DETERMINANTS OF DATA DRIVEN DECISION MAKING AMONG HEALTH PROVIDERS IN MOMBASA COUNTY

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DECLARATION AND APPROVAL

Declaration by the Candidate

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

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DEDICATION

This thesis is dedicated to my loving family for their continuous encouragement. Thank you for being supportive and enabling me to complete my research.

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ABSTRACT

The utilization of data by healthcare providers remains deficient, particularly concerning routinely collected data. Utilizing health information (HI) for decision-making by healthcare managers in the country, Kenya lacks incentives or motivations to cultivate an information improvement culture. The regulations within the HMIS are lacking, and there is limited awareness concerning practicality of HIS data in decision-making. The primary objective was to explore the variables shaping data-driven decision-making among Mombasa County public health facilities' health providers. Specifically, the study investigated the effect of technical, organizational, and behavioral factors on data-driven decision-making among these health providers. The theoretical frameworks guiding the study were the socio-technical theory, technology acceptance model, and resource-based view theory. The study employed an analytical cross-sectional survey design, targeting 303 healthcare staff in Mombasa County. The sample size consisted of 172 respondents, recruited via Taro Yamane formula, alongside stratified random sampling technique. Primary data were gathered through a Likert-scale questionnaire and SPSS version 25 helped in analysis. The researcher used Pearson correlation analysis, descriptive statistics, and multinomial logistic regression to predict influence of technical, behavioral, organizational factors, and government policies on data-driven decision-making (with a significance level of 0.05). The coefficient of Pearson correlation exhibited a positive and significant association between technical factors and data-led decision-making. Similarly, a strong positive correlation existed between behavioral factors and data-driven decision-making. Organizational factors also exhibited a positive and significant relation with data-driven decision-making. Based on a significance level of $p=0.05$, the likelihood ratio tests demonstrated that both technical and organizational factors significantly predicted data-driven decision-making among health providers, whereas behavioral factors did not have a statistically significant impact. The researcher's recommendations include providing training for health workers at the county level to enhance data utilization skills, ensuring thorough data verification before submission, promoting the use of HI in decision-making, addressing perceptions and attitudes toward health information system use, establishing feedback mechanisms for data utilization, and allocating sufficient resources for supportive supervision of data systems.

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LIST OF ABBREVIATIONS AND ACRONYMS

DAR	Daily Activity Register
EHR	Electronic Health Records
EMR	Electronic Medical Records
IBIS	Internet-Based, Inter-Organizational Information Systems
HI	Health Information
HIS	Health Information System
HMIS	Health Management Information System
HMTs	Hospital Management Teams
HR&I	Health Records and Information
KDHS	Kenya Demographic and Health Survey
MDGs	Millennium development goals
MOH	Ministry of Health
RHIS	Routine Health Information Systems
SCHMTs	Sub County Health Management Teams
SPSS	Statistical Package for Social Sciences
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

A functional healthcare system necessitates data utilization across all levels, spanning from individual providers to sub-national and national health management teams. This approach aids in making evidence-based adjustments for enhanced quality of care (Wagenaar et al., 2017). The healthcare sector faces the challenge of improving access, cost-effectiveness, and quality amidst changing reimbursement models and regulations (Krumbolz, 2016). Quality data availability empowers managers to make informed decisions, while poor data quality can impede decision-making, negatively impacting organizational performance (Muinga et al., 2018). Managers need to comprehend the data they require, its generation, and utility for accurate, relevant, complete, and timely information to drive managerial activities (Sultan, Challi & Waju, 2017). Collected data must undergo processing, dissemination, and utilization to make managerial decisions intended to enhance health outcomes (WHO, 2014).

In economies like the US, Canada, France, and Sweden, both public and private health facilities harness big data to enhance services (Aqil, Lippeveled & Dairiku, 2019). In the U.S healthcare sector, big data stems from diverse sources like hospital records, patient medical records, and medical examination outcomes. Biomedical research contributes significantly to the pool of big data relevant to public healthcare (Dimitrov, 2016). Managing and analyzing such data necessitates expertise, as improper handling can render the search for meaningful insights akin to finding a needle in a haystack (Senthilkumar et al., 2018). Bates et al. (2018) highlight challenges tied to handling big data, suggesting that high-end computing solutions are crucial for analyzing it, allowing health providers to make informed decisions. Thus, healthcare providers must be equipped with infrastructure to systematically generate and analyze big data to improve public health (Alhadhrami et al., 2017). France's healthcare industry, as indicated by Wagenaar et al. (2017), is taking strategic measures encompassing technical, behavioral, and organizational aspects to leverage big data for enhanced services and financial benefits. Integrating healthcare and biomedical data has the potential of revolutionizing personalized medicine as well as medical therapies (Wagenaar et al., 2017).

Drawing insights from Mozambique, Rwanda, and Zambia, Bhattacherjee & Hikmet (2016) explore data-led quality improvement within middle and low-income economies' health systems (HI). HI decentralization in most LMICs has expanded sub-national management teams' decision-making responsibilities. With the evolution of quality improvement, emphasis has shifted to high-quality data utilization to identify service delivery gaps and inform enhancement strategies, guarantee data-led decision-making as well as resource allocation, thereby strengthening evaluative designs for quality improvement (Wagenaar et al., 2016). While the term "data-driven" typically references quantitative data usage, such as routine HIS, chart appraisals, and sporadic survey data, evidence from LMICs indicates that county and sub-county managers utilize diverse data sources, including written, verbal, observational, experiential, and training data, to guide decision-making (WHO, 2019).

Ajuwon (2017) illustrates an assessment in 2016 where health officials and stakeholders evaluated the HMIS in Zanzibar. The assessment uncovered a fragmented system that didn't support data-driven decisions. Challenges included excessive data collection unrelated to indicators, resulting in inconsistencies and overlaps in data reporting. Muinga et al. (2018) note that data utilization reforms, encompassing feedback mechanisms, supportive supervision, and resource availability, have bolstered data quality and contributed to RHIS performance in Rwanda. Mboro (2017) emphasizes the effectiveness of these reforms in allocating resources for health system strengthening, performance-based financing, and quality improvement at health center and district levels. These reforms elevated health workers' engagement with data, and quantitative analyses confirmed enhancements in various areas (Karisa & Wainaina, 2020).

Although hospitals are recognizing the advantages of data-driven approaches for improvement, the healthcare sector lags behind other industries. Many healthcare programs in Kenya possess the capability to extract valuable information, conduct detailed analyses, and uncover new opportunities (WHO, 2019). Essential elements such as patient details, medical products, purchases, and employee records have become integral for daily operations in local health facilities (Wekesa, 2014). Decision-making decentralization to county-wise creates a distinctive opportunity to advocate for data utilization closer to delivery of service. All 47 counties underwent a three-phase process led by development partners to enhance data ownership and quality (Otieno, Muiruri & Kawila, 2020).

Data flows from health volunteers within the community at health facilities and household level, aggregating in the health information system for analysis. The insights are subsequently conveyed to the community, health facility, and county levels for to be acted on. In Kenya, health facility data are submitted to higher levels in health system, implying data collectors aren't the final users at the facility level (Mboro, 2017). Health information utilization facilitates healthcare worker mobility for community dialogues and outreach, enhancing patient access to healthcare (Sure, 2016). This communication fosters efficient stakeholder interaction, enhancing service delivery. These issues underscore the importance of understanding determinants of data-driven decision-making among health providers in Mombasa County. It is clear from that background that certain implications and insights makes researching this topic into detail an inevitability.

On critical role of data in healthcare the background underscores the fundamental role of data in the healthcare sector. It highlights that data utilization is pivotal across all levels of healthcare, from individual providers to national health management teams. This indicates that addressing the challenges and determinants of data-driven decision-making is essential for improving healthcare quality and access. As such, this research becomes highly significant in contributing to the understanding of how data can be effectively harnessed for informed decision-making in healthcare, particularly within Mombasa County.

The study draws attention to global trends where countries like the United States, Canada, France, and Sweden have successfully leveraged big data in healthcare for enhanced services and financial benefits. This indicates that the effective utilization of data is not only relevant locally but also aligns with global advancements in the healthcare sector. Therefore, understanding the determinants of data-driven decision-making becomes crucial for Mombasa County to stay aligned with international best practices and advancements in healthcare management.

