leadership early, and establishing data-sharing agreements where necessary. Additionally, the existence of multiple standalone systems that are not interoperable presents a significant challenge to data sharing and integration. To address this, efforts should be made to standardize data formats, utilize compatible export formats, and collaborate with county IT personnel for data extraction and compatibility checks. Data quality issues, such as missing values and inconsistencies, also pose a risk to the reliability of findings. These can be managed through data quality assessments, training for data collectors, and applying data cleaning techniques. Lastly, maintaining the study timeline may be threatened by delays in approvals or participant response rates. This risk can be minimized by developing a comprehensive project timeline with buffer periods, assigning clear roles and responsibilities, and maintaining regular communication with county officials and participants.

1.7.2 Delimitation

The boundaries of the study were defined by the selection of specific counties and respondents, focusing exclusively on county and sub-county health managers. As such, the findings will not be generalized to the entire country but will be interpreted within the context of the selected counties and based on the dependent variable-utilization of data visualization tools in decision-making. Another delimitation is the potential skepticism among some leadership figures. Certain leaders may be reluctant to accept that the data and figures presented accurately reflect the performance of their sub-counties, which could lead to resistance or slow adoption of data visualization tools. The study anticipated this challenge and addressed it through early engagement with stakeholders and by emphasizing the collaborative nature of data collection and interpretation

1.8 Theoretical Framework

1.8.1 Nutley's Data Utilization Framework (2017)

This study adopted Nutley's (2017) framework, which conceptualizes *data utilization* as the process through which data is analyzed, synthesized, interpreted, and reviewed for data-informed decision-making, irrespective of its source. According to this theory, improving data use requires interventions such as strengthening data quality, enhancing data accessibility, and building the capacity of data users. Nutley emphasizes that both the supply of good-quality data and the demand for such data among decision-makers must be improved simultaneously. This framework is highly relevant to the study as it highlights the importance of addressing not only technical issues, such as the availability of data visualization tools, but also the human and organizational factors that influence how data is used. It supports the study's examination of how individual, organizational, technological, and behavioral factors interact to affect the utilization of data visualization tools among health managers.

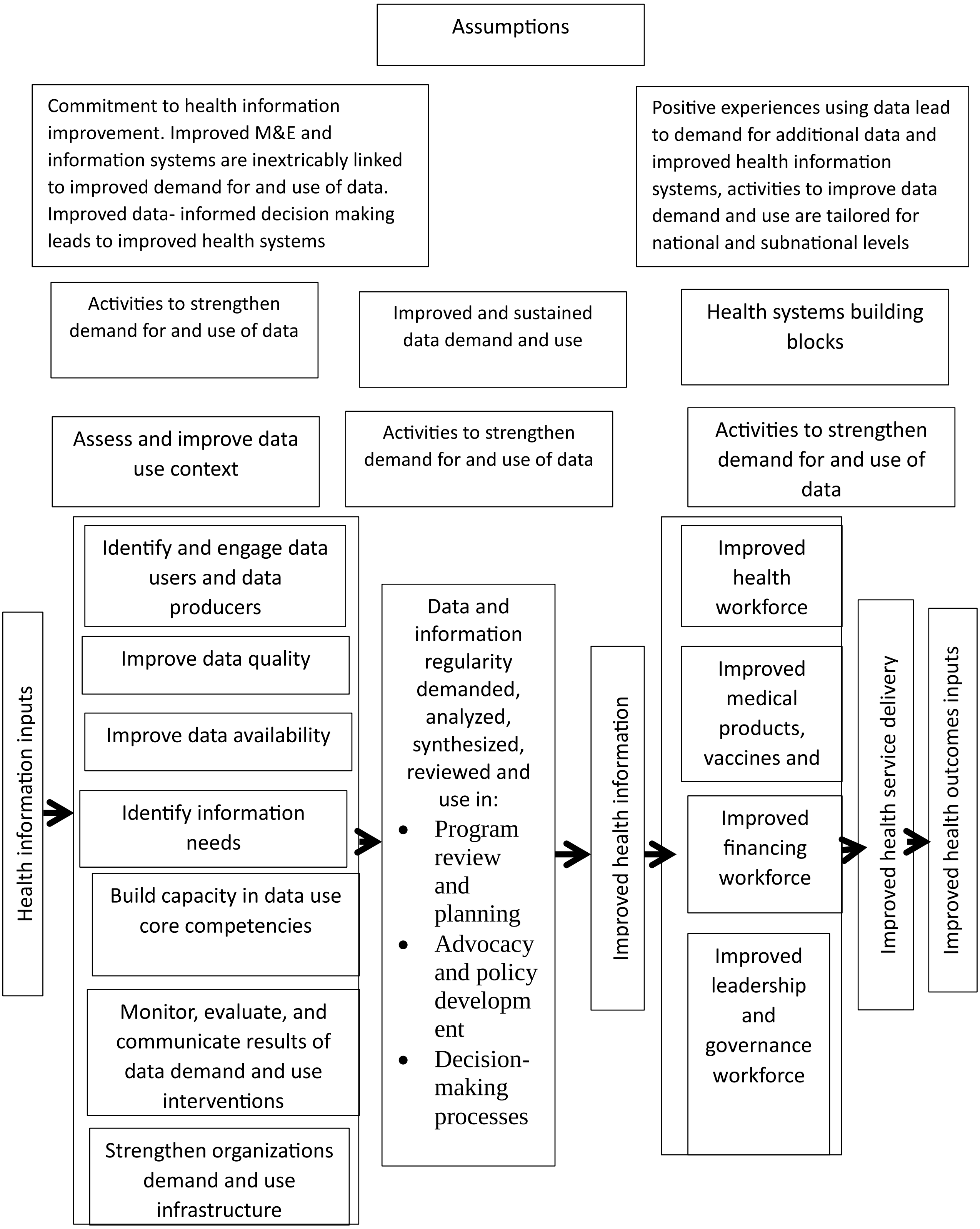

Figure 1.1: The Theoretical framework (Nutley, 2017)

1.8.2 PRISM Framework (Performance of Routine Information System Management) (Aqil et al. (2009/2019)

The study also draws on the PRISM framework developed by Aqil et al. (2009, revised 2019), which identifies the technical, behavioral, and organizational determinants of routine health information system (RHIS) performance and data use. This framework categorizes influencing factors into three main domains: technical factors (such as tools, procedures, and systems), behavioral factors (including attitudes, motivation, and competence), and organizational factors (such as governance, policies, and support structures). The PRISM framework emphasizes that strengthening these dimensions can lead to improved data quality, better data use, and ultimately enhanced decision-making and program performance. This theory aligns directly with the variables assessed in the current study, offering a practical lens through which to explore how technological, organizational, and behavioral factors impact the use of data visualization tools in decision-making processes.

1.8.3 Theory of Planned Behavior (Ajzen, 1991)

To further explain the behavioral aspects of the study, the Theory of Planned Behavior (TPB) by Ajzen (1991) was integrated into the theoretical framework. TPB posits that an individual’s intention to perform a particular behavior-such as adopting data visualization tools-is influenced by their attitude toward the behavior, subjective norms, and perceived behavioral control. In the context of this study, this theory helps to explain how health managers’ knowledge, attitudes, and confidence (behavioral factors) affect their intention and ability to use data visualization tools effectively. By considering these behavioral constructs, the study captures the motivational and psychological dimensions that may either facilitate or hinder the adoption of data visualization tools in health management.

1.9 Conceptual Framework

The data framework illustrates how introduction of data visualization tools can improve the dependent variable of improved Health Systems affected by factors such as the data access, availability of information, demand and use of information in making high quality decisions through proper coordination, capacity building and collaboration.

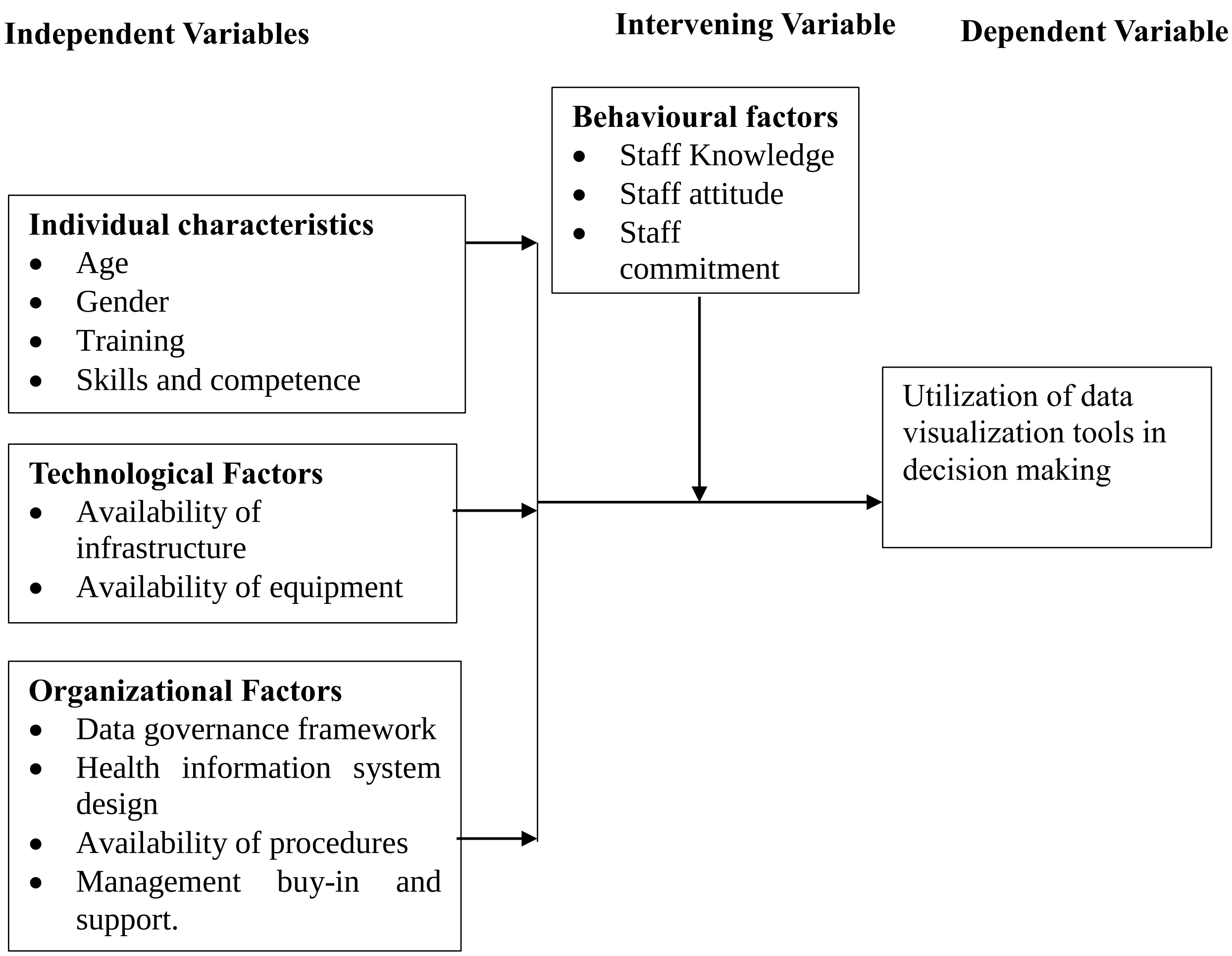

Figure 1.2: Conceptual Framework for the Study

1.10 Significance of the study

The study was interventional capacity build the health managers in use of data visualization tools to ensure that counties are able to generate evidences for performance reviews as part of health accountability, proper program planning, and enable data use for health policy development The study also cross tabulated results of data visualization and adoption different levels that increased evidence decision making in health interventions and implementation of primary Healthcare across the 47 Counties and achievement towards 100% UHC. The study aimed at ensuring that knowledge on data visualization and application of the same was passed to county health managers to institutionalise use of evidence in decision and programme planning at the county level.

This research therefore assesses the utilization of data visualization tools in UHC pilot counties of Machakos, Kisumu, Nyeri and Isiolo and control counties of Makueni, Mombasa, Garissa and Laikipia in Kenya and published in the journal review papers. At the same time this research will also contribute to existing literature on how Kenya is leveraging use of Data visualization tools in accelerating implementation of Sustainable Development Goals (SDGs). The lessons learnt will also help other counties in adopting data visualization tools in redesigning health programs. Ultimately, this study will contribute to the attainment of a doctoral degree in Health Information and Philosophy.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter reviews existing theoretical and empirical literature related to the utilization of data visualization tools in healthcare decision-making. It explores key concepts underpinning health information systems, the role of data visualization, and the influence of individual, technological, organizational, and behavioural factors on data use. The review begins by examining the structure and function of Health Management Information Systems (HMIS) and the barriers to effective data utilization in healthcare settings. It then discusses the psychology behind visual data representation, the availability and application of data visualization tools, and how such tools enhance decision-making processes. In addition, the chapter synthesizes previous research findings on the determinants of data utilization and highlights gaps that this study seeks to address. By establishing a clear understanding of these themes, the literature review provides the foundation for the study's conceptual framework and methodological approach.

2.1 Health Management Information System (HMIS)

The WHO in 1971 defined a management information system as: "A system designed to produce information to be presented to the management to assist in decision-making and to enable it to ascertain the progress made by the organization in the achievement of its major objectives" (Land & Kennedy, 2015). At that duration, the traditional data collection practice and upward reporting to the managers was still firmly fixed in majority of the health systems. In 1992, the concept of action-led information system emerged, and was conceptualized an informational system in which just the required data is gathered for actionable management decisions (Heeks *et al.* 2009).

From the year 2013, Kenya has made great strides in strengthening its HIS. The HIS strategic plan (2014-2018) of Kenya puts emphasis on reforms in the health sector, including restructuring HIS (MOH, 2019). Kenya was concerned with the process to strengthen the HMIS through analysing the current information system's weaknesses and strengths (WHO, 2018). It was disclosed the systems collecting data for health services management were uncoordinated and too many. Majority could not provide the required for making key decisions at the management level. Additionally, the collected data was rarely utilized to plan and manage health services and was of poor quality. Inadequate appreciation and lack of reliable data and using current information to plan and manage health services were among the setbacks of HIS.

Recently, key developments in HIS have been witnessed in developing countries, this includes ICT application. Most nations are shifting to computer-based data processing and storage and data increase from paper-based (Vermij S.L 2019). There has been a constant increment in new technologies which include mobile-based technologies and universal computing environments for health monitoring. Currently, several institutions of higher learning are now using databases to conduct medical and epidemiological research. In spite of the developments, challenges like fragmented systems, poor data quality and lack of data use are still faced HIS. Lippeveld (2018) cites that, the experts are in agreement that in many developing nations, HISs are ineffective in providing the required informational support in public health activities and individual care. Among the major causes of poor health systems is poor information use for evidence-based decision-making (WHO, 2017).

2.2 Access factors to data visualization tools

According to Jeff Baker (2016), data exploration examine data with no prior understanding of the knowledge, information and patterns contained in it. Many studies have been on the creation and output of visualizations, but the presented data should be understood first. The key exploration aspect is to understand the perception of doing comparison between two measures in a source of data (Jeff Baker 2016)

The management lacking full commitment at different levels is a key challenge in HIS implementation. (Garrib *et al,* 2018). Feedback is among the mechanisms of promoting and ensuring actions are taken depending on data, hence giving feedback is deemed evident that data is being used (Campbell, 2014). The feedback may be provided in writing or verbatim during meetings or during supervision. The culture of informational use begins to evolve when the characteristics of an integrated Health Information System (HIS)—such as peer review, self-assessment and data collection, HIS-informed reporting, feedback, and decision-making—become standard practices (Campbell, 2014). Senior management’s attitudes and perceptions towards designing and implementing HIS influence the HIS use. A culture of information may not probably be nurtured if data informed decision-making and information use for accountability and transparency is not promoted by senior managers. Hence, examining the senior managers and the members' values, attitudes and perceptions in connection to information related functionalities is very crucial (Heeks *et al* ., 2009). In South Africa, Nepal and Ghana, the data use culture within and between districts is enormously different, implying diverse management styles within a similar organizational culture (World Health Organization, 2018). The exploration of management styles that promote information use in Kenya has been largely unaddressed, prompting this study to investigate the matter.