Quality Improvement in Low and Middle-Income Countries (LMICs) insights from LMICs like Mozambique, Rwanda, and Zambia reveal that data-led quality improvement is gaining prominence. The research highlights the shift toward utilizing high-quality data to identify service gaps and improve healthcare delivery in these regions. Given that Mombasa County operates within a similar context, understanding the determinants of data-driven decision-making is essential for enhancing the quality of healthcare services and resource allocation within the county.

The background mentions successful data utilization reforms in countries like Rwanda, which led to improved data quality and healthcare performance. This suggests that targeted reforms and strategies can significantly enhance the effectiveness of data-driven decision-making. Therefore, researching the determinants of data-driven decision-making in Mombasa County can provide valuable insights into potential reform areas that can lead to better healthcare outcomes.

In terms of challenges in data utilization the background highlights challenges faced by healthcare systems, such as excessive data collection, fragmented systems, and inconsistencies in reporting. These challenges emphasize the need for a comprehensive understanding of the determinants of data-driven decision-making to address existing barriers and bottlenecks. By uncovering these challenges, the research can contribute to the development of tailored solutions for Mombasa County's healthcare system.

The background notes the decentralization of decision-making to the county level in Kenya. This creates an opportunity to advocate for data utilization closer to the delivery of healthcare services. Understanding the determinants of data-driven decision-making at the county level is, therefore, crucial for ensuring that healthcare data is effectively utilized for improved service delivery, particularly in the context of Mombasa County.

The flow of data from community health volunteers to health facilities and up to the county level underscores the importance of effective stakeholder interaction and its impact on service delivery. This implies that data-driven decision-making is not an isolated process but involves multiple stakeholders. Researching the determinants of data-driven decision-making can shed light on how these interactions can be optimized to enhance healthcare access and quality.

In summary, the background provides valuable insights and implications that point towards the significance of researching the determinants of data-driven decision-making among health providers in Mombasa County. It highlights the critical role of data in healthcare, aligns with global trends, emphasizes quality improvement in LMICs, underscores the need for reforms, addresses existing challenges, and recognizes the importance of local relevance and stakeholder interactions. This research holds the potential to drive positive changes in Mombasa County's healthcare system by addressing the identified determinants of data-driven decision-making.

1.2 Statement of the Problem

Healthcare professionals recognize the value of converting health data into info for sound decision-making (Okoth & Mahinda, 2020). However, inadequate investment in collecting analyzing, disseminating, and usage infrastructure results in a lack of reliable and timely health information (Mboro, 2017). As a consequence, decision-makers struggle to identify issues, monitor progress, evaluate intervention impacts, and make evidence-based decisions on health policies, resource allocation, and program design. Evaluating data quality and information use practices is crucial to addressing this challenge (Sure, 2016).

Studies show that fewer than 50% of mid-level health managers possess the ability to analyze and use HMIS data (Okoth & Mahinda, 2020). An assessment by Kenya Ministry of Health and Health Metric Network (2018) highlights weak utilization of data, particularly for routinely collected data, with only 51% of health workers utilizing data. Factors include inadequate human capacity, varied abilities in data collection and analysis, lack of standardized databases, and delayed reporting. Health providers in many counties lack the capacity to use data effectively, hindering healthcare improvement (Namageyo-Funa et al., 2018).

Otieno et al. (2020) reports inadequate incentives and motivation for information use among healthcare managers, low adherence to HMIS rules, and insufficient technologies for data utilization. Mombasa County's reliance on HIS reports for monitoring and evaluation exposes challenges, including incomplete, underutilized data and unknown factors influencing information utilization (Nzomo, 2017). These issues drive the need to explore how technical, behavioral, and organizational factors, influenced by government policies, impact data-driven decision-making among health providers in Mombasa County.

Furthermore, the existing studies reveal a multifaceted problem within Mombasa County's healthcare system that hinders effective data-driven decision-making among health providers. While some of these issues have been identified, it is essential to delve deeper into the determinants of data-driven decision-making to gain a comprehensive understanding of the challenges faced by health providers.

Existing research suggests that fewer than 50% of mid-level health managers possess the ability to analyze and use HMIS data effectively. This inadequacy in data analysis skills is a critical determinant of the problem. Health providers' capacity to make informed decisions is directly linked to their ability to analyze and interpret health data accurately (Okoth & Mahinda, 2020).

The lack of standardized databases and outdated or insufficient technologies for data utilization pose significant barriers to data-driven decision-making. Outdated or inadequate technology can hinder the collection, storage, and retrieval of health data, undermining the entire decision-making process (Otieno et al., 2020). The issue of inadequate incentives and motivation for information use among healthcare managers) raises questions about the psychological determinants of data-driven decision-making. Understanding what motivates or demotivates health providers to engage with health data is vital for designing effective interventions (Otieno et al., 2020).

It is evident that organizational factors, including adherence to HMIS rules, play a role in data-driven decision-making (Otieno et al., 2020). These organizational challenges may encompass bureaucratic obstacles, hierarchical structures, or resistance to change within healthcare institutions. Government policies can either facilitate or hinder data-driven decision-making among health providers. Exploring how government policies influence the availability and use of health data is essential for understanding the broader determinants of the problem.

Accordingly, the problem of data-driven decision-making among health providers in Mombasa County is multifaceted, encompassing issues related to data analysis skills, infrastructure, motivation, organizational dynamics, and government policies. A comprehensive analysis of these determinants is necessary to develop effective strategies for improving data-driven decision-making in the county's healthcare system. It is clear from the foregoing that the issue of data-driven decision-making among health providers in Mombasa County is of paramount importance and demands comprehensive investigation. This problem is both timely and critical for several compelling reasons.

First and foremost, timely and informed decision-making in healthcare is directly linked to patient outcomes and the overall well-being of the population. Inaccurate or delayed decisions can result in suboptimal patient care, increased healthcare costs, and even loss of lives. In an era where healthcare systems worldwide are grappling with the challenges posed by emerging diseases, pandemics, and other public health crises, the need for efficient and data-informed healthcare decision-making cannot be overstated. The ongoing COVID-19 pandemic has underscored the significance of rapid, data-driven decision-making in healthcare, as the allocation of resources, vaccination strategies, and containment measures rely heavily on real-time health data.

Secondly, Mombasa County, like many other regions in Kenya and across the globe, is witnessing rapid advancements in healthcare technologies and data collection mechanisms. The proliferation of electronic health records (EHRs), telemedicine, and health information systems (HIS) has generated an unprecedented volume of health data. While the potential benefits of this data are immense, the healthcare system's ability to harness it for meaningful decision-making remains a challenge. Therefore, it is timely to investigate how health providers in Mombasa County are coping with this influx of health data and whether they are equipped with the necessary skills and resources to translate it into actionable insights.

Additionally, the importance of this research problem is highlighted by its potential to lead to substantial improvements in healthcare delivery, resource allocation, and policy formulation within Mombasa County. Effective data-driven decision-making can enhance the county's healthcare system's efficiency, leading to better patient outcomes, reduced healthcare costs, and improved overall health indicators. This, in turn, can contribute to the county's socio-economic development and the well-being of its residents.

Moreover, understanding the determinants of data-driven decision-making in Mombasa County holds relevance beyond the county's borders. The insights gained from this research can inform strategies and best practices applicable to other regions within Kenya and similar healthcare settings globally. As data-driven decision-making becomes increasingly pivotal in healthcare, the lessons learned from Mombasa County's experiences can be invaluable for addressing similar challenges in diverse healthcare contexts.

In conclusion, investigating the determinants of data-driven decision-making among health providers in Mombasa County is not only timely but also essential for improving healthcare outcomes, leveraging technological advancements, and contributing to the broader discourse on healthcare data utilization. This research has the potential to catalyze positive changes in healthcare practices, benefiting both the local population and serving as a valuable reference for healthcare systems worldwide.

1.3 Broad Objective

The primary aim of this study was to explore the determinants of data-driven decision-making among health providers in Mombasa County.

1.3.1 Specific Objectives

i. To analyze the association between technical factors and data-driven decision-making among health providers in Mombasa County.

ii. To evaluate the association between behavioral factors and data-driven decision-making among health providers in Mombasa County.

iii. To establish the connection between organizational factors and data-driven decision-making among health providers in Mombasa County.

iv. To examine the influence of government policy as a moderating factor on data-driven decision-making among health

1.4 Research Questions

i. How do technical factors relate to data-driven decision-making among health providers in Mombasa County?

ii. What is the correlation between behavioral factors and data-driven decision-making among health providers in Mombasa County?

iii. How do organizational factors impact data-driven decision-making among health providers in Mombasa County?

iv. How does government policy moderate data-driven decision-making among health providers in Mombasa County?

1.5 Significance of the Study

The government may use the findings of this study to legislate and implement policy across various relevant public health facilities. County governments' policy makers may also utilize this information and channel it towards formulation of policies in the sector. Different members of the academic community are expected to utilize this study's findings to further explore the subject of quality data driven decision making. Researchers for instance, who wish to further understand the subject of quality data driven decision making shall utilize the knowledge generated by this research to effectively comprehend the subject of health facilities' data-driven decision making. The leadership of county health facilities will use this study findings to improve their data driven decision making thus enhance service delivery. Some of specific benefits to be drawn from this study are outlined below:

The findings of this study carry significant weight in influencing policy decisions and legislative actions by the government. As healthcare is a critical sector with far-reaching implications for the well-being of the population, the insights generated from this research can guide the government in crafting policies that enhance data-driven decision-making in public health facilities. This, in turn, can lead to more efficient resource allocation, improved healthcare services, and ultimately better health outcomes for the citizens of Mombasa County. Government policymakers may find this research instrumental in formulating evidence-based policies aimed at strengthening the healthcare system's capacity to leverage data for informed decision-making.

Beyond national-level policy implications, the findings can also be a valuable resource for county governments within Kenya, especially those facing similar challenges in healthcare data utilization. County-level policymakers can draw upon the knowledge generated by this study to develop and implement policies tailored to their specific contexts. Understanding the determinants of data-driven decision-making at the county level can empower local authorities to address data-related issues effectively, thereby improving healthcare service delivery and resource management within their jurisdictions.

The academic community stands to benefit significantly from this study's findings. Researchers, educators, and scholars interested in the broader field of data-driven decision-making, particularly within healthcare settings, can use this research as a foundational reference. It provides a real-world context for exploring the nuances of quality data-driven decision-making in health facilities. Subsequent research endeavors can build upon the knowledge generated here to delve deeper into specific aspects of data utilization, potentially leading to the development of best practices and innovative strategies for optimizing data-driven decision-making processes.

The leadership of county health facilities plays a pivotal role in the effective utilization of data for decision-making. The study's findings can be a valuable resource for these leaders, offering insights into the factors that impact their ability to leverage data effectively. Armed with this knowledge, healthcare administrators and facility managers can make informed decisions about resource allocation, staff training, and technology investments. This, in turn, can result in more streamlined operations, improved service quality, and better healthcare outcomes for the communities they serve.

Essentially, the significance of this study extends far beyond its immediate scope. It has the potential to influence policy decisions, guide county-level healthcare strategies, contribute to academic research, and empower healthcare leaders to make data-driven decisions that enhance the quality of care and the overall health of the population in Mombasa County. By addressing the critical issue of data-driven decision-making, this research stands as a stepping stone toward a more data-informed and efficient healthcare system, with implications reaching across the academic, governmental, and healthcare sectors.

1.6 Scope of the Study

This study was conducted within the geographical confines of Mombasa County, with a primary focus on examining the factors influencing data-driven decision-making among health providers within this specific locale. The study's scope encompassed a total of 303 healthcare professionals affiliated with Mombasa County's healthcare system. This participant pool consisted of 21 members from the County Health Management Team (CHMT), 56 individuals from the Sub-County Health Management Team (SCHMT), representing all 4 sub-counties, forty-three facility in-charges from the forty-three public health facilities, and finally, 183 HODs. The study's duration spanned a period of 9 months, during which data collection and analysis were carried out.

1.7 Assumptions of the Study

The study's underlying premise is that its outcomes would be advantageous for various stakeholders, including students, researchers, and scholars. Furthermore, the research operated under the presumption that the participants possessed a comprehensive understanding of the factors impacting data-driven decision-making among health providers in Mombasa County. Additionally, it was assumed that the respondents would exhibit honesty and transparency in conveying an accurate representation of the state of data-driven decision-making among health providers within Mombasa County.

1.8 Limitation of the Study

During the process of data collection, certain limitations became evident. A subset of respondents exhibited hesitancy in completing the questionnaire due to concerns that their shared information might be used for drives other than academic research. To address this issue, the researcher adhered to ethical principles of confidentiality, reassuring participants that the information they provided was solely intended for academic purposes and would not be utilized otherwise. Furthermore, respondents were guaranteed anonymity, eliminating the need for them to disclose their names on the questionnaire.

Another challenge encountered in this study was the time taken by respondents to complete the questionnaires. In certain instances, the process extended over a period of several weeks. This prolonged timeframe was attributed to the bustling nature of healthcare facilities, characterized by continuous foot traffic throughout working hours, leaving employees constantly occupied. Those who managed to complete the questionnaires expressed the need to find time during evenings and weekends. The researcher exercised patience and maintained persistent communication with the participants, engaging in diplomatic discussions to address these challenges. As a result of these efforts, 98% of the respondents successfully completed the survey. This response rate is considered satisfactory within the context of social science research.

1.8 Operational Definition of Terms

Behavioral Factors: Refer to an individual's convictions, principles, and viewpoints regarding health information.

Health Information Management: Constitutes one of the six fundamental pillars crucial for the advancement of health systems. It encompasses a specialized data compilation system tailored to facilitate the planning, administration, and choice-making within health establishments and entities.

Health Care Providers: Encompass both individual healthcare professionals and healthcare facility entities authorized to furnish diagnostic, treatment, and therapeutic services, including medical procedures and devices. Compensation for their services is frequently obtained from health insurance providers.

Organizational Factors: Encompass aspects that pertain to an organization's arrangement, auxiliary services, protocols, resources, and ethos aimed at supervising, enhancing, and refining the functionality and operations of a HIS.

Data-Driven Decision Making: Involves employing concrete facts, information, and metrics to steer strategic business judgments that harmonize with goals, intentions, and ventures.

Technical Factors: Encompass elements related to specialized knowledge, proficiencies, and aptitude required for developing, managing, overseeing, and enhancing the effectiveness and operations of HIS to ensure high-quality data.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section encompasses an exploration of empirical literature, conceptual and theoretical frameworks, as well as a recapitulation of the literature review. The focus is on the impact of technical factors, organizational factors, and behavioral factors on data-driven decision-making within the context of health providers in Mombasa County.

2.2 Empirical Literature Review

Macharia and Maroa (2014) conducted an investigation into the characteristics of management information systems that affect healthcare quality in private hospitals in Kenya. Their findings demonstrate that effectively implementing a HMIS in healthcare institutions for data quality is a complex endeavor. Even facilities with HMIS and substantial resource investments in these systems confront various challenges that must be resolved to fully leverage these technologies for enhancing healthcare quality. Improved quality absentia in healthcare can result in undesirable patient discernments, possibly deterring them from seeking medical care at such facilities. The study also underscores that the Relative Advantage of HMIS and specific healthcare dimensions such as Quality Responsiveness, Responsibility, and Reliability significantly impact its successful utilization.

Chorongo (2016) delved into factors determining the effective health management information utilization to make decisions among managers of health program. This cross-sectional study employed mixed methods, using stratified and purposive sampling to select respondents from a population of 280 health workers. It revealed that Malindi Sub County's health program management continue to use HMI for decision-making. However, such utilization is influenced by technical, organizational, and behavioral variables, with organizational factors particularly playing a pivotal role in the enhancement of and technical and behavioral aspects. This study recommends bolstering and reinforcing these three factors to optimize information utilization in decision-making processes in Malindi Sub County.