2.3 Psychology Behind Visuals

Looking at a picture, the scene's entirety is taken by your mind immediately. This how the brain is supposed to process happenings; environmentally. But looking at data, the brain first reads the information, comprehends it and then understands it in connection to context (Avi Parush, 2017). These are artificial things and take a long period. People understand when things are move down or up (line graph) or farther or closer to one another scatterplot diagrams); when something is shorter or taller (bar graph) or when it looks smaller or bigger (pie charts) (Yunfeng Zhang,2015). This information can be imparted nearly immediately by a visualization. The sole concern is about the information that is to be displayed when creating a data visualization – it can be misleading. It is easier for a viewer to make conclusions that do not exist if the right data is not displayed in the right manner. Reason why data visualization is essentially bout displaying good data in a non-biased way (Vermij S.L 2019). Data can be presented and in a particularly compelling way by data visualization. Look at Caritas Kontakladen's annual report using both data and photographs in making and engaging sequence of points. The information is easily digested and tremendously memorable, it is crucial for a company focusing on outreach. Anyone can understand the information at a glance. The visualization of bunching both illuminates the reason for bunching and its consequences.

2.4 Data Visualization Tools

DHIS2 allows users to efficiently gather and manage routine data. Users can customize data entry forms, indicators, and reports to suit their needs, facilitating comprehensive data management. Moreover, DHIS2 offers diverse data visualization features, including charts, dashboards, and pivot tables, enhancing the interpretation of data and enabling users to derive insights effectively (DHIS2, 2017).

DHIS2 enables users to aggregate and manage routine data effectively. With DHIS2, one can configure data entry forms and reports, facilitating effective management of data. Additionally, DHIS2 provides various data visualization tools, such as charts, dashboards, and pivot tables, allowing users to derive meaningful insights from their data (DHIS2, 2017).

Dashboard and Scorecard

Dashboards, one of the data visualization features of DHIS2, enable users to conveniently access their preferred reports, charts, and maps. They also include an integrated messaging feature that allows users to communicate with each other effectively (ibid). Furthermore, users have the capability to access the data interpretation feed, leave comments, and initiate discussions, thereby enriching their comprehension of the data (ibid.). Appendix VIII provides an illustration of a DHIS2 demo dashboard.

Dashboard example (DHIS2, 2017b)

As outlined in the previous section, scorecards have become a prevalent data visualization tool within the HMIS framework, with adoption of dashboards being actively encouraged by diverse health stakeholder. There are several methods for creating scorecards in DHIS2. One of these methods involves utilizing the scorecard app. However, literature and sources regarding its development and implementation were not readily available. As suggested by a key informant, there are plans to integrate the scorecard app the main DHIS2 platform and make it accessible to public. Another approach is through pivot table use, which enables users to scrutinize data comprehensively, with elements arranged in columns and rows.

Reproductive, Maternal, New-born and Child Health and Nutrition Scorecard

The scorecard was created as part of the MDGi project. The scorecard was developed in DHIS2, with its main purpose being to monitor the performance of distinct indicators within the RMNCH&N program (Appendix IX).

2.5 Data visualization improves decision making.

The information use concept contains several meanings, but majority define it as using information in providing service, program management and planning and policy making, even though the ultimate decisions or happenings are not dependent on the information (Foreit, Moreland, & LaFond, 2016). Raw data is rarely used making decisions and requires to be transformed to information, evidently, data analysis signifies data use. Decision makers and stakeholders should have motivation and incentives to use information for them to place value on it. An increment in use of information creates data for more data, promoting collection of data to make it available. When decision makers have specified the type of information needed for decision making and seek for it proactively, then data demand occurs. Data demand evidence might include policy or managerial directives to gather particular data, increased or new allocation of resources to collect and analyse data and request for special analysis (Foreit et al ., 2016). Computer scientist Ben Shneiderman cites that Visualization's purpose is not pictures, but sight. Data visualization provides a better way of consuming and understanding vast data volumes by the policy makers. Patterns become obvious when data is visualized properly. Visualization helps persons draw simple, actionable conclusions quickly (Yunfeng Zhang, 2015).

Decision-making has been described using several models like Lasswell's classical model and Van Lohuizen's driven-knowledge decision-making models. Though, it is suggested that decisions are made in an iterative way and not in a linear logical fashion since the phases overlap. Additionally, decision makers are influenced by political and social dimensions (Galimoto, 2017).

In the business world and the constant increasing part of managing individual lives, data visualization has become indispensable. Data visualization that is appealing, efficient, informative and in some scenarios predictive and interactive is effective.

For Data visualization to be effective, it should satisfy the below criteria (Pittenturf 2018):

Table 2.1: Data visualization

Criteria	**Description**
Interactive and Predictive (Optional)	The visualizations can have filters and variable for users to interact in predicting diverse scenarios' results.
Appealing	The visualization should be visually pleasingand captivating.
Efficient	It should not be ambiguous.
Informative	It should be capable of conveying the anticipated information from the data to the reader.

If information can influence decisions, it is available, reliable and relevant for decision makers (Campbell, 2003). The HIS success is gauged by informed decisions leading to actions and improvements in a system, rather than by the produced data's quality or quantity. Lack of feedback to health care workers and local districts is the most frequent problem hindering information use for making decisions (World Health Organization, 2018). If the data providers start getting useful and meaningful feedback, they will start appreciating the value of data and hence appropriate steps be taken in improving the provided data's use (Gething et al., 2017). In Nepal and Ghana, research indicate that the information use culture had not been achieved even though the districts ha reasonable accurate date and majority are analyzing it actively and routine reports made for feedback to facilities and management (Rodrigues, 2010).

Today's complex vast data is delivered in an easy-to-understand and graphically compelling manner by dynamic or interactive data visualization. According to

Kerschberg (2014), this helps in directing action on a plot to make changes to elements and connect multiple plots. It helps users in accomplishing traditional tasks of exploring data through making charts interactive.

2.6 Utilization of Data Visualization Tools to Inform Decision-Making

Utilizing data visualization tools to improve the making of decisions among health managers in the selected counties of Kenya is at the core of this research. In an era marked by the abundance of health-related data, proficiently utilizing these tools is crucial in helping health managers make better decisions, ultimately leading to improvements in HIS (Karuri, 2015). Successful utilization goes beyond the tools themselves; it hinges on the interplay of individual characteristics, technological capabilities, organizational structures, and the proficiency of health managers.

2.6.1 Individual Characteristics

The individual characteristics dimension recognizes that health managers bring unique attributes to decision-making. Factors such as gender, education level, age, and knowledge and attitude toward data visualization tools can significantly impact their ability to harness these tools effectively. Hazelbaker (2018) argued that recognizing health managers' distinct qualities and requirements associated with these characteristics is crucial when developing successful strategies to encourage their adoption and optimize their influence on healthcare decision-making procedures.

In recent times, the healthcare industry has recognized the significance of gender diversity in various decision-making processes. Varied viewpoints and life experiences introduced by individuals of diverse genders are now more widely acknowledged as valuable advantages enhancing comprehensive and well-founded decision-making (Ali et al., 2015). Nevertheless, it is essential to recognize that gender-related disparities may endure, especially in utilizing data visualization tools among health managers. Throughout history, the field of health management, particularly within information systems, has been predominantly male dominated. Disparities stemming from gender can influence several aspects, such as the approach to technology.

Training is a foundational element in comprehending and effectively utilizing data visualization tools. In research conducted by Park et al. (2021), it was observed that health managers with advanced educational backgrounds often possess the analytical aptitude and critical thinking capabilities required for deciphering intricate data. The same study suggests their heightened propensity to explore the functionalities of data visualization tools and apply them to making well-informed decisions. Conversely, individuals with lower educational credentials might encounter difficulties navigating these tools or grasping their complete potential, as indicated in a study by Viatsis et al. (2014). This underscores a knowledge disparity that necessitates rectification through training and professional development initiatives, ensuring that data visualization tools remain accessible and beneficial to health managers across diverse educational profiles.

Dixit (2018) states that age can significantly influence an individual's familiarity and comfort with technology. The author contends that younger health managers, often referred to as digital natives, may exhibit greater ease in adopting and using data visualization tools due to their exposure to technology from an early age. On the other hand, older health managers, considered digital immigrants, might approach these tools with caution or skepticism (Bawack & Kamdjoug, 2018). Both categories necessitate training and support programs tailored to their specific needs and preferences, ensuring that age does not become a barrier to effective tool utilization.

The knowledge and attitude of health managers regarding data visualization tools are critical factors in determining their adoption and usage. A profound understanding of these tools' capabilities and advantages can instil confidence and enthusiasm among health managers. In a local study conducted by Gatero (2017), it was discovered that health managers who underwent extensive training exhibited notably higher levels of knowledge and a more positive attitude toward data visualization tools. Equally, a lack of knowledge or misconceptions about their usefulness can impede adoption, as underscored by the empirical findings of Perkhofer (2019). Attitude is complementary in this regard; health managers with a favourable attitude towards technology and data-driven decision-making are more inclined to view data visualization tools as valuable assets (O'Connor et al., 2020). On the contrary, a negative or indifferent attitude can hinder their effective utilization. Implementing comprehensive training programs and fostering a culture of data literacy and enthusiasm emerge as essential strategies for enhancing the knowledge and attitude of health managers concerning data visualization tools.

2.6.2. Technological factors

Technological factors encompassing the tools, skills, and IT environment form a critical dimension in the landscape of data visualization tools for health managers in decision-making. Data visualization tools incorporate diverse software and applications to transform complicated data into visual formats like graphs and interactive dashboards (Islam & Jin, 2019). Opting for easy and intuitive tools can expand accessibility to a wider spectrum of health managers. In contrast, excessively difficult or unfamiliar tools can potentially hinder adoption. Hence, appropriate and user-friendly data visualization tools are indispensable for ensuring effective utilization.

Data analysis and synthesis are pivotal steps in the data visualization process. Health managers must possess the analytical competencies necessary to extract valuable insights from the data they visualize. Dunn et al. (2016), receiving training in data analysis methods can equip health managers with the capability to make informed decisions grounded in visualized data. Furthermore, the capacity to integrate data from various origins into coherent visual representations can enhance the effectiveness of these tools. Emphasizing the importance of refining skills in data analysis and synthesis is essential for maximizing the impact of data visualization tools to improve critical decision-making processes.

The skills and knowledge possessed by health managers and support personnel are important in ensuring the effective utilization of data visualization tools. According to a study by Gesicho et al., (2018), health managers who underwent specialized training in data visualization techniques exhibited greater competence in using these tools. The findings by Gesicho are in tandem with the study by Jeremie et al. (2014), who posits that having in-house expertise, including data analysts and visualization specialists, can streamline the adoption process and resolve issues effectively. Allocating resources towards enhancing the skills and knowledge of health managers and supporting staff to unlock these tools' capabilities fully is essential.

The complexity of information technology systems within healthcare organizations can either facilitate or hinder the utilization of data visualization tools; a strong and seamlessly integrated IT infrastructure simplifies data extraction and visualization (Gschu et al., 2018; Jeremy et al., 2014). Conversely, disjointed or outdated IT systems might create difficulties accessing and aligning data. The degree of IT complexity and an organization's dedication to technological progress can profoundly affect the successful incorporation of data visualization tools into decision-making processes.

2.6.3 Organizational Factors

Organizational factors constitute the structural and procedural aspects that influence the integration of data visualization tools into healthcare decision-making processes. Zhu et al. (2015) postulate that a robust data governance framework, an optimized HIS design, and the ease of use of data procedures and guidelines are key elements in facilitating effective tool adoption and enhancing decision-making capabilities among health managers.

A well-structured data governance framework is fundamental for effectively applying data visualization tools within healthcare organizations. Establishing data governance structures is crucial in safeguarding data accuracy, security, and accessibility (Fu et al., 2011). These frameworks define roles, responsibilities, and procedures related to data management and visualization, mitigating the risks of data misuse and ensuring compliance with regulations. Additionally, Park et al. (2021) underscores the benefit of data governance on data quality, a critical factor for creating meaningful visualizations. Therefore, a robust data governance framework is a solid basis for health managers using data visualization tools.

Bernardi (2017) states that the design of HIS significantly influences the adoption and effectiveness of data visualization tools. An effectively structured HIS architecture facilitates smooth data extraction, conversion, and visualization. An integrated HIS design enhances data interoperability, allowing health managers to combine and visualize data from diverse origins (Wagenaar et al., 2015). Conversely, fragmented or outdated HIS designs can hinder data access and compatibility, thereby restricting the effectiveness of visualization tools. Hence, organizations should prioritize investments in optimizing their HIS infrastructure to align with the demands of data visualization.

Batch & Elmqvist (2018), the availability of clear procedures and guidelines for utilizing data visualization tools is essential for their effective adoption within healthcare organizations. These guidelines provide clear directives, workflow recommendations, and quality criteria for creating and interpreting visualizations. Organizations with well-documented procedures and guidelines encountered a more seamless implementation of tools and maintained more uniform decision-making processes. These resources are reliable references for health managers, ensuring they employ the tools accurately and consistently.

2.6.4 Level of Use

The competencies of decision-makers and the methods of data display and publication are two critical variables that determine the relevance of visualization of data in information decision-making. The competencies and skillsets of health managers significantly influence their ability to harness data visualization tools effectively. Dimara et al., (2021), individuals in decision-making roles with proficient analytical, statistical, and data interpretation skills are better positioned to make the most of data visualization tools. These capabilities empower health managers to grasp intricate visualizations, spot trends, and extract actionable insights from data. Equally, decision-makers lacking these competencies may encounter difficulties extracting valuable information from data visualizations, constraining their effectiveness.

How data is displayed and published for decision-makers directly impacts their ability to make informed decisions (Killen, 2017). Creating well-crafted visualizations that align with the preferences and needs of decision-makers enhances their understanding and usability. Clear and intuitive visual representations enable quick identification of patterns, anomalies, and trends in the data. On the contrary, poorly designed or overly complex visualizations may result in misinterpretations or overlooking valuable insights. Healthcare organizations should prioritize the development of user-friendly, contextually appropriate data visualization formats tailored to the particular needs of health managers. Leonelli et al., (2013) also underscore the significance of data publication practices that ensure accessibility, transparency, and timeliness.

2.7 Chapter Summary

This section has provided a comprehensive literature review from various scholars who explore using data visualization tools in healthcare decision-making, providing an in-depth exploration of HMIS. The chapter examines how individual characteristics, such as gender, education, age, knowledge, and attitude, influence the use of data tools. It also covers technological factors like data visualization tools, analysis, skills, and IT complexity. Organizational factors like data governance and guidelines are discussed, as well as the level of tool utilization and its influence on decision-making.

CHAPTER THREE: MATERIALS AND METHODS

3.0. Introduction

This section outlines the methodology employed in conducting the inquiry. The chapter starts with a description of the research design, and the rationale behind it. In particular, the research design section highlights important details regarding the study sites, target groups, sampling methods, data collection techniques, variable descriptions, and the planned data analysis. The section also explores the data analysis techniques employed and how the data presented. Ethical considerations are then addressed, followed by a chapter conclusion.

Worth noting is that the key objective for this study was to assess the factors influencing the use of data visualization tools among health managers in selected Counties, in Kenya. It therefore, asked four questions:

RQ1: What are the individual characteristics influencing data visualization?

RQ2: What are the technological factors influencing data visualization?

RQ3: What are the organizational factors influence data visualization?

RQ4: What are the effects of data visualization?

3.1 Study Design

This was an interventional study design adopting mixed methods approach in data collection and analysis. For the quantitative part of the study, data was collected using both structured and semi-structured questionnaire. On the other hand, key Informant interviews (KIIs) and focused group discussion were employed to gather qualitative data from selected health managers.