Omambia et al. (2016) analyzed the design criteria pertinent to implementing HMIS, with KNH as a case study. Their cross-sectional descriptive research targeted 263 healthcare workers involved in implementing the system. The study identified a disparity in age, gender, alongside class at Kenyatta National Hospital, suggesting equilibrium in the anticipated direction of HMIS implementation. However, challenges such as providing staff with essential equipment, like personal computers, posed difficulties. This aligns with previous assertions that the quality of healthcare delivery is linked to ICT infrastructure level available and utilized by a nation. The findings emphasized the significance of health workers' characteristics, such as age and duration of employment, in influencing perceptions of HMIS implementation.

Karuri, Waiganjo, and Orwa (2014) investigated the variables shaping the acceptance and utilization of a web-based RHIS in Kenya. Through qualitative exploration, they examined enablers and barriers to the efficacious scaling up as well as implementation of DHIS2 in the country. Interviews with key informants revealed that DHIS2 represented a substantial improvement over previous systems, enabling improved dissemination of public health information and simplified data analysis. Nevertheless, challenges like inadequate infrastructure, limited computer proficiency, staffing constraints, leadership gaps, and unmet demands for quality health data persisted.

Teklegiorgis et al. (2016) evaluated data quality level from HMIS in eastern Ethiopia's resource-restrained context and its related factors. They conducted a cross-sectional study in Dire Dawa Administration health facilities, targeting heads of departments and units. The study concluded that data quality levels in health facilities were below the national standard, with hospitals and health centers outperforming health posts. The absent of training, inadequate decision-based supervision, as well as feedback mechanisms were identified as factors affecting data quality. To enhance data quality, timely supervision and feedback were recommended, alongside continuous training for healthcare providers.

This study underscores the imperative for collective commitment across the health industry to generate high-quality information from daily data. Addressing core issues within routine health management information systems, implementing technological practices, and fostering responsiveness in health services management are critical to sustaining advancements in health service delivery. Beyond resource-intensive initiatives, such as investing in IT and adopting effective platform, controlling data and reporting system drivers is essential for solidifying RHMIS and elevating quality of data.

2.2.1 Technical Factors

Globally, the influence of technological advancements on data quality has been noted. A study by Njoka (2015) found that manual completion of reporting forms by staff led to increased errors and compromised data quality. Technical determinants encompass specialized expertise and technologies necessary for the development, management, and enhancement of HIS performance and processes. This domain includes indicator development, design of forms for data collection, creation of procedural manuals, selection of IT, and development of software to process and analyze data. The PRISM framework posits that indicators' relevance, data collection forms' complexities, and computer software's user-friendliness affect HIS implementers' confidence and motivation. Moreover, inadequate software processing can impede meaningful analysis, impacting decision-making's informational foundation.

The acquisition of analytical, interpretive, and decision-making skills is vital for information utilization. A Zambian study found that a well-designed HMIS, coupled with health worker training in internationally documented practices, contributed to data quality supporting informed decisions. Chen and Hsieh (2014) emphasize the necessity of training health personnel at local and district levels to effectively utilize health data for management as well as enhancement healthcare deliveries. Inadequate skills in Monitoring and Evaluation (M&E) basics not only influence data qualities but also hamper information utilization in making decisions. Janssen, van der Voort, and Wahyudi (2017) further elucidate that interpreting and applying health information to contexts of programs and policy demand a skill set often overlooked while training health professionals.

Training in management of data and its relevance at the level of facility might optimize utilization of information. This approach could transform the system into a conduit for high-quality data that informs decision-making processes. A system's accessibility, compatibility, user-friendliness, stability, reliability, and need for minimal training and robust after-sales support contribute to its quality, according to Teklegiorgis et al. (2016).

The system's quality encompasses ease of utilization, learning, accuracies, flexibilities, integration, complexities, alongside customization. Equally, dimensions of information quality, including clarity, usability, relevance, as well as conciseness, are integral to the system's effectiveness.

A study in India highlighted inadequate analytic and data use skills as common constraints, with respondents seeking to additionally be trained on quality assurance, analysis and usage of data. While poor data quality was not deemed a significant impediment, issues like data duplication and inconsistencies hindered data use. Harrison and Moreland (2019) recommended addressing these challenges, alongside decentralizing routine health information systems management to empower local-level data utilization. This entails incorporating local-level management and healthcare providers into design of tools for collecting and reporting data. The presence of designated personnel or teams responsible for information at the district level is crucial, alongside facilitating data accessibility to all potential users.

Technical factors weigh heavily in organizations' decisions regarding internet-centric inter-organizational information systems adoption. Factors like network reliabilities, costs, data securities, scalabilities, and complexities significantly impact implementation decisions. Soliman and Janz (2014) emphasized data quality and security as vital technical factors. Hardware and software reliability are also essential for successful system implementation. The value of data and the flow through the system underscores the importance of factors such as data quality, security, and infrastructure (Fenz et al., 2014).

The broader global context underscores the importance of a well-trained health workforce in Routine Health Management Information System (RHMIS) processes. A technologically skilled human resource is pivotal for supporting the RHMIS process. Increasing recruitment and ensuring appropriate skills through regular data management and benchmarking training can elevate data quality. The findings of Kawila and Odhiambo-Otieno (2019) indicate that clinic staff prioritized patient care over data collection, leading to delays in data submission that could compromise data quality.

2.2.2 Behavioural Factors

Behavioral determinants encompass the influence of HIS users' confidence, demand, competence, and motivation on HIS performance as well as processes. The perception of task utility, confidence in task execution, and task complexity collectively influence task execution likelihood (Abajebel et al., 2017). High-quality data remain indispensable for instilling confidence in information users regarding completeness, timeliness, and accuracies. The absence of quality data obstructs data-centric decision-making as well as potentially impairing program efficacy (Mavimbe et al., 2019). Poor data quality can diminish the demand for information, creating a cycle of diminished data-informed decisions (Asiimwe, 2016). To facilitate data-informed decisions, robust data quality protocols, training, and retraining of healthcare professionals are vital.

Behavioral factors delve into health workers' data collection and utilization practices. Often, data collectors' primary focus centers on healthcare tasks, with additional duties, like stockkeeping and evidence-based planning, considered secondary to providing healthcare (Ajuwon, 2017). Unclear expectations regarding information use can diminish health professionals' motivation and commitment. The attitudes and values of senior management significantly impact health information use. Promoting evidence-based decision-making and transparency fosters a culture of information. Janssen et al. (2017) showcases the significance of comprehending senior managers' perceptions and attitudes to enhance information-related functions.

The study by Karisa and Wainaina (2020) underscores the negative influence of factors like lack of incentives and insufficient understanding of data utility on HIS performance. Managers' disinterest in utilizing generated information further compounds the situation. Collectively, these behaviors impact health information utilization. A focus on strengthening a sense of health workers' data possession and eliminating perceptions that data collection concludes their role is essential.

Ultimately, addressing technical and behavioral factors is critical for optimizing data-driven decision-making in the healthcare context. These factors collectively shape the foundation upon which health information systems operate and the degree to which the generated information is effectively utilized for informed decision-making.

2.2.3 Organizational Factors

Mboro (2017) suggests that when organizations establish systems that promote a data-led decision-making culture, it enhances the understanding of the worth of data within health system. This leads to improved data quality, effective communication and sharing of data throughout the health system, ultimately resulting in its utilization for decision-making. On the other hand, the absence of consistent systems to support Monitoring and Evaluation actions undesirably affects the supposed significance and data quality collection and utilization. Nevertheless, establishing an info-oriented culture stays a complex task that requires a sustained behavioral intervention over the long term (Ajuwon, 2017). The HMIS system primarily aims to enhance efficiency, data quality, minimize data loss, reduce data storage requirements, and facilitate automation and integration of hospital processes. These goals drove Kenyatta National Hospital (KNH) to re-focus its strategies and interventions, including the adoption of ICT to meet international standards (Omambia et al., 2016).

Within healthcare organizations, such as health workers, decisions related to seeking and utilizing information are driven by the aspiration to make informed choices and enhance services (Aqil et al., 2019). A culture of information is realized whenever individuals actively seek well-defined data and clear indicators for planning, action, and proposing new initiatives. This culture thrives when data takes precedence in decision-making processes (Karuri, Waiganjo & Orwa, 2014). The organization's culture plays a role in either fostering or inhibiting information use. A robust information culture is characterized by regular data use, presentation of tables as well as graphs to public and workers, and dissemination of information to the public, providers, alongside decision-makers across the health sector and society. Building a culture, which supports use of information in decision-making remains as essential as technological advancements for the sustainability of the HIS (Kihuba et al., 2014).

For effective data utilization, organizations need structures and processes that facilitate interaction between producers as well as users of data. Clear data quality processes guidelines, along with well-defined roles and responsibilities for data use, enhance other interventions aimed at improving data-informed decision-making (Shiferaw, Zegeye, Woreta & Yenit, 2017). Documents related to human resources should explicitly outline workers responsibilities alongside roles concerning use of data. A Ugandan-based study found weak organizational variables like limited promotion of an information and quality supervision culture (MEASURE, 2017). Effective communication about performance targets, data use in decision-making, advocacy, and sharing of success stories was lacking (MEASURE, 2017).

Feedback mechanisms are essential for health facilities and organizations to utilize health information to enhance service provision. Timely communication of reports to facilities, followed by relevant actions, ensures that the feedback loop is complete and informs informed decisions (Teklegiorgis et al., 2016). A study by Karijo (2013), cited by Kawila et al. (2019), exposed that inadequate supportive supervision from county supervisors resulted in incomplete data reporting cycles. Conversely, Chorongo (2016) highlighted that sub-county together with authorities of county health enabled supportive primary-level centers' supervision, promoting adherence to skills as well as guidelines reinforcement for high-quality services.

The missing interaction between data producers, who are designing and managing information systems and research, and professionals using data for program improvement disrupts the decision-making cycle (Manya & Nielsen, 2015). Collaborative work between data users and producers increases awareness of data collection methods, quality, and available sources. This partnership addresses barriers to data use and encourages data resource sharing, enabling joint analysis and interpretation of data for program-related queries. This collaborative approach builds data ownership, ensuring buy-in for data-informed decisions (Asiimwe, 2016; Karisa & Wainaina, 2020).

2.2.4 Quality Data Driven Decision Making

Data-driven decision-making (DDDM) entails utilizing factual information, metrics, as well as data for guiding strategic decisions thereby aligning with organizational initiatives as well as goals. The complete realization of data value extends to all individuals within an organization, empowering them to make enhanced decisions informed by data. However, achieving this is not as simple as selecting suitable analytics technology to identify strategic opportunities (Jeremie, Kaseje, Olayo & Akinyi, 2014). Macharia and Maroa (2014) emphasize that fostering a culture that promotes critical thinking and curiosity is essential for health facilities to make data-driven decision-making a norm.

Manya and Nielsen (2015) suggest that at each level, health providers engage in exchanges grounded in data, building their data skills via practice. Such demands a self-service modelling for data accessibility, balanced with security and governance. It also entails offering training and developmental opportunities to enhance employees' data skills. Furthermore, executive support and a community that values data-driven decisions encourage widespread adoption. Aligning with this perspective, Obare, Brolan, and Hill (2016) assert that establishing these fundamental capabilities fosters data-driven decision-making across various job levels, enabling consistent questioning and exploration of information for impactful insights.

Despite the wealth of collected data, its complexity poses challenges for organizations to effectively manage and analyze. Remarkably, New Vantage Partners' report highlights that while 98.60% of executives were aspiring a data-propelled culture, only 32.40% reported successful implementation (WHO, 2019). Similarly, an IDC study from 2018 indicates that many organizations allocate substantial resources to modernize their businesses, but 70 percent of these initiatives fail due to inadequate development of a data culture (Ogondi, Otieno & Koome, 2019). To transition towards data-driven practices, healthcare providers focus on three fundamental capabilities, including data proficiencies, analytics agilities, alongside community involvement. Though challenging, integrating data besides analytics into cycles of decision-making results in transformative benefits for health facilities (MEASURE Evaluation PIMA, 2017).

Regarding data quality, Ogondi et al. (2019) describe it across 4 dimensions, including completeness, consistency, accuracy as well as timeliness. Completeness encompasses filling data elements within facility reports and fraction of facilities reporting within a specific area. Timeliness involves timely report submission, while data accuracy is compared between various records. Ensuring consistency refers to the patient data similarity across cards as well as registers. Addressing timeliness ensures health facility reporting adheres to set schedules (Karisa and Wainaina, 2020).

In contexts like developing countries, quality health information is crucial for monitoring, evaluating, and improving healthcare programs as well as services. However, gaps persist in availability and accessibility of such information (Mboro, 2017; Ogondi et al., 2019). To bridge these gaps, interventions focus on streamlining health data reporting processes and transitioning from paper-based systems to computerized information systems. Kenya, like other developing nations, has moved away from paper-based systems toward more reliable methods due to the limitations of the former approach (Omambia, Odhiambo-Otieno, Mwaura & Adoyo, 2016).

2.2.5 Government Policy

Data-driven governance requires the quantitative measurement of problems and policy responses to inform decision-making. To achieve this, several steps are essential (Mucee et al., 2016). Decision-makers need to define the issues they intend to address, invest in data collection and statistical analysis facilitated by information technologies, and openly share both data and conclusions. To effectively devise policy solutions, these data must be employed to gauge progress toward quantitative objectives, compare performance across peer groups, such as states, and guide policy adjustments and everyday management choices (Mboro, 2017).

A core aspect of data-driven policymaking is that decisions should be transparent and openly conducted. Data sharing should be unrestricted, and decision rationales should be clear (Senkubuge, Modisenyane & Bishaw, 2016). Wekesa (2014) asserts that budget allocations should be intricately linked to data, especially in prioritizing different budget segments. Nevertheless, Ahanhanzo et al. (2014) emphasize that data-driven policymaking isn't an exclusive solution for quality data-driven decision-making challenges. Data alone won't unveil the ideal policy option or dictate resource allocation. Policy determinations necessitate a blend of facts, analysis, judgment, and values (Omambia et al., 2016).

Integrating problem evaluation and performance measurement data into decision-making poses a significant challenge. Deciphering regulatory decisions, for instance, is often complex, with data dispersed among dense, technical documents (Mucee et al., 2016). Mboro (2017) advocates that performance measurement data should illuminate policy response efficacy and compare varied strategies within peer groups, facilitating learning from real-world experiences. Decision-makers should utilize this data to expand successful strategies and motivate underperforming entities to match top performers. Additionally, performance indicators can be analyzed against data on policy inputs and drivers to statistically identify the factors influencing policy success (WHO, 2014).

According to MEASURE Evaluation PIMA (2017), decision-makers should predetermine the crucial data required for each policymaking process and establish a "data form" for agency staff to complete. These forms should present easily understandable data about the addressed problem, as well as anticipated outcomes from various policy alternatives, derived in part from performance measurement data. While standardized forms may work for certain policies, tailored forms might be necessary for specific cases, especially major policy decisions that may benefit from external advisory panel involvement (Ogondi et al., 2019). Data-driven decision-making enhances policy processes by providing insights and rationality. It systematically challenges assumptions, highlights issues, clarifies choices, prioritizes resources, targets interventions, and identifies effective policy solutions (Ahanhanzo et al., 2014).

An equally critical yet less tangible policy intervention involves establishing a culture of quality and transparency in health information management. Shielding from political interference and empowering health statistics offices to publicly respond to report critiques and methodological queries is vital (Teklegiorgis et al., 2016). Ethical protocols safeguarding privacy and confidentiality must be comprehensively understood, with procedures in place for breaches. Ensuring accuracy and reliability through periodic data collection method reviews and benchmarking against credible international indicators is crucial. Promoting a client-focused approach and regularly consulting data users when defining data presentation formats are essential practices (Wekesa, 2014; Seitio-Kgokwe et al., 2015; Njoka, 2015).

Chorongo (2016) recommends that regulatory authority is imperative to ensure comprehensive reporting across all health service delivery sources, public and private. While the Ministry of Health (MOH) can incentivize or penalize publicly owned health facilities to report data, private providers are subject to the regulatory power of the government. Consequently, compelling reporting, especially from the private sector, is crucial for the timeliness and completeness of health data (Iddi, 2020).