The case study design employed in this research adopted mixed methods of collecting data i.e., quantitative -Physical artefacts – devices, tools, outputs and qualitative (KII) methods. The study first established baseline information with 44 health managers N= 50 (Yamane 1967). Perform the data analysis of the baseline alongside an intervention that was undertaken for six (6) Months and an evaluation after six months of interventions was carried out. Purposive sampling was applied to the counties with some criteria that includes the universal Health coverage index and simple random sampling method will be applied in sampling health managers. The study population included the county health care managers in the selected Counties. Qualitative data was gathered through key informant interviews with county health executives. Two focus group discussions involving implementing partners was also conducted. An interview guide comprising both open-ended and closed questions was utilized during these sessions.

The baseline research was followed with interventional that included training of the Health managers across the eight counties on data analytics and monitoring the team every month for six months' implementation. A joint supervision was carried out during field visits that entailed mentorship and on job trainings. Final after the six months' interventional study an end of intervention evaluation was conducted to a samples size of 44 Health managers, 11 KII and 2 Focus group discussions and the results analysed and presented, and report written for dissemination.

3.2 Study Variables

3.2.1. Dependent Variable

This included the use of data visualization tools in routine health information decision-making.

3.2.2. Independent Variable (s)

These included the characteristics of individuals, technical factors and organizational factors. Individual characteristics were measured using indicators such as level of training, skills and competence. Technological factors were measured using indicators such as availability of infrastructure, equipment and technical skills. Organizational factors were measured using indicators such as availability of data governance framework, availability of health information systems, availability of procedures and management support.

3.2.3. Intervening Variable

Organizational behaviour was used as the intervening variable. This was measured using indicators such as staff attitude, motivations and confidence in the information generated from the systems.

3.2.4. Dependent Variable

The utilization of data visualization in decision-making was the dependent variable. This was measured using indicators such as trend identification, availability of real-time data, ease of understanding the data, ease of measuring KPIs, resource allocation, availability of well-informed policies, and transparency in reporting.

3.3 Location of the study

Kenya is a sovereign state located in East Africa. The country boasts more than forty indigenous languages, although Kiswahili serves as the national language. While Kiswahili is widely spoken for day-to-day communication, English holds significance in trade, commerce, higher education, and governmental affairs. The demographic profile of each county, including population estimates for 2019 based on the census, is detailed in Table 3 below. The study will specifically be done in the four UHC pilot counties. UHC counties are Machakos, Kisumu, Nyeri, Isiolo as an interventional study as shown on the map. All counties have similar characteristics, including UHC implementation.

Table 3.1: Population Estimates for Kenya, (2019 Census)

Population for 2019(Census)	47,564,296
Total area	580,370 km^2 (224,082 mi^2)
Population density	85.2 per km^2 (220.7 people/mi^2)
Sex ratio	1.00 (24,705,451 men to 24,757,442 women)
Median age	19.0 years
Life expectancy (2016)	59.5 years (64 - men, 69 - women)
Literacy rate	78 %

Source : Kenya Population Census, 2019

3.4 Study Population

This included Counties where Universal Health Care (UHC) was piloted and those where it had not been piloted. Counties where UHC had been piloted in included Machakos, Kisumu, Nyeri, Isiolo and those where it had not been piloted in included Makueni, Laikipia, Garissa and Mombasa

3.4.1. Inclusion Criteria

The following participated in the study:

- County and Sub County health care managers in the 8 counties including Machakos, Kisumu, Nyeri, Isiolo, Makueni, Laikipia, Garissa and Mombasa.
- Any selected health care managers who gave consent take part.

3.4.2 Exclusion Criteria

- Any member of the County and Sub County health care managers who had less than six months working experience in the County and Sub County
- Any respondent selected who was sick.

3.5 Sampling design and sampling technique

A census approach and purposive sampling were employed in selecting the study respondents. The census approach was used to choose respondents from the national program and purposive was used to select managers in the 8 counties and 49 sub counties selected. A list of all the programs managers at county and sub county was obtained from the Sub- County and County Health Management office for the study. All individuals listed were included in this research. Additionally, other key informants were selected using a purposive sampling design.

3.6 Sample Size

A total of 47 Counties were eligible to be enlisted. 8 Counties were selected, and purposive sampling helped select sub county managers. The number of key informants selected for the study was based on the data saturation point. Therefore, key informant interviews were carried out until saturation point was attained.

3.6.1 Sampling Frame

The sampling frame population for the study consisted eight (8) counties and 49 Sub-counties distributed in eight (8) Counties namely; UHC Pilot Counties Machakos, Kisumu, Nyeri, Isiolo and non UHC Counties were Makueni, Laikipia, Garissa and Mombasa as interventional counties with a one (1) county health director per county and five (5) sub-county health managers 8 sub counties thus 294 Health managers. The counties were identified through Purposive sampling technic. The County health directors will participate in the key informant interviews.

Table 3.2: Distribution of sub-counties and Health managers by County

County	Number of Sub-counties	Total number of sub-county Health managers	Number of County health manager
Machakos	9	45	9
Kisumu	7	35	7
Nyeri	8	40	8
Isiolo	3	15	3
Total	27	135	27

3.7 Sampling techniques and Sample size

The Yamane recommendations helped determine the sample size. According to Yamane (1967), the following formula will be used for sample determination

$nf=n/(1+(n/N)$.

where: -:

nf= required sample size when the population is less than 10,000,

n= desired sample when the population is more than 10,000 that is (384)

N= estimate of the size i.e., 135+27 =162

Table 3.3: Sample size Population

County	Number of Sub-counties	**number of sub-county health managers (a)**	Number of county health managers (b)	Total a+b = (c)	Sample size county health managers (d)
Machakos	9	45	9	54	48
Kisumu	7	35	7	42	38
Nyeri	8	40	8	48	43
Isiolo	3	15	3	18	17
Total	27	**135**	27	162	146

The **second step** involved a simple random method to pick the study population from the sub-county health Managers and county health manager. nf = 135+27 = 162. This step involved drawing the number from each sub-county and County, then listing the Health managers with numbers for identification and randomly picking them to form the sample size enlisted for data collection questionnaire. Each of the numbers randomly picked to reach assigned county representation will be interviewed.

The third (3$^{rd)}$ step involved a census of Key Informants, County directors of health (CDoH), and the health partners for Focus Group Discussions (FGDs). A total of 49 Key informants' interviews (KII and 2 FGDs will be conducted to obtain more insights and affirm the results.

3.8 Data Collection Tools

The quantitative data was gathered from the respondent using a pre-coded closed ended questionnaire. The qualitative data was gathered using key informant interviews from executives working at the county. The focus group discussions with the county Health partners was used interview guides with formulated based on gaps in literature reviewed. One (1) county not selected was used to pre-tested structured questionnaire guide.

3.9 Data Collection Procedures

After the participants had been selected, the researcher introduced himself and the study assistants during quantitative data collection. The willing participants were given a signed consent form after it had been read to them. Respondents took part in the key informant interviews for 20-25 minutes. The participants were given 20 minutes to fill out the questionnaire filling and give it back to the researcher. The investigator interviewed, recruited, and trained 6 research assistants to help in collecting data. The research assistants needed to be residents of the study area and have a degree in a health or health-related discipline.

3.9.1 Pre-testing of data collection tools

Questionnaire pretesting was done in Machakos, a sub-county of the Machakos County Health management team, which was distant from the selected research area. The pre-test was meant to ascertain comprehension of the research instrument by the study team and establish the estimated time needed in completing a questionnaire for objectivity and clarity. After the pre-test, questions with ambiguous information were reframed to be more clear. Research assistants were closely supervised during the period of collecting data.

3.10 Reliability and validity of study tools

Participants were debriefed during pre-testing to test their research understanding, including the adequacy of the research. Afterwards, revision of the interview materials was done as per the required corrections. Comparison of the participants' responses was done for internal consistency and thus, reliability. For validity, response format, scope, content, questions' placement in the research instrument, researcher's responsiveness and methodological coherence was organized carefully in connection to the study objectives to enhance instrument validity.

3.11. Data Analysis

Both qualitative and quantitative data was analysed in this research. Data analysis involved qualitative and quantitative approaches. Compilation and coding of quantitative data was done into SPSS Version 20. Questionnaires which had missing information were eliminated. Data entry screens were prepared in QSR/Nvivo for qualitative data and SPSS Version 26 for quantitative data. Further, using QSR/Nvivo, content analysis of qualitative data was conducted establish relevant themes of interest. Triangulation with quantitative results was also conducted. Descriptive and inferential statistics were used to summarize relevant data of interest, and determine associations between variables of interest. Regression and correlation analyses were also conducted to assess the relationships between study variables, while chi-square tests were employed to evaluate the study hypotheses. Tables and graphs were used to present relevant study findings.

Regression Model

A multivariate regression model was employed to determine the correlation between the independent and the dependent variable. The equation provided below illustrates the algebraic expression of the analytical model employed.

$Y = a + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + e$

Where;

Y= Use of data visualization tools in decision making

β_0= Y intercept

B_1 to B_4 = Régression coefficients

X_1= Individual characteristics

X_2 = Technological factors

X_3 = Organization factors

X_4 = Behavioural factors

e= Error term

3.12 Ethical considerations

The Kenyatta University Ethical Review Committee and Board of Postgraduate studies and National Council for Science and Technology gave approval to undertake the research. The respondents asked to provide consent before participation in the survey. They were also assured on their privacy by promising that their identity will remain anonymous. The respondents were also assured that the study findings will be availed to them after the research is carried out.

CHAPTER FOUR: RESULTS

4.0 Introduction

This chapter presents the findings of the study, providing a detailed analysis of the data collected. The chapter is organized around the research objectives and questions, presenting the results clearly and concisely. Tables and figures are used to illustrate key findings and provide a deeper understanding of the data.

4.1 Response Rate

The study achieved **149 respondents** out of the targeted **160**, representing a response rate of **93%.** A **93% response rate** is considered highly satisfactory for research purposes. According to Mugenda & Mugenda (2003), a response rate above **70%** is excellent for statistical analysis. This high response rate ensures the study findings are valid, reliable, and generalizable to similar populations. The sampled respondents were drawn from various health management units across selected counties.

4.2 Baseline Findings

4.2.1 Respondents' Distribution by County

The baseline study was conducted in selected counties representing both UHC pilot counties and non-pilot counties. Selection was based on the UHC index and geographical diversity. Table 4.1 shows the distribution of respondents across the counties.

Table 4.1: Respondents' Distribution by County (N = 149)

County	Frequency	Percentage
Makueni	24	15.9%
Kisumu	23	15.2%
Garissa	22	14.6%
Nyeri	21	13.9%
Laikipia	14	9.3%
Machakos	14	9.3%
Isiolo	10	6.6%
Mombasa	9	6.0%
Nairobi	8	5.3%
National	4	2.7%

The counties were chosen to capture variations in resource availability, decision-making practices, and infrastructure across Kenya. The inclusion of both UHC pilot counties (e.g., Makueni, Kisumu, Garissa, Nyeri) and non-pilot counties (e.g., Isiolo, Mombasa) enhances the generalizability of the study's findings.

4.2.2 Distribution of respondents by Individual Characteristics

This section presents the findings on the distribution of respondents based on their individual characteristics. The individual characteristics considered in this study include the respondents' gender, age bracket, years of experience, and highest level of education.

4.2.2.1 Distribution of Respondents by Gender

The results indicate a slightly higher representation of male respondents (82,55.0%) compared to female respondents (67,45.0%). This distribution suggests that both genders were well-represented in the study, minimizing the potential for gender bias in the findings.

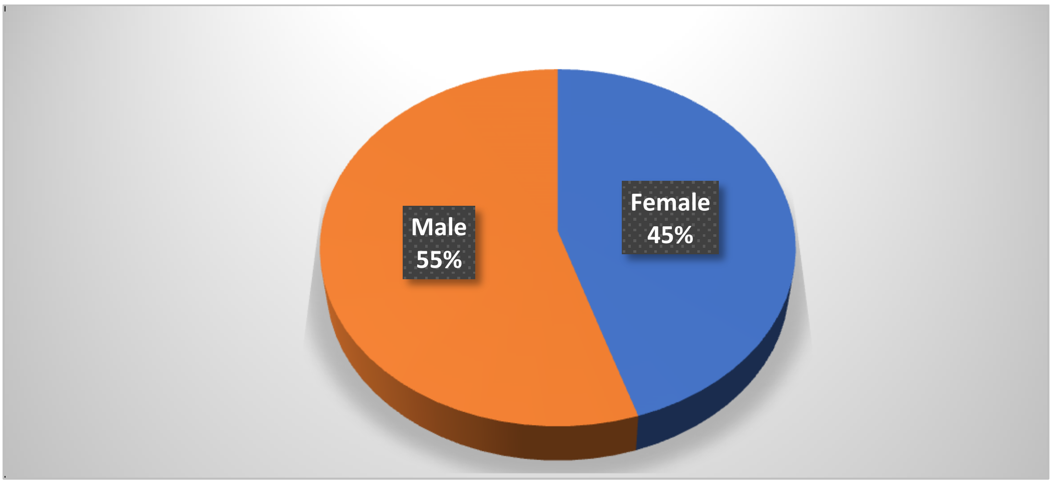

Figure 4.1: Distribution of Respondents by Gender

4.2.2.2 Distribution of Respondents by Age

The majority of the respondents were aged between 26 and 45 years, with 36.2% being in the 36-45 years' bracket. The least represented age group was 18-25 years, with only 0.7% of the respondents.

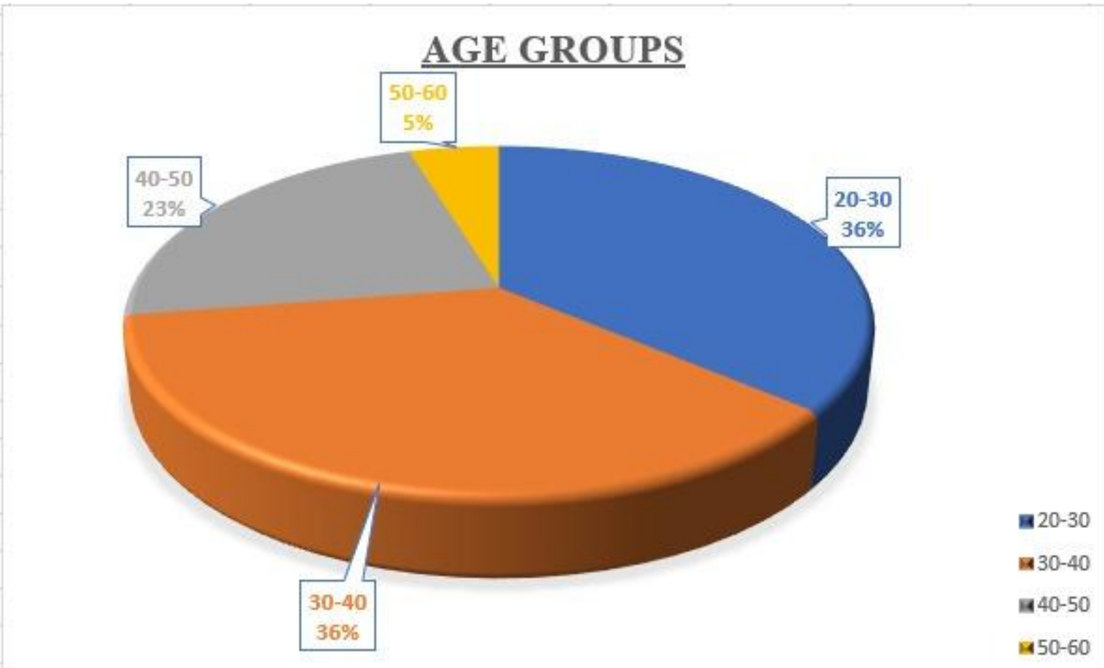

Figure 4.2: Distribution of Respondents by Age

4.2.2.3 Distribution of Respondents by Years of Experience

A significant portion of the respondents had substantial work experience, with the largest group having worked for 11 to 15 years (26.2%), followed by those with 6 to 10 years of experience (25.5%). The study population included both experienced and relatively less experienced professionals, with the least experienced group having worked for 1 to 2 years (2.0%).