2.3 Theoretical Framework

The study's theoretical review stood hinged on three theories that are relevant to the determinants of quality data driven decision making. These theories included socio-technical theory, technology acceptance model and resource base view theory. Each one of them is conversed in the succeeding segments.

2.3.1 Socio - Technical Theory

The socio-technical theory emphasizes the interconnectedness of people-centric (socio) aspects, including human and organizational aspects, and IT aspects (technical) within a system. It underscores the need to evaluate these components together rather than in isolation (Ajuwon, 2017). This theory is particularly relevant for complex adaptive systems like health information systems, as it acknowledges the interplay between technical and social aspects (Asemahagn, 2017). The technical system involves tasks executed through technologies, while the social system includes individuals involved in technology development, their attitudes, skills, and the governing social structures (Asiimwe, 2016).

Elements like tools and skills are more amendable over short periods compared to staff, infrastructure, structures, systems, and roles due to standardization processes (Omambia et al., 2016). Tools, representing hardware and software in health information systems, impact performance capacity. Personal capacity is shaped by the skills of healthcare providers. The future workforce must be trained in emerging data-oriented technologies and understand sociotechnical dynamics for effective data-led decision-making (Muinga et al., 2018; Sultan et al., 2017).

Sociotechnical theory is relevant for investigating dynamic data quality in HIS and aligning health providers' interests with data quality (Aqil et al., 2019). It explains the processes through which technological systems succeed or fail. Stakeholders' perceptions and interests impact network stability, reflecting the focal actor's view of data quality's importance (Senthilkumar et al., 2018). This approach leads to systems more acceptable to end users and better value for organizations (Ajuwon, 2017).

2.3.2 Technology Acceptance Model

In 1986 Fred Davis created Technology Acceptance Model (TAM) for explaining computer usage behavior, by identifying perceived ease of use (PEU) and perceived usefulness (PU) as key beliefs affecting user behavior. PU relates to the potential impact of a system on users' actions, while PEU concerns the expected ease of using the system (Alhadhrami et al., 2017; Sultan et al., 2017; Muinga et al., 2018).

TAM's applicability extends to health providers' acceptance of information technology (Wagenaar et al., 2017). External variables can influence health providers' beliefs toward data systems, modifying TAM's basic beliefs (Alhadhrami et al., 2017). While TAM predominantly focuses on perceived convenience and usefulness, it can also address factors impacting technology adoption, such as data stakeholders' varying perceptions (Bates et al., 2018).

TAM's relevance is evident in studies linking health workers' innovativeness and voluntariness to data-driven decision-making (Manimaran and Lakshmi, 2007). It explains acceptance of technologies like e-prescribing (Karisa & Wainaina, 2020) and physician order entry (Rahimi et al., 2018). Effective health-related data use relies on behavioral intention, particularly when data collection isn't fully automated (Okoth and Mahinda, 2020). TAM's adaptability and integration with other theories are crucial for understanding complex health information contexts (Karisa & Wainaina, 2020).

2.3.3 Resource Base View Theory

Resource-Based View (RBV) emphasizes on organizational distinctive capabilities alongside resources. It emphasizes internal organizational properties as drivers of success. Assets (intangible and tangible) and capabilities (competencies and knowledge) constitute internal property (Chuang & Lin, 2017). RBV encompasses various organizational resources like management competencies, capabilities, assets, processes, and knowledge and technology (Iddi, 2020).

RBV’s applicability extends to healthcare, linking internal resources to organizational performance (Innocent, 2015). Organizational commitment and culture are regarded as exceptional internal resources fostering health information system adoption and data-driven decision-making (Ahmed et al., 2018). RBV provides insight into organizational factors influencing quality data and complements the study's focus on organizational culture and commitment.

2.4 Conceptual Framework

A conceptual framework (CF) is a compilation of interconnected concepts that explain or predict an event, offering a broader understanding of a phenomenon (Drost, 2016). The framework in Figure 2.1 illustrates independent variables—technical, behavioral, and organizational factors—moderated by government policy. These variables stem from both theoretical and empirical literature, aiming to influence data-driven decision-making among health providers in Mombasa County.

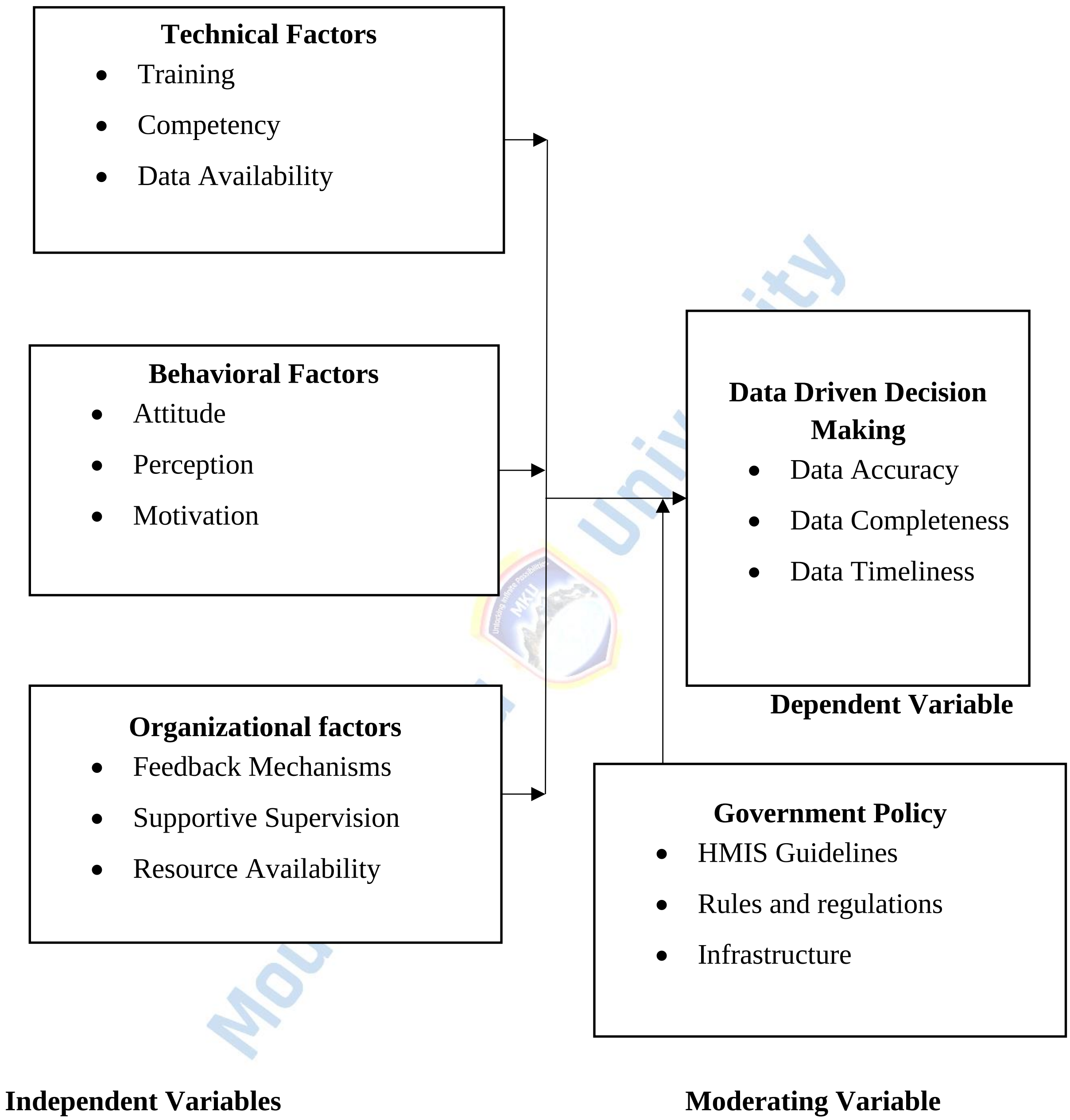

Figure 2.1: Conceptual Framework

2.5 Recap of the Literature Review

In this section, the previous research regarding the factors influencing data-driven decision-making among health providers in Mombasa County has been examined. These ideas have formed the foundation for the theoretical framework. Additionally, the chapter introduced a CF that illustrates the relations among independent variables (behavioral factors, organizational factors, and technical factors), dependent variable (data-driven decision-making), and the moderating variable (Government policies).

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This segment encompasses the approach embraced in undertaking this investigation. It commences with the chosen research design for the research. It encompasses details about the study's target population, the sample selected, and the methods of sampling utilized. The tools for data collection, along with the pilot test to assess their validity and reliability, are discussed. The procedures for collecting data and the techniques employed for data analysis are also covered, culminating in study’s findings’ presentation.

3.2 Research Design

As outlined by Yin (2017), a research design constitutes a comprehensive strategy employed to execute a research investigation that aims to explore specific, empirically testable research inquiries. Creswell (2013) elucidated a research design as a central blueprint that outlines the techniques and protocols to amass and scrutinize essential data. In the current study, an analytical cross-sectional design was embraced. This choice was motivated by its suitability in gauging the prevalence of a phenomenon, state, complication, perspective, or concern within a population snapshot at the study's juncture. The analytical cross-sectional design facilitated the inquiry into the correlation between exogenous variables (technical, organizational, alongside behavioral factors) and outcome of data-driven decision-making (dependent variable), all while factoring in the influence of government policy. A fundamental trait of this research design is the acquisition of all measurements from a sample during a singular instance using a sole questionnaire (Mohammed, 2017).

The selection of an analytical cross-sectional research design for this study can be justified based on several key considerations: Exploring Correlations: The research aims to investigate the determinants of data-driven decision-making among health providers in Mombasa County, with a specific focus on technical, organizational, and behavioral factors. An analytical cross-sectional design is well-suited for exploring correlations between variables, as it allows for the collection of data at a single point in time from a diverse sample. This design facilitates the examination of how different factors may be associated with the outcome of data-driven decision-making.

Snapshot of the Population: The design is appropriate for capturing a snapshot of the population at a specific moment in time. In this case, it enables researchers to assess the prevalence of data-driven decision-making practices among health providers in Mombasa County. This snapshot is valuable for understanding the current state of data utilization in healthcare decision-making within the county.

Efficiency and Resource Management: Analytical cross-sectional studies are typically more efficient in terms of time and resources compared to longitudinal designs, which would require data collection over an extended period. Given the research objectives, the cross-sectional design allows researchers to gather comprehensive data from a diverse sample within a manageable timeframe.

Single Instance Data Collection: The design involves collecting data from a single instance using a single questionnaire. This approach ensures uniformity in data collection and minimizes the potential for variations introduced by multiple data collection points or instruments. It enhances the reliability of the study's findings.

Examination of Government Policy Influence: The design also aligns with the research's aim to factor in the influence of government policy on data-driven decision-making. By collecting data at a specific point in time, researchers can assess the impact of existing policies on health providers' decision-making practices, providing insights into the role of policy in data utilization. Empirical Testing of Research Inquiries: The analytical cross-sectional design is suitable for empirically testing specific research inquiries. It allows researchers to gather quantitative data that can be analyzed statistically to assess the relationships between variables and answer research questions effectively.

In summary, the selection of an analytical cross-sectional research design is justified based on its suitability for exploring correlations, capturing a population snapshot, efficient resource management, uniform data collection, examining government policy influence, and enabling empirical testing of research inquiries. This design aligns with the research objectives and facilitates the investigation of determinants of data-driven decision-making among health providers in Mombasa County.

3.3 Location of the Study

The exploration was situated in Mombasa County, encompassing 4 distinct sub-counties: Jomvu/ Changamwe, Nyali/Kisaun, Mvita, and Likoni. The evaluation of technical factors, behavioral factors, and organizational factors was conducted across the entirety of the 43 health facilities within Mombasa County. The cumulative count of healthcare personnel involved in the study was 303 individuals. This composition encompassed 21

County Health Management Team (CHMT) members, 56 Sub-County Health Management Team (SCHMT) members across the 4 sub-counties, 183 Heads of Departments (HODs) alongside forty-three facility in-charges hailing from forty-three public health facilities. The principal aim was to delve into the variables shaping data-driven decision-making among health providers in the precinct of Mombasa County.

3.4 Target Population

Bell, Bryman, and Harley (2018) expounded upon the concept of a population, defining it as the encompassing assembly of individuals or items that share a common attribute and fall within the scope of investigation across various fields. This collective comprises the bedrock from which a study's sample can be drawn and conclusions can be extrapolated (Kumar, 2014). The study, in particular, directed its attention towards a comprehensive assemblage of 303 healthcare personnel within Mombasa County. This cohort consisted of a variety of roles, including 21 members constituting the CHMT, 56 individuals comprising the SCHMT hailing from 4 distinct sub-counties, forty-three facilities in-charges affiliated with forty-three public health facilities, alongside one hundred and eighty-three HODs, as meticulously outlined in Table 3.1.

Table 3.1 Target Population

S/No	Categories	Target Population	Percentage
1	County Health Management Team	21	6.9
2	Sub-county Health Management Team	56	18.5
3	Facility In-Charges	43	14.2
4	Heads of Departments	183	60.4
	Total	**303**	**100**

3.5 Sampling Size and Sampling Technique

Yin (2017) delineates that the process of sample size determination pertains to the methodology of selecting the appropriate count of observations for inclusion within a sample. Employing a stratified random sampling approach, this study methodically identified pertinent participants spanning the diverse categories comprising the overarching target population. Golafshani (2018) contends that stratified random sampling involves the randomized selection of a specific quantity of cases from each subset of the population. This methodology guarantees the incorporation of subgroups that might otherwise remain completely unrepresented under alternate sampling methodologies. The determination of the sample size was effectuated by employing the Taro Yamane formula.

$$\mathbf{n} = \frac{\mathbf{N}}{\mathbf{K} + \mathbf{N}(\mathbf{e})^2}$$

N = Population of study

K = Constant (1)

e = degree of error expected

n = sample size

$$n = \frac{303}{1 + 303(0.05)^2}$$

n = 172

Proportionate Sample Size formula:

Proportionate sample size = (Category population / Total Target Population) X Sample size

Table 0.2: Proportionate Sample Size

S/No	Categories	Sample Size
1	County Health Management Team	12
2	Sub-county Health Management Team	32
3	Facility In-Charges	24
4	Heads of Departments	104
	Total	**172**

3.6 Data Collection Instruments

Primary data pertains to information gathered for the first time (Golafshani, 2018). In this study, primary data was acquired via meticulously devised questionnaires to elicit information on the crucial variables of interest from the designated participants. The questionnaire comprised structured queries, employing a 5-point Likert scale. Yin (2017) affirms the utility of Likert scales, as they effectively gauge the intensity of an individual's sentiments toward the subject of the questions.

Moreover, they facilitate straightforward analysis, expedite data collection, afford extensive responses, and offer promptness. The chosen respondents were strategically selected based on their capacity to furnish pertinent insights for the study. Supplementary data was procured from documents, articles, reports, journals, and books pertinent to the research, serving to complement the primary data. Marshall and Rossman (2016) underscore the advantages of questionnaires, citing their ability to engage a substantial number of respondents with ease. Furthermore, questionnaires generate quantifiable responses conducive to simplified analysis. The instruments were designed to procure statistics concerning various variables.

The choice of data collection instruments, primarily utilizing meticulously devised questionnaires with structured queries and a 5-point Likert scale, can be justified based on several key considerations: Quantitative Data Collection: The research aims to investigate the determinants of data-driven decision-making among health providers, which involves assessing various technical, organizational, and behavioral factors. Likert scale-based questionnaires are well-suited for quantitative data collection, as they allow respondents to express the intensity of their sentiments or perceptions on these factors in a structured and standardized manner.

Likert scales offer a standardized format for data collection. Respondents are presented with a consistent set of response options, which simplifies the data collection process and ensures that all participants are providing data in a uniform format. This efficiency is particularly valuable when engaging a substantial number of respondents, as mentioned by Marshall and Rossman (2016). Likert scale data can be easily quantified and analyzed, making it conducive to statistical analysis techniques. Researchers can calculate means, standard deviations, and conduct various statistical tests to assess the relationships between variables and test research hypotheses. This analytical ease aligns with the research's quantitative nature.