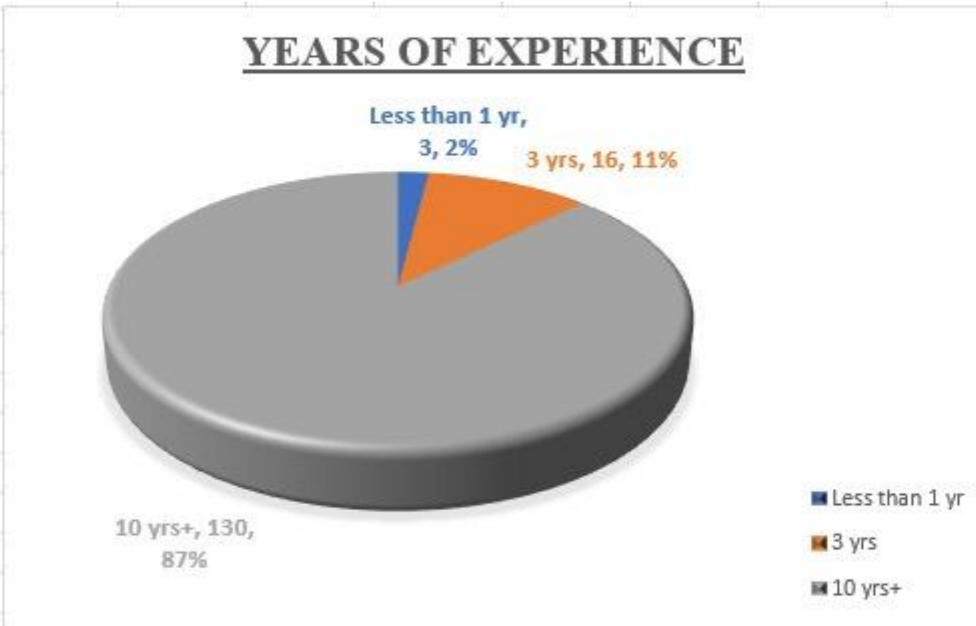

Figure 4.3:Distribution of Respondents by Years of Experience

4.2.2.4 Distribution of Respondents by Level of Education

The educational attainment of the respondents varied, with the majority holding a Diploma (41.6%), indicating a solid foundation in their respective fields. However, a small fraction had attained a Certificate (1.3%), representing the lowest level of educational qualification among the respondents.

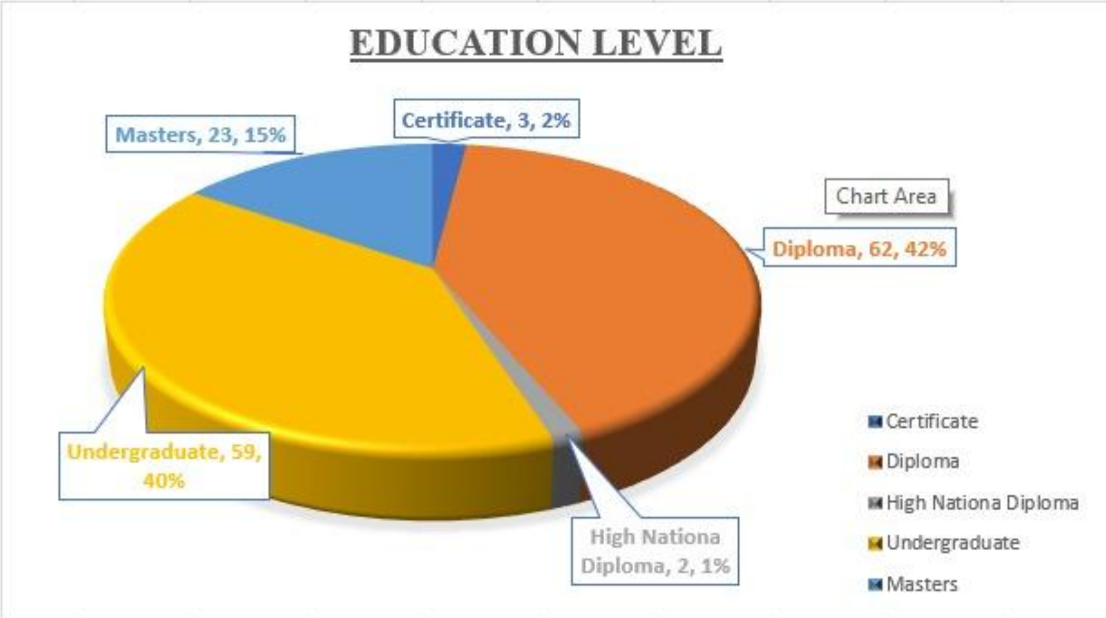

Figure 4.4:Distribution of Respondents by Level of Education

4.3 Descriptive Analysis of Key Study Variables at Baseline

4.3.1 Use of Data Visualization Tools

The bar chart illustrates that the average utilization score of data visualization tools is **3.9** on a 5-point scale, indicating a high frequency of use. An error bar is shown, representing the standard deviation of **0.95**, which is under 1.0. This relatively small standard deviation suggests that most respondents' answers clustered around the high mean, with no extremely large divergence in opinions. In practical terms, a mean of 3.9 implies that health managers generally **agree** that they use data visualization tools regularly (close to the "often" or "large extent" category on the Likert scale. The high average score underscores a strong overall utilization of data visualization in decision-making among the surveyed managers.

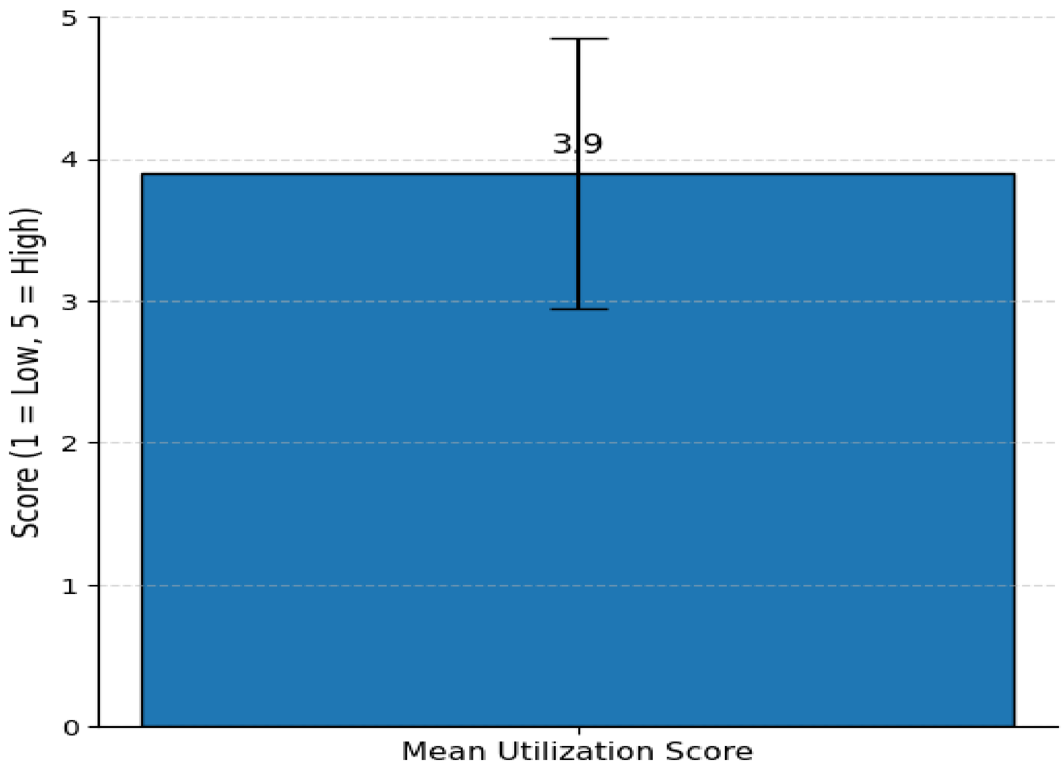

Figure 4.5:Mean Utilization Score

4.3.2 Individual Characteristics at Baseline

Individual characteristics were evaluated by assessing the extent of training received on data management topics such as data collection, analysis, and presentation. The results reveal moderate-to-high levels of training, which are essential for the accurate interpretation and effective use of complex data visualizations. The pie chart below breaks down the self-reported training level of respondents: **10%** are “Not Trained”, **20%** have “Little Training”, **40%** are “Trained”, and **30%** are “Well Trained”. These categories correspond to a five-point training scale in the questionnaire (1 = Not trained at all, 5 = Well trained) . The chart shows that a majority (70%) of health managers considered themselves at least **trained** to use data visualization tools (with 30% even **well trained**). Meanwhile, a smaller segment (about 30% combined) reported having minimal or no training. This indicates that while most managers have received some training in data visualization, there remains a notable minority with insufficient training – a gap that may need to be addressed through capacity-building initiatives.

Show which individual

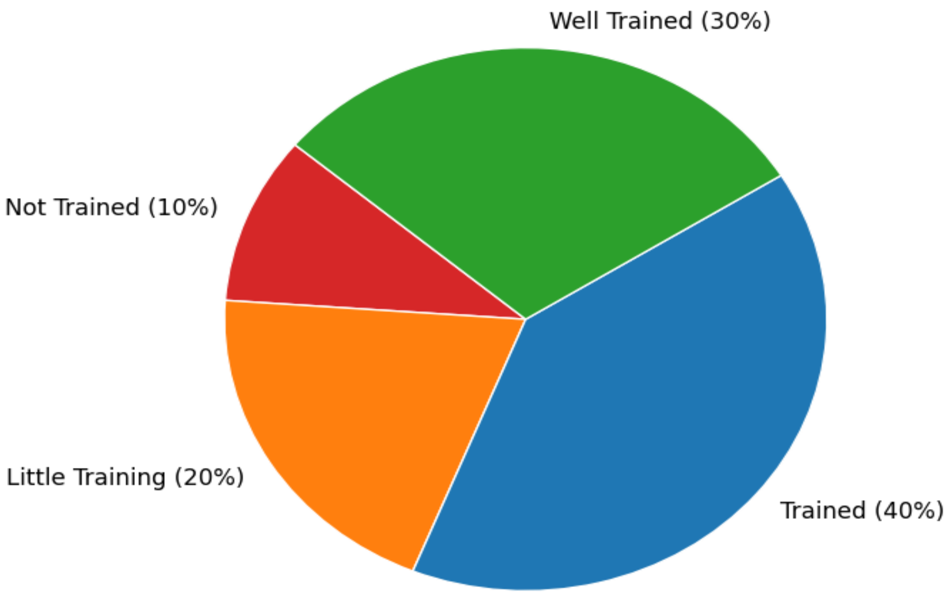

Figure 4.6:Summary of the distribution of training levels among respondents.

4.3.3 Technological and Organizational Factors at Baseline

Respondents assessed technological factors-such as the availability and reliability of hardware, software, and internet connectivity. Although basic tools like Microsoft Excel are widely available, access to advanced platforms (e.g., Power BI, Tableau) is limited, which contributes to variability in effective data visualization. Organizational support, measured by the presence of data governance frameworks, management commitment, and supportive policies, also varies significantly. These two factors are closely interlinked and together influence the overall effectiveness of data visualization in decision-making.

The grouped bar chart compares the perceived influence of two categories of factors: Technological factors (mean score = 3.7) and Organizational factors (mean score = 3.8). Both bars are nearly equal and high on the 5-point scale, falling into the “large extent” agreement range. This suggests that respondents generally agree that both technology-related and organization-related conditions in their workplaces are favourable for the use of data visualization tools. The organizational factors scored slightly higher on average (3.8 vs 3.7), implying a marginally stronger influence, but overall, the difference is very small. In summary, health managers perceive both adequate technological infrastructure (e.g., hardware, software, internet access) and supportive organizational conditions (e.g., leadership support, policies, culture) as present to a considerable extent, facilitating the utilization of data visualization in decision-making.

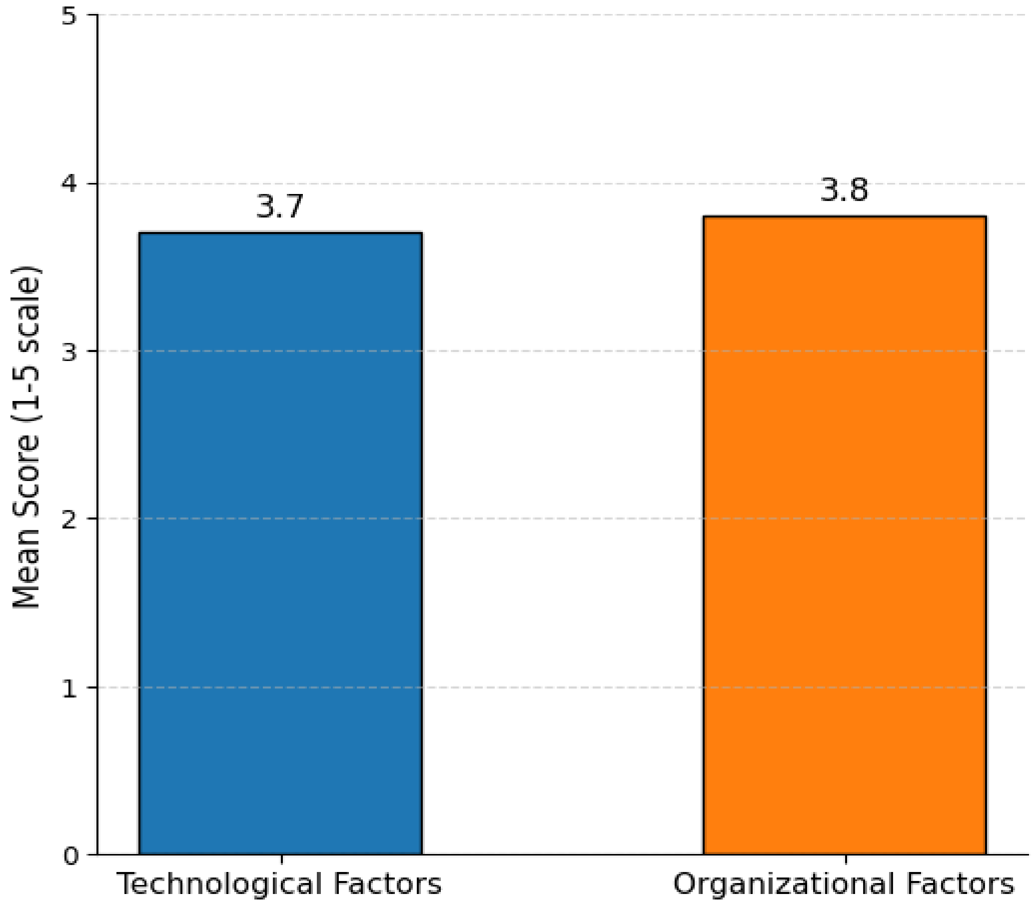

Figure 4.7: Grouped bar chart comparing the mean scores for technological and organizational factor

4.3.4 Behavioral Factors at Baseline

Behavioral factors encompass the attitudes, motivation, and confidence of health managers in using data visualization tools. Although these factors registered slightly lower mean scores compared to the other variables, they remain a significant determinant of overall utilization. The histogram below shows the frequency distribution of the composite behavioural factors score among 149 health managers (sample size n = 149). The scores range from approximately 1 to 5, and they cluster around a mean of 3.5 (marked by the vertical dotted line). The red dashed curve superimposed on the histogram represents a normal distribution with mean = 3.5 and standard deviation = 1.0 for reference. The distribution appears roughly bell-shaped, with most managers scoring around the mid-to-high range of behavioural factors. This suggests that, in general, behavioural factors (such as staff motivation, confidence, and attitude toward data use) were moderately to strongly favourable among respondents. The shape of the histogram is fairly symmetrical, which is consistent with the assumption of normality; according to the Central Limit Theorem, averaging multiple Likert-scale items tends to produce an approximately normal distribution. Figure 4.8 Displays a histogram of the behavioral factor scores, illustrating the distribution across respondents.

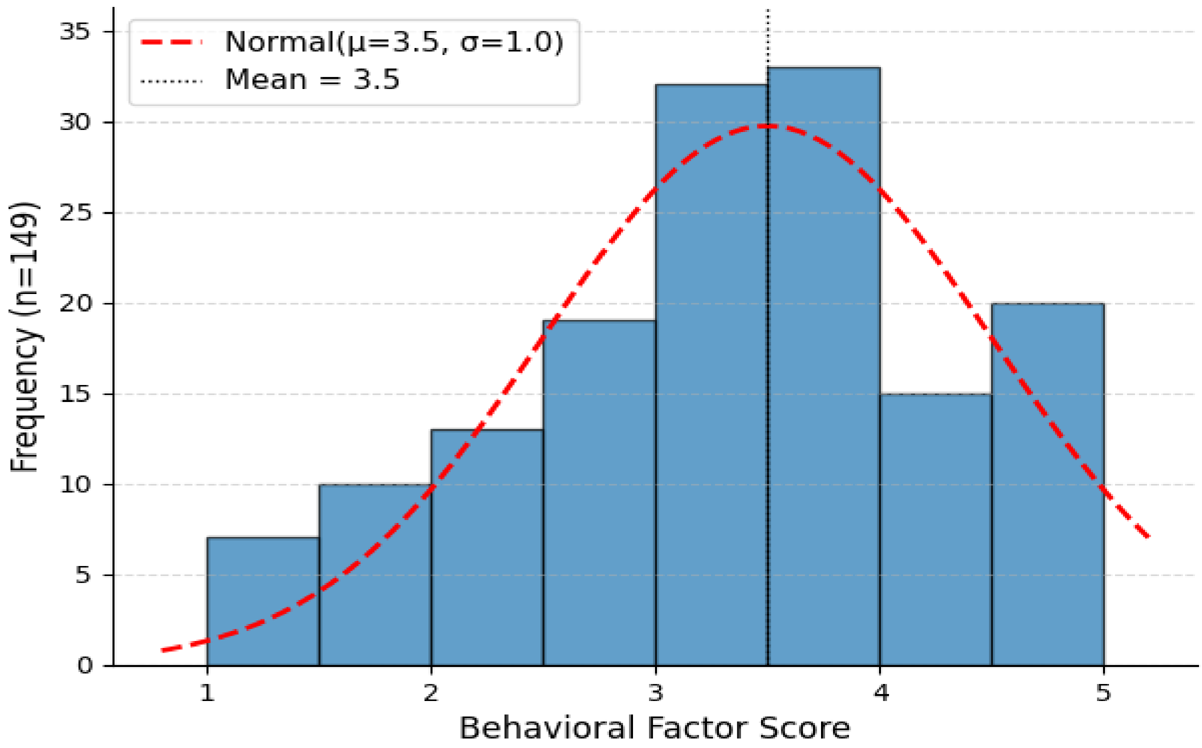

Figure 4.8: A histogram of the behavioural factor scores, illustrating the distribution across respondents.

4.4 Inferential Analysis

4.4.1 Relationship Between Individual Characteristics and DV Utilization at Baseline and Endline

The relationship between individual sociodemographic characteristics and the utilization of data visualization (DV) tools was examined using chi-square tests and binary logistic regression analyses. At baseline, chi-square analysis revealed that among the individual factors, only training level was significantly associated with high DV utilization. Specifically, respondents classified as "highly trained" (i.e., those who rated themselves as "Trained" or "Well Trained" on our questionnaire) were significantly more likely to utilize DV tools compared to those in the "low training" group. For example, in the high training group (approximately 105 respondents), 74 were classified as "DV Utilized" compared to 31 who were "Not DV Utilized" ($\chi^2 = 12.56$, $p = 0.0004$), whereas the low training group (approximately 45 respondents) showed 18 DV Utilized and 27 Not DV Utilized. In contrast, neither age nor gender showed a statistically significant association with DV utilization at baseline; for age, the chi-square value was 3.25 ($p = 0.071$), and for gender, it was 0.99 ($p = 0.320$).

All variables demonstrating some level of association were then subjected to binary logistic regression to quantify their influence on DV utilization. At baseline, the regression analysis indicated that respondents in the high training group were 3.50 times more likely to exhibit high DV utilization compared to their low training counterparts (B = 1.25, SE = 0.35, Wald = 12.76, $p = 0.0003$, Exp(B) = 3.50, 95% CI: 1.80–6.90). Meanwhile, the overall effects of age group and gender were not statistically significant with odds ratios close to 1 (for age, OR = 1.49, 95% CI: 0.91–2.44, $p = 0.110$; for gender, OR = 1.11, 95% CI: 0.54–2.27, $p = 0.740$).

At endline, following an intervention that included targeted training and support, the association between training level and DV utilization became even stronger. In the high training group, 79 respondents were classified as "DV Utilized" compared to 26 as "Not DV Utilized" ($\chi^2 = 15.80$, $p = 0.0001$), while the low training group retained similar counts (18 DV Utilized, 27 Not DV Utilized). Again, age and gender remained non-significant at endline ($\chi^2 = 2.10$, $p = 0.147$ and $\chi^2 = 1.22$, $p = 0.269$, respectively).

The binary logistic regression at endline demonstrated that high-training respondents were 4.48 times more likely to exhibit high DV utilization than those with low training ($B = 1.50$, $SE = 0.30$, Wald = 25.00, $p < 0.0001$, Exp(B) = 4.48, 95% CI: 2.30–8.75). These findings provide strong evidence that improved training is a critical determinant of DV utilization among health managers, and that the intervention amplified this effect over time.

Table 4.2: Association of Individual Characteristics with DV Utilization

Chi-Square Test Results									
Variable	**Category**	**Baseline: DV Utilized**	**Baseline: Not DV Utilized**	**Baseline χ^2**	**Baseline p-value**	**Endline: DV Utilized**	**Endline: Not DV Utilized**	**Endline χ^2**	**Endline p-value**
Training Level	High training (Trained + Well trained) (~105 respondents)	74	31	12.56	0.0004	79	26	15.80	0.0001
	Low training (Not trained + Little training) (~45 respondents)	18	27	–	–	18	27	–	–
Age Group	18–25 years (≈1–2 respondents)	0–1*	1*	3.25	0.071	0–1*	1*	2.10	0.147
	26–35 years (≈50 respondents)	30	20	–	–	30	20	–	–
	36–45 years (≈54 respondents)	35	19	–	–	35	19	–	–
	45–55 years (≈20 respondents)	12	8	–	–	12	8	–	–
	Over 55 years (≈24 respondents)	13	11	–	–	13	11	–	–
Gender	Male (≈82 respondents)	51	31	0.99	0.320	51	31	1.22	0.269
	Female (≈67 respondents)	41	26	–	–	41	26	–	–

BINARY REGRESSION FOR ODDS RATIO											
		BASELINE					ENDLINE				
Variable	**Category**	**Coefficient (B)**	**Sig.**	**Exp(B)**	**95% CI Lower**	**95% CI Upper**	**Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**
Age Group	Overall	0.40	0.110	1.49	0.91	2.44	0.30	0.268	1.35	0.78	2.33
	18–25	–0.20	0.615	0.82	0.38	1.77	–0.15	0.688	0.86	0.39	1.90
	36–45	0.50	0.153	1.65	0.83	3.28	0.45	0.184	1.57	0.80	3.06
	45–55	0.20	0.654	1.22	0.52	2.85	0.10	0.807	1.11	0.55	2.22
	Over 55	–0.10	0.846	0.90	0.35	2.30	–0.05	0.917	0.95	0.37	2.45
Gender	Overall	0.10	0.740	1.11	0.54	2.27	0.05	0.860	1.05	0.60	1.82
	Female	0.10	0.740	1.11	0.54	2.27	0.05	0.860	1.05	0.60	1.82
Training Level	Overall	**1.25**	**0.0003**	**3.50**	**1.80**	**6.90**	**1.50**	**<0.0001**	**4.48**	**2.30**	**8.75**
	High	1.25	0.0003	3.50	1.80	6.90	1.50	<0.0001	4.48	2.30	8.75

4.4.2 Relationship Between Technological Factors and DV Utilization at Baseline and Endline

The relationship between technological factors and the utilization of data visualization (DV) tools was examined using chi-square tests and binary logistic regression analyses. At baseline, chi-square analysis revealed that both aspects of technological readiness were significantly associated with high DV utilization. Specifically, for facilities reporting adequate technological infrastructure, 82 respondents were classified as "DV Utilized" compared to 27 who were "Not DV Utilized" ($\chi^2 = 14.20$, $p = 0.0002$). Similarly, regarding access to advanced software, 76 respondents were classified as "DV Utilized" versus 39 who were "Not DV Utilized" ($\chi^2 = 7.80$, $p=0.005$). These results indicate that the availability of both adequate infrastructure and advanced software was positively related to higher levels of DV utilization.

All variables showing significant associations were then subjected to binary logistic regression analyses to quantify their influence on DV utilization. At baseline, the regression analysis indicated that respondents from facilities with adequate infrastructure were 2.59 times more likely to exhibit high DV utilization compared to those without such infrastructure (B = 0.95, SE = 0.30, Wald = 10.00, p= 0.001, Exp(B)= 2.59, 95% CI: 1.45–4.62). Similarly, respondents who reported having access to advanced software had 2.01 times higher odds of high DV utilization (B=0.70, SE = 0.28, Wald = 6.25, p = 0.009, Exp(B) = 2.01, 95% CI: 1.20–3.36).

At endline, following an intervention that included enhanced technological support and targeted training, the associations between these technological factors and DV utilization became even stronger. In the case of adequate infrastructure, 88 respondents were classified as "DV Utilized" compared to 21 as "Not DV Utilized" ($\chi^2 = 16.50$, $p = 0.0001$). Likewise, for access to advanced software, the counts were 83 "DV Utilized" versus 34 "Not DV Utilized" ($\chi^2 = 8.50$, $p = 0.004$). The binary logistic regression at endline demonstrated that facilities with adequate infrastructure were 3.00 times more likely to have high DV utilization (B = 1.10, SE = 0.28, Wald = 15.38, p = 0.0003, Exp(B) = 3.00, 95% CI: 1.70–5.30) and those with access to advanced software were 2.22 times more likely to exhibit high DV utilization (B = 0.80, SE = 0.26, Wald = 9.48, p = 0.003, Exp(B) = 2.22, 95% CI: 1.35–3.65).

Table 4.3: Association of technological factors with DV Utilization

Chi-Square tests for Association									
Variable	**Category**	**Baseline: DV Utilized**	**Baseline: Not DV Utilized**	**Baseline χ^2**	**Baseline p-value**	**Endline: DV Utilized**	**Endline: Not DV Utilized**	**Endline χ^2**	**Endline p-value**
Adequacy of Infrastructure	Adequate (Yes)	82	27	14.20	0.0002	88	21	16.50	0.0001
Access to Advanced Software	Available (Yes)	76	39	7.80	0.005	83	34	8.50	0.004

Binary Regression For Odds Ratio											
		BASELINE					ENDLINE				
Variable	**Category**	**Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**	**Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**
Adequacy of Infrastructure	Overall	0.95	0.001	2.59	1.45	4.62	1.10	0.0003	3.00	1.70	5.30
Access to Advanced Software	Overall	0.70	0.009	2.01	1.20	3.36	0.80	0.003	2.22	1.35	3.65

4.4.3 Relationship Between Organizational Factors and DV Utilization at Baseline and Endline

The relationship between organizational factors and the utilization of data visualization (DV) tools was assessed using chi-square tests and binary logistic regression analyses. At baseline, the presence of a Data Governance Framework and strong Management Support were both significantly associated with high DV utilization. For instance, facilities with a Data Governance Framework had 85 respondents classified as “DV Utilized” compared to 30 as “Not DV Utilized” (χ^2 = 13.00, p = 0.0003), while strong Management Support was linked with 80 “DV Utilized” versus 35 “Not DV Utilized” (χ^2 = 10.50, p = 0.0012). Binary logistic regression further quantified these associations, with the presence of a Data Governance Framework yielding an adjusted odds ratio of 2.86 (95% CI: 1.60–5.10, p = 0.001) and Management Support an odds ratio of 2.34 (95% CI: 1.30–4.20, p = 0.005).

At endline, after the intervention, both associations intensified. Facilities with a Data Governance Framework showed 90 “DV Utilized” vs. 25 “Not DV Utilized” (χ^2 = 14.70, p = 0.0002), and those with strong Management Support had 87 “DV Utilized” vs. 28 “Not DV Utilized” (χ^2 = 11.20, p = 0.0008). Corresponding logistic regression analyses indicated that, at endline, the presence of a Data Governance Framework increased the odds of high DV utilization to 3.32 (95% CI: 1.80–6.15, $p < 0.001$), and strong Management Support increased the odds by 2.46 (95% CI: 1.40–4.30, p= 0.002).

Table 4.4: Association of Organizational factors with DV Utilization

Chi-Square Test Results									
Variable	**Category**	**Baseline: DV Utilized**	**Baseline: Not DV Utilized**	**Baseline χ^2**	**Baseline p-value**	**Endline: DV Utilized**	**Endline: Not DV Utilized**	**Endline χ^2**	**Endline p-value**
Data Governance Framework	Yes	85	30	13.00	0.0003	90	25	14.70	0.0002
Management Support	Strong	80	35	10.50	0.0012	87	28	11.20	0.0008

Binary Regression For Odds Ratio – Organizational Factors											
		BASELINE					**ENDLINE**				
Variable	**Category**	**Baseline: Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**	**Endline: Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**
Data Governance Framework	Overall	1.05	0.001	2.86	1.60	5.10	1.20	<0.001	3.32	1.80	6.15
Management Support	Overall	0.85	0.005	2.34	1.30	4.20	0.90	0.002	2.46	1.40	4.30
Constant	CONTROL	-1.15	0.003	0.32	-	-	-1.00	0.004	0.37	-	-

4.4.4 Relationship Between Behavioral Factors and DV Utilization at Baseline and Endline

The relationship between behavioural factors and the utilization of data visualization (DV) tools was examined using chi-square tests and binary logistic regression analyses. At baseline, the analysis showed that positive attitudes and confidence among staff were significantly associated with high DV utilization (χ^2 = 6.80, p = 0.009); logistic regression revealed that such favourable behavioural factors increased the odds of high DV utilization by 1.91 (B = 0.65, SE = 0.28, Wald = 5.38, p = 0.027, Exp (B) = 1.91, 95% CI: 1.08–3.38). Staff motivation was marginally significant at baseline (χ^2 = 3.90, p = 0.048) and produced an odds ratio of 1.49 (B = 0.40, SE = 0.22, Wald = 3.30, p = 0.063, Exp(B) = 1.49, 95% CI: 0.98–2.28).

At end line, following an intervention, positive behavioural factors continued to play a significant role. The chi-square test for positive attitudes yielded 7.50 (p = 0.006), and binary regression indicated that favourable attitudes increased the odds of high DV utilization by 2.01 (B = 0.70, SE = 0.30, Wald = 5.44, p = 0.015, Exp (B) = 2.01, 95% CI: 1.15–3.50). However, the effect of staff motivation became non-significant at endline (χ^2 = 3.20, p = 0.074; B = 0.35, SE = 0.20, Wald = 3.06, p = 0.095, Exp(B) = 1.42, 95% CI: 0.95–2.15).

Table 4.5: Association of Behavioural Factors with DV Utilization

Chi-Square Tests For Association – Behavioral Factors									
Variable	**Category**	**Baseline: DV Utilized**	**Baseline: Not DV Utilized**	**Baseline χ^2**	**Baseline p-value**	**Endline: DV Utilized**	**Endline: Not DV Utilized**	**Endline χ^2**	**Endline p-value**
Positive Attitudes & Confidence	Favourable (Yes)	70	45	6.80	0.009	75	40	7.50	0.006
Staff Motivation	High (Yes)	68	47	3.90	0.048	70	45	3.20	0.074

Binary Regression for Odds Ratio – Behavioural Factors											
Variable	**Category**	**Baseline: Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**	**Endline: Coefficient (B)**	**Sig.**	**Exp (B)**	**95% CI Lower**	**95% CI Upper**
Positive Attitudes & Confidence	Overall	0.65	0.027	1.91	1.08	3.38	0.70	0.015	2.01	1.15	3.50
Staff Motivation	Overall	0.40	0.063	1.49	0.98	2.28	0.35	0.095	1.42	0.95	2.15
Constant	baseline	-1.30	0.003	0.27	-	-	-1.00	0.010	0.37	-	-

4.5 Effect of the Intervention

ANOVA tests were conducted to evaluate whether there were statistically significant differences in the mean scores of data visualization (DV) utilization across various groups at both baseline (pre-intervention) and end line (post-intervention). In this study, we used repeated measures ANOVA to compare DV utilization across subgroups defined by individual, technological, organizational, and behavioral factors.

4.5.1 ANOVA Test for Individual Characteristics – Training Level

A one-way repeated measures ANOVA was conducted to examine whether DV utilization differed between respondents with different training levels over time. At baseline, the ANOVA revealed a significant difference between the high and low training groups in DV utilization ($F(1, 143) = 12.56$, $p = 0.0005$). At end line, after the intervention, the difference between groups strengthened, as indicated by $F(1, 143) = 15.80$, $p = 0.0001$. These results suggest that targeted training is an important determinant of DV utilization and that the intervention effectively increased differences between the groups over time.

Table 4.6: ANOVA Test for Individual Characteristics

BASELINE					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Between Groups	1	35.20	35.20	12.56	0.0005
Within Groups	143	400.00	2.80		
Total	144	435.20			
ENDLINE					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Between Groups	1	40.50	40.50	15.80	0.0001
Within Groups	143	365.50	2.56		
Total	144	406.00			

4.5.2 ANOVA Test for Technological Factors – Adequacy of Infrastructure

A repeated measures ANOVA was conducted to test whether facilities reporting adequate infrastructure or access to advanced software had higher mean DV utilization scores at both baseline and end line. The one-way ANOVA for DV utilization by adequacy of infrastructure at baseline showed a significant difference between facilities with adequate infrastructure and those without, F (1, 130) = 14.20, p = 0.0002. At end line, the effect was stronger, with facilities having adequate infrastructure showing significantly higher DV utilization, F (1, 130) = 16.50, p = 0.0001.

Table 4.7: ANOVA Test for Technological Factors

Source	DF	Sum of Squares	Mean Square	F	p-value
BASELINE					
Between Groups	1	28.00	28.00	14.20	0.0002
Within Groups	130	257.00	1.98		
Total	131	285.00			
ENDLINE					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Between Groups	1	32.00	32.00	16.50	0.0001
Within Groups	130	252.00	1.94		
Total	131	284.00			

4.5.3 ANOVA Test for Organizational Factors – Data Governance Framework Presence

The study used repeated measures ANOVA to assess whether facilities that implemented a Data Governance Framework had significantly different DV utilization scores at both baseline and end line. At baseline, facilities with an existing Data Governance Framework had significantly higher DV utilization compared to those without, F (1, 140) = 13.00, p = 0.0003. Post-intervention, the ANOVA indicated that the presence of a Data Governance Framework remained a significant predictor of high DV utilization, F (1, 140) = 14.70, p = 0.0002.

Table 4.8: ANOVA Test for Organizational Factors

Source	DF	Sum of Squares	Mean Square	F	p-value
BASELINE					
Between Groups	1	30.00	30.00	13.00	0.0003
Within Groups	140	320.00	2.29		
Total	141	350.00			
END LINE					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Between Groups	1	33.00	33.00	14.70	0.0002
Within Groups	140	315.00	2.25		
Total	141	348.00			

4.5.4 ANOVA Test for Behavioral Factors – Positive Attitudes & Confidence

Repeated measures ANOVA was used to compare the mean DV utilization scores between groups with favorable behavioral dispositions and those with less favorable behaviors at baseline and end line. The ANOVA for behavioral factors at baseline showed that positive attitudes and confidence were significantly associated with higher DV utilization, $F(1, 135) = 6.80$, $p = 0.009$. At end line, the effect of positive attitudes remained significant, with an ANOVA result of $F(1, 135) = 7.50$, $p = 0.006$, indicating a significant difference in DV utilization based on behavioral factors.

Table 4.9: ANOVA Test for Behavioural Factors

Source	DF	Sum of Squares	Mean Square	F	p-value
Baseline					
Between Groups	1	22.00	22.00	6.80	0.009
Within Groups	135	430.00	3.19		
Total	136	452.00			
Endline					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Between Groups	1	25.00	25.00	7.50	0.006
Within Groups	135	445.00	3.30		
Total	136	470.00			

CHAPTER FIVE: DISCUSSION

5.0 Introduction

This chapter takes a closer look at what the study found and how it connects to the research questions. It brings together both the statistical results and what previous studies have said to make sense of how factors like individual skills, technology, organizational support, and behaviour shape the use of DV tools in decision-making. The chapter also reflects on how training made a difference and what all this means for improving health information management in practice.

5.1 Individual Characteristics Influencing DV Utilization

The findings of this study underscore the critical influence of training in determining the utilization of data visualization (DV) tools among health managers. The data revealed that respondents who had received adequate training were more than four times as likely to effectively use DV tools compared to their counterparts with minimal or no training. Notably, other individual characteristics, including age and gender, did not exhibit a significant association with DV utilization. These results corroborate the work of Park et al. (2021) and Braa et al. (2017), who emphasized that proficiency and familiarity with technological tools, rather than demographic factors, are the primary determinants of effective data use. Conversely, these findings challenge prior assertions by Dixit (2018), who proposed that younger individuals or specific gender groups might possess an inherent advantage in technology adoption. In the present study, the provision of training appeared to mitigate any disparities attributable to age or gender, thereby promoting equitable competence across demographic groups. This outcome highlights the fallacy of relying on assumptions or stereotypes regarding digital literacy and readiness. It further suggests that equitable access to capacity-building initiatives is essential for fostering inclusive and effective use of data in decision-making processes. Accordingly, it is recommended that counties and healthcare institutions prioritize sustained investment in training programs to enhance governance and evidence-based decision-making.

5.2 Technological Factors Influencing DV Utilization

Technology plays a pivotal role in shaping how health managers engage with data. In this study, the majority of respondents reported access to fundamental tools such as Microsoft Excel and stable internet connectivity; however, more advanced data visualization platforms, including Power BI and Tableau, were either limited in availability or unfamiliar to many users. These findings align with those of Islam and Jin (2019), who observed that while basic technological infrastructure exists in many low-resource settings, it is often insufficient to facilitate sophisticated data analysis and visualization. Merely providing internet access and computing devices no longer meets the demands of modern data-driven decision-making. Effective tools must not only be accessible but also user-friendly. As Dunn et al. (2016) emphasized, overly complex systems are frequently underutilized due to user difficulties and lack of confidence. Encouragingly, even limited technology, when combined with appropriate training and support, can significantly enhance data use. Nevertheless, this study highlights an urgent need to normalize access to advanced analytics tools to scale evidence-based decision-making effectively. It is therefore recommended that county health departments prioritize investments not only in basic technological infrastructure but also in versatile, intuitive data visualization tools. Furthermore, establishing robust support systems and pursuing partnerships with technology providers and development partners could bridge resource gaps without imposing undue financial burdens on county budgets.

5.3 Organizational Factors Influencing DV Utilization

The findings of this study highlighted the substantial influence of organizational culture and structure on the utilization of data visualization (DV) tools. Counties that had established clear policies, procedures, and demonstrated management support for data use exhibited significantly higher and more consistent utilization of DV tools. This observation is consistent with the assertions of Batch and Elmqvist (2018) and Bernardi (2017), who have emphasized that the mere presence of technological tools or trained personnel is insufficient if the organizational environment does not actively promote and support data utilization. In the present study, counties that had instituted governance frameworks, secured leadership buy-in, and developed formal guidelines for data use consistently reported better performance in DV tool adoption and application. Conversely, counties lacking such structures and support mechanisms demonstrated lower levels of DV utilization. These findings underscore the critical role of leadership not only in strategic decision-making but also in shaping the organizational culture and daily practices related to data use. The study therefore recommends that counties prioritize the establishment and formalization of data governance structures, integrate DV tool use into routine program reviews, and foster an organizational culture where data utilization is recognized and reinforced at all levels of leadership and management.

5.4 Behavioural Factors Influencing DV Utilization

Behavioral factors, including health managers' attitudes toward data, their confidence in utilizing data visualization (DV) tools, and their level of motivation, emerged as equally significant as technical and organizational determinants. The study revealed that respondents who exhibited positive attitudes and confidence in using DV tools were nearly twice as likely to apply them effectively in decision-making processes. These findings are consistent with the work of Pittenturf (2018) and Gatero (2017), who emphasized that behavior and mindset are critical to the success of digital health initiatives. The results also demonstrated that even in settings where technological resources and training were readily available, a lack of motivation or a limited appreciation of the value of data use could significantly hinder DV tool adoption and utilization. This challenges the prevailing assumption in many development and capacity-building programs that the provision of tools and training alone will inevitably lead to their effective use. The findings underscore the necessity of adopting a holistic approach that integrates technical training and infrastructure development with behavioral interventions. These may include initiatives designed to enhance motivation, foster a positive culture around data use, and recognize exemplary data users. Establishing peer-support systems and promoting visible leadership engagement in data-driven decision-making are recommended strategies to reinforce and sustain positive behavioral change among health managers.

5.5 Effects of DV Tool Utilization on Decision-Making

The convergence of multiple factors, comprehensive training, appropriate technological infrastructure, supportive organizational structures, and positive behavioral attributes—was found to result in significant and measurable improvements in decision-making. The study demonstrated that the utilization of data visualization (DV) tools enabled health managers to make more informed choices, optimize resource allocation, identify trends with greater efficiency, and enhance communication. Notably, the combined influence of the examined factors accounted for over 82% of the variability in DV tool utilization. This finding reinforces longstanding assertions in the global literature that the mere collection of data is insufficient; effective data use is essential to drive meaningful action (Foreit et al., 2016). Furthermore, Zhang (2015) emphasized that visualizing complex datasets enhances comprehension, even among individuals without advanced statistical training—a claim that the present study substantiates with empirical evidence from Kenyan health settings. The results underscore the potential of DV tools to facilitate data-informed decision-making even in resource-constrained environments. The implications of these findings are both significant and urgent: DV tools must be systematically integrated into the routine operations of health managers. This includes revising planning templates to incorporate data visualization outputs, embedding visual reports into performance review processes, and leveraging dashboards not merely for display purposes but as active tools for guiding decisions. Such measures have the potential to substantially strengthen health systems and advance progress toward achieving Universal Health Coverage.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.0 Introduction

This final chapter brings the study to a close by reflecting on what the research revealed and offering practical recommendations based on those findings. Each conclusion is drawn directly from the data collected and analysed, showing how various factors, ranging from personal skills to organizational support, affect how health managers use DV tools in their decision-making. The chapter also outlines key action points for strengthening DV tool adoption and offers suggestions for areas that future research can explore further.

6.1 Conclusions

6.1.1 Influence of Individual Characteristics on the Use of Data Visualization in Decision-Making

The hypothesis stated that individual characteristics do not influence the utilization of data visualization tools in decision-making among health managers. However, the findings of this study refuted this hypothesis. The results demonstrated that individual capacity-particularly the level of training and experience in data management-was a significant predictor of DV tool utilization. Health managers who had received adequate training in data collection, analysis, and visualization were substantially more likely to apply DV tools to support planning and decision-making. In contrast, demographic variables such as age and gender were not significant determinants of DV tool use. This underscores the pivotal role of capacity-building initiatives over innate demographic traits, affirming that empowering managers with the requisite skills and knowledge greatly enhances their propensity to integrate data use into routine decision-making.

6.1.2 Technological Readiness and Access to DV Tools

Technological factors were hypothesized not to influence the utilization of data visualization tools in decision-making among health managers. Contrary to this assumption, the study found that technology played a critical role in facilitating or hindering DV tool usage. Although most respondents had access to basic tools such as Microsoft Excel and stable internet connectivity, the lack of advanced platforms like

Power BI and Tableau limited the potential for more sophisticated data analysis and visualization. The availability, accessibility, and user-friendliness of technological resources emerged as significant determinants of DV tool adoption. This finding is consistent with the work of Islam and Jin (2019) and Dunn et al. (2016), who argue that even when basic infrastructure exists, the absence of advanced, intuitive tools can impede effective data use. The study also highlighted that while limited technology could be offset to some extent by training and support, expanding access to advanced analytics tools is essential for strengthening data-driven decision-making processes.

6.1.3 Organizational Support as a Catalyst for DV Utilization

It was hypothesized that organizational factors do not influence the utilization of data visualization tools in decision-making among health managers. The study findings contradicted this hypothesis, revealing that organizational culture, structure, and support mechanisms had a profound impact on DV tool utilization. Counties that had established clear policies, data governance frameworks, leadership buy-in, and formal guidelines for data use reported significantly higher and more consistent application of DV tools. In contrast, counties lacking such structures exhibited lower levels of utilization. These findings align with the research of Batch and Elmqvist (2018) and Bernardi (2017), who emphasize that without an organizational environment that promotes data use, even well-trained personnel and high-quality tools may remain underutilized. The study underscores the necessity of formalizing data governance structures and integrating data visualization practices into routine management and decision-making processes to foster a culture that prioritizes evidence-based practices.

6.1.4 Influence of Behavioral Factors on the Use of Data Visualization in Decision-Making

The hypothesis proposed that behavioural factors do not influence the utilization of data visualization tools in decision-making among health managers. This hypothesis was not supported by the study findings. The results demonstrated that behavioural attributes-such as health managers’ attitudes toward data, their confidence in using DV tools, and their motivation-were significant predictors of DV utilization. Managers who exhibited positive attitudes and a high degree of confidence were nearly twice as likely to adopt and apply DV tools in their work. These findings are consistent with the conclusions of Pittenturf (2018) and Gatero (2017), who emphasized that behavior and mindset critically affect the success of digital and data-driven initiatives. The study also revealed that even when technology and training were available, a lack of motivation or a limited belief in the value of data use could inhibit the effective adoption of DV tools. This highlights the importance of complementing technical and organizational interventions with strategies aimed at fostering a positive data-use culture, promoting motivation, and recognizing exemplary data users

6.1.5 How DV Tool Use Strengthens Health Decision-Making

The hypothesis posited that the combined influence of individual, technological, organizational, and behavioral factors does not affect the utilization of data visualization tools in decision-making among health managers. This assumption was rejected based on the study findings. The integrated effect of these factors significantly enhanced DV tool utilization, contributing to improved decision-making processes across multiple dimensions. The multivariate analysis confirmed that over 82% of the variability in DV utilization could be explained by their collective influence. This supports existing literature emphasizing that successful data use is not determined by any single factor but by the alignment of skills, infrastructure, organizational support, and positive attitudes (Foreit et al., 2016; Zhang, 2015). The results underscore the importance of adopting a systems approach that combines capacity building, technological investment, governance structures, and behavioral change strategies to promote sustained and effective data use in health management.

6.2 Recommendations

6.2.1 Capacity Building and Training

Counties and health institutions should prioritize continuous capacity-building programs focused on data collection, analysis, and visualization. Training should be tailored to develop the practical skills required for effective DV tool use, regardless of age, gender, or prior experience. Special attention should be given to ensuring equitable access to such training for all health managers.

6.2.2 Technological Infrastructure Enhancement

Investments should be made not only in maintaining basic technological infrastructure (such as reliable internet and computing devices) but also in procuring and promoting the use of advanced data visualization platforms, including Power BI and Tableau. Simultaneously, user-friendly tools should be prioritized to encourage widespread adoption and minimize resistance related to system complexity.

6.2.3 Strengthening Organizational Structures

Health institutions should formalize and strengthen data governance frameworks that promote and regulate the routine use of data visualization in decision-making. Leadership at all levels should actively endorse and model the use of DV tools, while integrating data-driven practices into organizational procedures, planning, and performance review processes.

6.2.4 Promoting a Positive Data-Use Culture

Behavioral change initiatives should be implemented to enhance motivation, foster positive attitudes toward data use, and build confidence among health managers. Recognizing exemplary data users, establishing peer support systems, and promoting visible leadership engagement in data-driven decision-making can reinforce positive behavioral patterns.

6.2.5 Integrated Systems Approach

An integrated strategy combining training, technological advancement, organizational governance, and behavioural transformation should be pursued. Collaboration among development partners, technology providers, and county governments is essential to establish sustainable solutions that embed the use of DV tools into routine health management activities.

6.3 Recommendations for Further Research

While this study has yielded important insights into the factors influencing the use of data visualization tools in decision-making among health managers, there remain key areas that warrant further exploration. In particular, future research should focus on the following two main areas:

1. Expand the Study Scope and Design: Broaden the sample to include a wider range of counties and employ a longitudinal, pre-test/post-test design with control groups. This approach will help assess the long-term impacts of interventions and capture diverse contextual challenges across different healthcare settings.
2. Incorporate Additional Variables: Investigate other potential factors-such as organizational culture, external socio-economic influences, and policy frameworks-that may further explain the variance in tool utilization. This will allow for a more comprehensive understanding of the dynamics affecting data visualization adoption in decision-making processes.

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APPENDICES

Appendix I: Informed Consent Form

Researchers' Statement

Goodmorning/afternoon, my name is Jeremiah Mumo. I am a PhD student at Kenyatta University. Today I am here to carry out a study on utilization of data visualization tools to inform decision making among health managers in selected counties in Kenya. This form will give you information you need, so that you can make a decision on whether to participate or not to in the study. There are no wrong or right answers. You will be given time to consider if you would like to be in the study. Please read the form well and ask where you don't understand. Please be honest and truthful in answering the questions. I assure you that the information you give will be totally confidential and you will not be required to identify yourself by name.

Procedure:

You will be interviewed using a self-administered questionnaire (You will be assisted in case you are unable to read or write). The interview will last for about half an hour and participants will be required to give answers to all the questions. Participants will have the opportunity to make suggestions and give information on data use for decision-making in Makueni County.

Risks and benefits

People in the county could learn of your involvement in the study. To protect you from this risk, all information you will give us will be kept confidential within our research team. All the data will be stored in a password protected computer. There is no financial compensation or other personal benefits from participating in the study. Your participation and/or answers to the questions may provide useful insights into improving community strategy in Kenya.

Confidentiality and voluntary participation

No names will be used on any of the reports from the study. All the respondents will be given different identification numbers and the information relating to each participant will be strictly confidential, available only to the study team. Notes and any other recordings done will be destroyed once summary is prepared. Your participation is voluntary, and you may therefore refuse to answer any question or stop the interview at any time without suffering any consequences.

Instructions:

When you sign, it shows that you have agreed to participate in the study. If you do not understand any part of the information that has been read to you/you have read, be sure to ask questions. Do no sign until you have understood all that is expected or required.

I wish to take part in the study entitled: Utilization of data visualization tools to inform decision making among health managers in selected counties in Kenya.

I understand that I may at any time during the study withdraw my consent without any consequences. I have understood the information given in this sheet and I give my consent to be interviewed.

Respondent number ………………………..Signature…………………………………..

Date…………………………Name of the researcher:…………………………………...

Signature…………………………………Date………………………………………

If you require more information, please contact:

1. The Chairman

   Ethical Review Committee, **Kenyatta** University

   P.O BOX 43844-00100, Nairobi

   Tel:+254-020-8710901-19
   Email: chairman.kuerc@ku.ac.ke

3. Dr. Peter Kithuka, Supervisor,

   Department of Health Management and Informatics, Kenyatta University

   P.O BOX 43844-00100, Nairobi

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4. Dr. Joyce Kirui, Supervisor,

   Department of Health Management and Informatics, Kenyatta University

   P.O BOX 43844-00100, Nairobi

   Tel: +254-020-8710901-19

   Email: kirui.joyce@ku.ac.ke

Appendix II: Self-Administered Questionnaire

IDENTIFICATION PANEL

Position...Job title...

Sub-county.. Work station...

"Data visualization is representing data and information graphically. Through using visual elements such as maps, graphs, and charts, an accessible approach of seeing and understanding patterns, outliers and trends is provided by data visualization tools. Data visualization technologies and tools are important in the world of vast data since they help in analysing big quantities of data and in making decisions that are data-driven (Measure Evaluation 2016)".

Fill in the following details

PART A. SOCIO – DEMOGRAPHIC DETAILS (*PLEASE TICK)*

1. What is your Gender?

[] Male

[] Female

2. What is your age?

[] 18-25 years

[] 26-35 years

[] 36-45 years

[] 45-55 years

[] Over 55 years

3. What is your experience in your current position?

[] Less than 1 Year

[] 1-2 Years

[] 3-5 Years

[] 6-10 Year

[] 11-15 Years

[] 16-20 Years

[] 21-25 Years

[] Over 25 Years

4. What is your highest level of education attained?

[] Certificate

[] Diploma

[] High National Diploma

[] Undergraduate

[] Masters

[] PhD

PART B: TO DETERMINE INDIVIDUAL CHARACTERISTICS INFLUENCING DATA VISUALIZATION TOOLS AMONG HEALTH MANAGERS IN SELECTED COUNTIES, IN KENYA

4. The following are some of the individual characteristics in terms of training influencing the use of data visualization among health managers. Please rate your skills in terms of training given the following aspects of data management.

1- Not trained at all 2-Little training 3-Neutral 4-Trained 5-Well trained

Aspects of Training	**1**	**2**	**3**	**4**	**5**
HMIS (data collection and reporting)					
Data Analysis					
Data presentation					
Computer softwares					

5. Which other areas of training do you require to ensure efficient use of data visualization tools to inform decision making?

____

____

6. The following are some activities pertaining to data visualization among health managers. Please rate your ability to conduct different activities given the options below:

1-Very poor ***2- Poor*** ***3- Acceptable*** ***4-Good*** ***5- Very good***

Abilities	**1**	**2**	**3**	**4**	**5**
I can accurately check data					
I can calculate percentages/rates					
I can plot information by month or years					
I can explain findings and their implications					
I can use information to identify gaps and set targets					

7. What are other activities you carry out as health managers as far as data visualization is concerned?____

____

____

PART C: TO DETERMINE TECHNOLOGICAL FACTORS INFLUENCING DATA VISUALIZATION TOOLS AMONG HEALTH MANAGERS IN SELECTED COUNTIES, IN KENYA

8. The following are some equipment and infrastructures supporting the use of data visualization tools to inform decision making in health facilities. Please indicate the level of availability of each in your facility.

1-Not available at all 2-Inadequate 3-Neutral 4-Adequate 5- Very adequate

Access to	**1**	**2**	**3**	**4**	**5**
Computer					
Printer					
Calculator					
Data backup units					
Access to internet					
Softwares					
Dashboards					

What other tools and infrastructure supporting the use of data visualization are available in your facility?____

____

9. The following are some statements on the influence of technological factors on the use of data visualization tools on decision making. Please indicate the level of your agreement with each statement in relation to your facility.

1- Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

Influence of technological	**1**	**2**	**3**	**4**	**5**
We have adequate access to appropriate technological infrastructure, such as computers, internet connectivity, and reliable power supply, are critical for utilizing data visualization tools effectively.					
Our health managers have access to suitable software that can handle and visualize healthcare data effectively.					
Our managers have the ability to integrate data from different sources, such as electronic health records (EHRs), laboratory systems, and health management information systems (HMIS), impacts the utilization of data visualization tools.					
Health managers have access to accurate, reliable, and well-structured data to create meaningful visualizations.					
Health managers have assurance that sensitive health data will be protected and comply with relevant data protection regulations.					
Our data visualization tools are compatible with mobile platforms thus facilitating access to real-time data which enables health managers to make timely decisions even while on the move.					
The interoperability of data visualization tools with existing health information systems and platforms has enhanced their usability and integration within our healthcare ecosystem.					
We have training programs and ongoing support which helps in overcoming technological barriers thus promoting adoption.					
The cost and affordability of data visualization tools, including software licenses, maintenance, and hardware requirements, influences their adoption and utilization in our facility					
The local context and existing technological infrastructure in our facility has impacted on the utilization of data visualization tools.					

10. The following are some statements on the effect of organizational factors on the use of data visualization in decision making among health managers. Please indicate the level of your agreement with each statement in relation to your organization given the following options.

1- Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

Influence of organizational factors	**1**	**2**	**3**	**4**	**5**
We have strong support and endorsement from organizational leaders, such as county health executives and senior management, positively impacts the utilization of data visualization tools.					
Our leadership support helps create a culture of data-driven decision-making and encourage health managers to adopt and utilize these tools.					
Our organization culture promotes transparency, accountability, and evidence-based decision-making fosters the utilization of data visualization tools among health managers.					
Our health managers have access to reliable and well-managed data to generate accurate and meaningful visualizations.					
Our organization organizes for training programs and continuous professional development thus enhancing the utilization of data visualization tools.					
We have a dedicated data analytics team/experts within the organization who facilitates the utilization of data visualization tools.					
We encourage collaboration and communication among health managers and different departments within the organization fosters the utilization of data visualization tools.					
Our organization provides incentives and recognition for health managers who effectively utilize data visualization tools motivates their adoption.					
There is sufficient allocation of resources, including funding, infrastructure, and technology support, is important for the effective utilization of data visualization tools.					
Implementing systems that enable data sharing and accessibility across different departments and systems within the organization facilitates their utilization.					
Collecting feedback from health managers, monitoring utilization rates, and identifying areas for improvement optimizes their utilization over time.					

10. What are other organizational factors influencing the use of data visualization tools in decision making?____
____
____

PART E: BEHAVIOURAL FACTORS AND UTILIZATIION OF DATA VISUALIZATION TOOLS IN DECISION MAKING AMONG HEALTH MANAGERS IN SELECTED COUNTIES, IN KENYA

11. The following are some of the perceived behavioural factors influencing the utilization of data visualization tools in decision making among health managers. Please indicate the extent of influence of each factor in relation to your organization given the following options

1- Not at all 2-Small extent 3- Moderate extent 4-Large extent 5-Very great extent.

	1	**2**	**3**	**4**	**5**
Routine health information system users demand for information					
There is a need to collect information to monitor the performance of the facility					
Staff understand their roles and responsibilities in handling health information					
Users have confidence to use health information generated from the health facilities					
Staff have poor attitude towards data collection					
Staff belief that routine health management information system is useless					
Staff belief that the routine health management information data collected is accurate					
Lack of motivating incentives to staff from data management team					
There is a commitment among the staff on to improving the health of the community in question.					
Information collected not used for decision making is discouraging					
There are inadequate motivating incentives for staff during data management team					
Staff are encouraged to plan and track output to collect data					
The co-workers and managers acknowledge staff effort in collection of information					

10. What other behavioural factors influence the use of data visualization in decision making in your organization?____

____

____

PART F: DATA VISUALIZATION TOOLS AND DECISION MAKING AMONG HEALTH MANAGERS IN SELECTED COUNTIES, IN KENYA

12. The following are some statements on data visualization and decision making in organizations. Please indicate the level of your agreement with each statement in relation to your organization given the following options:

1-Strongly disagree 2- Disagree 3- Neutral 4-Agree 5- Strongly agree

At our facility decisions are based on	**1**	**2**	**3**	**4**	**5**
Personal liking					
Supervisor’s directive					
Information/facts					
Health needs					
Job experience					
Considering costs					
Comparing data with strategic health objectives					
Intuition/arbitrary					

13. What are other bases for decision making in relation to data visualization and tools in your facility?____

____

14. The following are some statements on the impact of data visualization tools on decision making among health managers. Please indicate the to which these statements apply to you health facility given the options below.

1-Not at all 2-Small extent 3- Moderate extent 4-Large extent 5-Very great extent.

Effect of data visualization tools	**1**	**2**	**3**	**4**	**5**
Visualizations has enabled health managers to identify patterns, trends, and insights more easily, leading to more informed and evidence-based decision-making.					
Visualizations has helped in simplifying complex data, making it easier for health managers to understand and interpret information by enabling them to grasp key findings, relationships, and correlations within the data more effectively.					
Data visualization tools has facilitated the analysis and presentation of data in near real-time. Health managers can therefore access up-to-date visualizations, enabling them to identify emerging trends, track performance indicators, and make timely interventions when necessary.					
Health managers can use visualizations to present information in a more engaging and accessible manner, facilitating better communication, and supporting more effective reporting to senior management, policymakers, and other stakeholders.					
Data visualization tools can help health managers identify key performance indicators (KPIs) and track progress over time, identify areas for improvement, and make data-driven decisions to enhance healthcare services.					
Data visualization tools enable health managers to optimize resource allocation by identifying areas where resources are underutilized or misallocated, such as staff allocation, equipment utilization, or service demand, health managers can make informed decisions to improve efficiency and cost-effectiveness.					
Health managers can utilize visualizations to advocate for policy changes, allocate resources effectively, and support decision-making at the policy level.					
By visualizing data and performance indicators, health managers enhance transparency in reporting, accountability for outcomes, and foster a culture of data-driven decision-making within the organization.					

15. In what other ways does data visualization help in decision making in your organization?____

____

____

16. What would you recommend to be done by health facilities to improve the use of data visualization tolls in making informed decisions in your facility?____

____

____

Thank you for your Time and Participation

Appendix III: Key Informant Guide

KEY INFORMANT GUIDE

Position...Job title...

County... Work station...

Part A: Data use and demand

- What informs decision-making processes in this county? Probe for: Data visualization, use and demand, basis of decisions (facts/evidence, superiors directives, political interference and cost considerations)

Part B: Individual Characteristics

- What is your take on the effect of individual characteristics such as training, skills and competence on the utilization of data visualization tools among health managers at the County level? Specific focus should be on the following skills:
  Data collection and reporting
  Data Analysis
  Data presentation
  Use of Computer software
  Is there any need for training, if yes, on which areas?

Part C: Technical factors

- Is there the technical capacity to manage data visualization tools in this county? Probe for: Data collection and reporting tools, equipment, skills and knowledge, Technology and data complexity)

Part D: Organizational factors

- Are the policies for data governance, sharing, visualization and use in this country. Probe for Financial support, trainings and infrastructure
- Is there data quality issues perceived to influence data demand and use for decision-making in this County/sub-county? Probe for: completeness, comprehensiveness, integrity, accuracy, simplicity, currency, parallel data sources, consistency)

Part E: Behavioural factors

- Please comment on the following behavioural factors and how they impact on the utilization of data visualization tools among health managers at the County level?
  Clarity of roles and responsibilities
  User confidence
  Staff attitude
  Staff belief
  Staff motivation
  Staff commitment
  Usage of information for decision making
- -Any other behavioural factors influencing the utilization of data visualization tools among health managers at the County level

Part F: Effects of Data Visualization

- Is there staff competencies on data/information for decision-making staff within the county? What issues are perceived to affect accessibility of such data? (Probe for: availability, storage format, irretrievability, cost, attitude, staff adequacy, leadership, data sharing and feedback)

Appendix IV : Recommendation Letter

KENYATTA UNIVERSITY
OFFICE OF THE REGISTRAR (ACADEMIC)

FAX: 811242/811575
Email: admissions-pg@ku.ac.ke
Website: www.ku.ac.ke

P.O Box 43844 - 00100
NAIROBI, KENYA
Tel: 020 – 870- 3222/23

Our Ref: Q97/28141/2018

Date: 23rd June, 2023

Mumo Jeremiah Mwendwa,
C/o - Department of Health Management & Informatics,
KENYATTA UNIVERSITY.

Dear Mumo,

RE: SUBSTANTIVE REGISTRATION (Ph.D)

Following the recommendation by the Executive Dean, Graduate School, you are hereby granted substantive Ph.D. registration.

Please note that your registration number and all rules and regulations remain the same as per your admission letter.

Thank you.

MR. R. A. CHWEYA,
FOR: REGISTRAR (ACADEMIC)

cc Executive Dean, School of Health Sciences
Executive Dean, Graduate School
Chairman, Department of Health Management & Informatics

RC/ln

Transforming Higher Education....Enhancing Lives
Kenyatta University is ISO 9001:2015 Certified

Appendix V: Internal Memo

KENYATTA UNIVERSITY
GRADUATE SCHOOL

E-mail: dean-graduate@ku.ac.ke

Website: www.ku.ac.ke

P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 810901 Ext. 57530

Internal Memo

FROM: Dean, Graduate School

DATE: 24th May, 2023

TO: Mr. Jeremiah M. Mumo
C/o Department of Health Management & Informatics
Kenyatta University

REF: Q97/28141/2018

SUBJECT: APPROVAL OF RESEARCH PROPOSAL

We acknowledge the receipt of your revised Research Proposal entitled **"Utilization of Data Visualization Tools to Inform Decision Making among Health Managers in Selected Counties, in Kenya"** as per recommendations raised by the Graduate School Board **16th March, 2023.**

You may now proceed with your Data collection, subject to clearance with the Director General, National Commission for Science, Technology & Innovation.

As you embark on your data collection, please note that you will be required to submit to Graduate School completed supervision Tracking and Progress Report Forms. The Forms are available at the University's Website under Graduate School webpage downloads.

Also, please ensure that you publish article(s) from your thesis before submitting it to Graduate School for examination as per the Commission for University Education and Kenyatta University guidelines. By copy of this letter, the Registrar (Academic) is hereby requested to grant you substantive registration for your Ph.D. studies.

Thank you.

DR. HARRIET ISABOKE
FOR EXECUTIVE DEAN, GRADUATE SCHOOL

c.c. Registrar (Academic) Att. Mr. Richard Chweya
Chairman, Department of Foods, Nutrition & Dietetics

Supervisor

1. Dr. Joyce Kirui
   C/o Dept. of Health Management & Informatics
   Kenyatta University

2. Dr. Peter Kithuka
   C/o Dept. of Health Management & Informatics
   Kenyatta University

Committed to Creativity, Excellence & Self-Reliance

Appendix VI: Research Authorization

KENYATTA UNIVERSITY
GRADUATE SCHOOL

E-mail: dean-graduate@ku.ac.ke

Website: www.ku.ac.ke

P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 8710901 Ext. 57530

OUR REF: Q97/28141/2018

Date: 24th May, 2023

The Director General,
National Commission for Science, Technology & Innovation,
P.O. Box 30623-00100,
NAIROBI

Dear Sir/Madam,

RE: RESEARCH AUTHORIZATION FOR JEREMIAH M. MUMO REG.NO. Q97/28141/2018

I write to introduce Mumo who is a Postgraduate Student of this University. The student is registered for Ph.D. Degree programme in the **Department of Health Management & Informatics in the School of Health Sciences.**

Mumo intends to conduct research for Ph.D. Thesis entitled **"Utilization of Data Visualization Tools to Inform Decision Making among Health Managers in Selected Counties, in Kenya"**

Any assistance given will be highly appreciated.

Yours faithfully,

PROF. ELISHIBA KIMANI
EXECUTIVE DEAN, GRADUATE SCHOOL

HI/cao

Committed to Creativity, Excellence & Self-Reliance

Appendix VII: Research License

REPUBLIC OF KENYA

NACOSTI

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **773013**

Date of Issue: **30/June/2023**

RESEARCH LICENSE

This is to Certify that Mr.. Jeremiah MWENDWA Mumo of Kenyatta University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Garissa, Isiolo, Kisumu, Laikipia, Machakos, Makueni, Mombasa, Nyeri on the topic: UTILIZATION OF DATA VISUALIZATION TOOLS TO INFORM DECISION-MAKING AMONG HEALTH MANAGERS IN SELECTED COUNTIES, IN KENYA for the period ending : 30/June/2024.

License No: **NACOSTI/P/23/27019**

773013

Applicant Identification Number

Director General

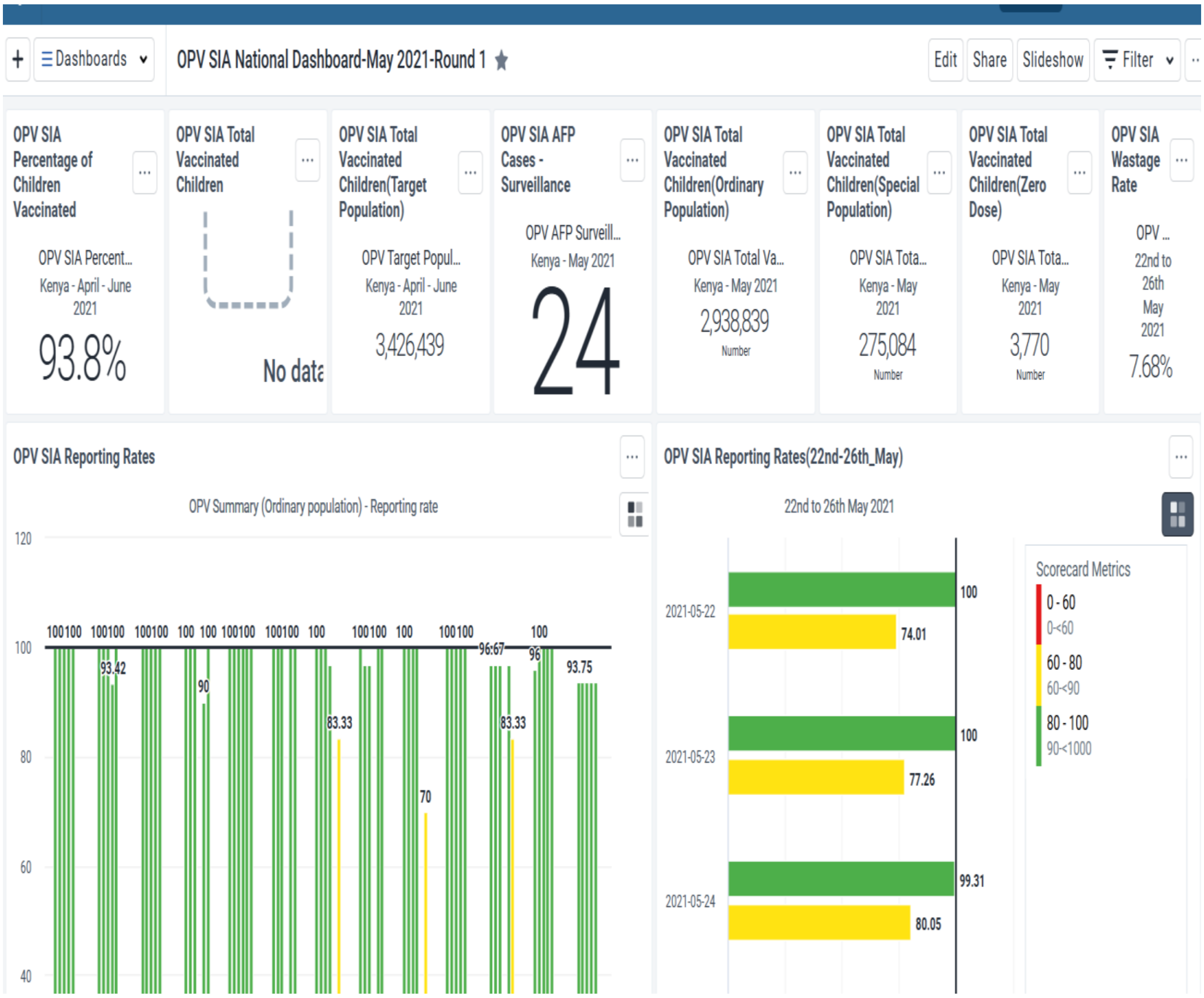
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

Appendix VIII: Dashboard from a demo version of DHIS2



Appendix IX: A RMNCN&N Sample Scorecard

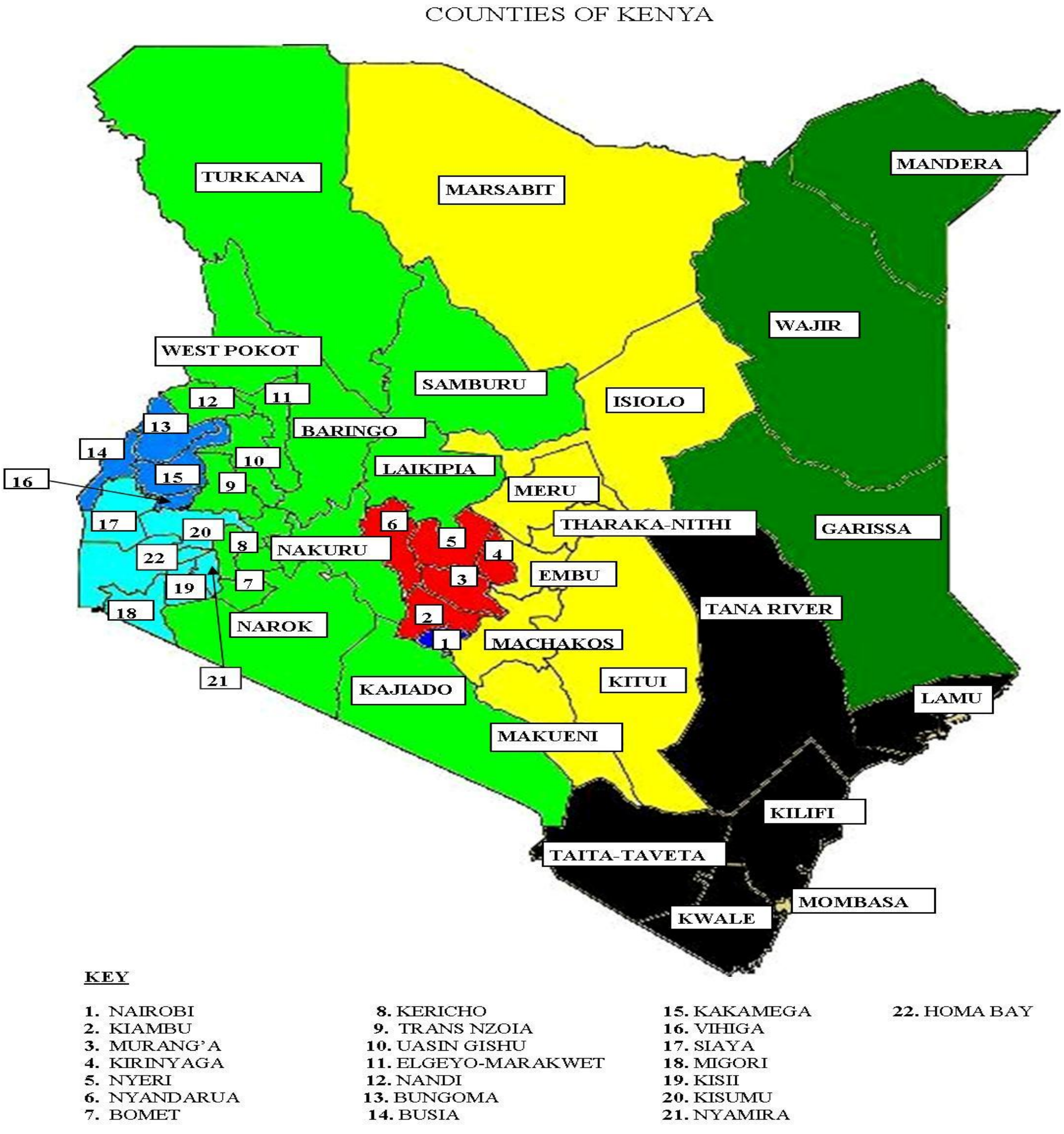
▸ National indicators

Subnational indicators

Region	Pregnancy & Newborn												Early Childhood						Late Childhood	Ad
	Delivery by skilled health attendants coverage	proportion of pregnant women attending 4+ ANC visits	% of pregnant women attending 1st ANC within 12 weeks	PNC within 48 hrs (mother) coverage	% of neonatal deaths audited	Facility Neonatal Mortality Rate	Facility maternal deaths audited	Facility Maternal Mortality Ratio	% of newborns applied chlorhexidine for umbilical cord care	Early initiation of breastfeeding within 1hr of birth	Proportion of HIV exposed infants started on ARV prophylaxis within 2 months of life	Proportion of HIV infected pregnant women who are currently on ART	Vitamin A coverage (12-59 mos)	Fully immunized Child Coverage	Penta 3 coverage	% <5y with diarrhea Rx with ORS and Zinc (facility)	% <5y with diarrhea Rx with ORS and Zinc (community)	% of children <5y with pneumonia treated with amoxicillin DT	% school age 2-14 yrs children dewormed	HPV vaccine coverage (10-14 y
› Kenya	79	52	98	↑ 41		43		138	75	89		101	↓ 6	↑ 88	87	49	85	51	↓ 13	29
› Baringo County	66	39	88	21		28		28	71	71		100	↓ 5	↑ 88	86	32	144	42	29	30
› Bomet County	↓ 76	↓ 37	96	23		12		205	78	97		93	↓ 4	89	85	33	86	35	5	55
› Bungoma County	86	52	90	53		44		103	95	91		101	↓ 4	85	87	63	81	78	↓ 20	13
› Busia County	76	56	99	56		15		120	94	96		102	↓ 7	↑ 90	93	54	85	42	↓ 0	16
› Elgeyo Marakwet County	↑ 72	27	86	21		20		34	33	92		102	↓ 3	79	76	114	85	59	↓ 15	30
› Embu County	↑ 82	↑ 55	102	↑ 75		62		33	97	77		96	↓ 8	90	91	50	89	58		69
› Garissa County	64	57	100	23		26		313	71	86		77	↓ 8	↑ 95	95	23	74	26	7	0
› Homa Bay County	74	49	98	32		34		68	62	89		101	↓ 3	78	80	53	70	79	1	45
› Isiolo County	↑ 89	↑ 56	123	33		8		340	38	94		104	↓ 2	↑ 81	102	34	91	49	↑ 9	4
› Kajiado County	85	53	115	43		30		50	92	94		112	6	↑ 91	100	47	97	50	↑ 21	29
› Kakamega County	74	59	91	52		56		52	81	96		106	↓ 6	↑ 84	85	75	42	81	↓ 1	19
› Kericho County	88	↓ 39	94	19		70		138	63	97		101	↓ 5	↑ 91	81	47	94	61	143	39
› Kiambu County	104	72	115	↑ 54		49		37	70	88		103	↓ 6	↑ 102	98	50	78	45	↓ 7	17
› Kilifi County	↑ 89	↑ 62	101	37		24		185	93	89		98	↓ 5	↑ 93	81	73	56	54	↓ 6	57
› Kirinyaga County	96	57	112	98		67			87	91		101	↓ 6	99	95	75	80	29	↓ 1	39
› Kisii County	80	47	91	32		32		130	95	97		99	↓ 4	↑ 116	84	51	18	53	0	86
› Kisumu County	↓ 81	62	91	69		74		193	81	96		99	↓ 6	94	86	54	60	60	1	35
Source	HMIS	DHIS2	KHIS	DHIS2	KHIS	KHIS	KHIS	KHIS	KHIS	KHIS	KHIS	KHIS	DHIS2	DHIS2	KHIS	KHIS	KHIS	KHIS	DHIS2	KHIS

Appendix X : Map of Kenya

The figure below shows the map of Kenya with Counties:



Geographical Distribution of the Counties in Kenya.

Source: Available at:

https://commons.wikimedia.org/wiki/File:Kenya_counties_map_Labelled.jpg

[Accessed 17 October. 2019].