Despite the structured format, Likert scale questions can be designed to elicit detailed insights from respondents. By offering a range of response options, researchers can capture nuances in participants' attitudes, perceptions, and behaviors related to data-driven decision-making. This depth of information is valuable for addressing the research objectives. Questionnaires are an efficient means of data collection, enabling researchers to gather data from a sizable sample within a relatively short period. This promptness is advantageous, considering the need to collect data from multiple health providers in Mombasa County.

While primary data collection via questionnaires serves as the core of the study, the use of supplementary data from documents, articles, reports, journals, and books enhances the research's comprehensiveness. These supplementary sources provide context, background information, and additional insights that can complement and triangulate the findings from primary data. Strategic Respondent Selection: The choice of respondents who are strategically selected based on their capacity to furnish pertinent insights is aligned with the research's objectives. By targeting individuals with direct involvement in healthcare decision-making, the study focuses on key stakeholders who can provide valuable perspectives on data-driven decision-making.

In summary, the choice of questionnaires with structured queries and a Likert scale is justified based on their suitability for quantitative data collection, efficiency, standardization, and ease of analysis, ability to capture in-depth insights, prompt data collection, and complementarity with supplementary data sources. These instruments align with the research's quantitative nature and the need to investigate various determinants of data-driven decision-making among health providers in Mombasa County.

3.7 Pilot Testing

Kumar (2019) outlined that a pilot test identifies deficiencies in instrumentation and design, as well as to furnish substitute data for the probability sample's selection. Through the execution of a pilot test, the researcher ensures the formulation of appropriate queries, collection of accurate data, and employment of suitable data collection methods. The pilot study was undertaken at the respective public health facilities within Mombasa County. The questionnaire underwent testing on 17 respondents who were part of the target population but excluded from the actual sample. This cohort comprised approximately 10% of the overall sample size, adhering to the common recommendation by social scientists (Kothari & Garg, 2014).

3.7.1 The validity of Research Instrument

Validity denotes to the degree to which the data analysis results accurately depict the phenomena being investigated, signifying the precision with which the gathered data represents research's variables (Kothari & Garg, 2014). To assess this, the researcher employed the commonly utilized internal consistency measure, namely the KMO-Bartlett's test. The range of this value is between 0 and 1, with a satisfactory score above 0.6 being essential for scale reliability. The conventional threshold for reliability is recommended at 0.7, and this study adhered to that recommended value.

In the assessment of the relationship among variables, this study employed the KMO Measures of Sampling Adequacy and Bartlett's Test of Sphericity, as visualized in Table

3.3. The factors were categorized as follows: Factor 1 consisted of six items representing technical factors; Factor 2 included six items for behavioral factors; Factor 3 comprised six items for organizational factors; Factor 4 encompassed six items for government policy as the moderating element; and Factor 5 featured six items for quality data driven decision making. The Kaiser-Meyer-Olkin Measures of Sampling Adequacy displayed a test statistic value of 0.842, surpassing the acceptable index of 0.5, thus indicating acceptability. Meanwhile, the Bartlett's Test of Sphericity demonstrated a 0.000 test statistic value, falling below the acceptable index of 0.05, further signifying an exceedingly significant association among the factors.

Table 3.3: KMO and Bart

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.842
	Approx. Chi-Square	613.807
Bartlett's Test of Sphericity	df	10
	Sig.	.000

3.7.2 Reliability of Research Instruments

As demarcated by Marshall and Rossman (2014), reliability relates to the extent of consistency displayed by a scale's outcomes when measurements are repeated. This involves assessing the correlation between scores drawn from diverse instances of using the scale. In this study, the relationship between scores derived from diverse administrations of the questionnaire was determined to ascertain the scale's consistency. If a strong association exists, the scale produces dependable outcomes, indicating its reliability. The questionnaire's internal reliability stood evaluated via Cronbach's alpha, a measure with values ranging from 0 to 1.0. While perfect reliability is represented by 1.0, a threshold of 0.7 is considered minimally acceptable. This assessment was crucial as it gauged the extent to which the scale maintains consistency across repeated measurements.

All identified factors' reliability statistics are outlined in Table 3.4. The data reveals that Cronbach's alpha for every independent variable significantly surpassed the acceptability threshold of 0.70. This analysis demonstrated that nearly all sections and questions attained a Cronbach's alpha of 0.7 or higher. The investigation also examined each question's responses to identify potential technical glitches with the questions. Consequently, the findings showcase that questionnaire employed exhibited a notably high reliability level.

Table 3.4 Reliability Test

Scale	Cronbach's Alpha	Number of Items	Comments
Technical Factors	.826	6	Acceptable
Behavioral Factors	.845	6	Acceptable
Organizational Factors	.894	6	Acceptable
Government Policy	.811	6	Acceptable
Data Driven Decision Making	.807	6	Acceptable

3.8 Data Analysis and Presentations

Given that the primary data formed the bedrock of this study, the research sought to amass quantitative data through the administration of questionnaires. Quantitative data was subjected to scrutiny through descriptive statistics (standard deviation and mean) as well as inferential statistics (multinomial logistic regression analysis and Pearson correlation examination). The SPSS version 28 stood employed to perform these analyses. The outcomes were elucidated using tables, chosen for their capabilities of facilitating comparison and enhance interpretability. The nexus between dependent and independent variables was probed via Pearson correlation analysis. To ascertain the collective influence of the variables, multinomial logistic regression analysis was executed, upholding a significance level of .05. This determination was established by the model, as outlined below:

Multiple Variables:

$Y=B_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\varepsilon$

$Y= \beta 0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4+ \beta_mM + \varepsilon$

$Y=B_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_1X_1M+ \beta_2X_2M+ \beta_3X_3M+ \varepsilon$

Where;

Y = Data Driven Decision Making

$\beta 0$ = is a constant, the results when all variables X_1 to X_4 are zero

β_i = Coefficient for X_i (i=1, 2,3,4)

βm = Coefficient of Moderator

β_iM = Coefficient of Interaction term

X_1 = Technical factors

X_2 = Behavioural factors

X_3 = Organizational Factors

M = Government Policy (moderating variable)

X_iM = Product term/interaction term of the moderating variable with each of the study variables (X_1, X_2, X_3, X_4)

ε = error term

3.8 Ethical Considerations

Prior ethical approvals were secured from the Institutional Ethical Review Committee (IREC) at MKU, and a study permit was duly acquired from NACOSTI. Stringent adherence to ethical standards was maintained, and informed consent stood conscientiously attained from all study subjects. Additionally, research permissions were diligently sought from both the Mombasa County Ministry of Health and the respective health facilities involved in this exploration. This meticulous approach was aimed at creating a conducive and uncontaminated research environment, free from internal disruptions and influences. Comprehensive information pertaining to the study's objectives was provided to all participants, enabling them to make an enlightened decision regarding their participation. Ensuring the highest degree of confidentiality, data gathered from study participants were handled with the utmost discretion. Study participation was wholly voluntary, further underscoring commitment to ethical principles.

Ethical approval for this study is crucial to ensure the protection of the rights, well-being, and confidentiality of the research participants, and it can be justified based on the following considerations: Informed Consent: The study explicitly mentions that informed consent was conscientiously attained from all study subjects. This ethical requirement ensures that participants were fully aware of the study's objectives, procedures, potential risks, and benefits before deciding to participate. Informed consent is a fundamental ethical principle that upholds participants' autonomy and right to make voluntary decisions regarding their involvement in the research.

Confidentiality: The study emphasizes the highest degree of confidentiality in handling data gathered from study participants. Protecting participants' privacy and confidentiality is an essential ethical consideration. It reassures participants that their responses will not be disclosed in a way that could identify them individually, thus promoting trust and openness in the research process. Ethical Oversight: Ethical approval was obtained from the Institutional Ethical Review Committee (IREC) at MKU, indicating that the research design, data collection methods, and ethical considerations were thoroughly reviewed and deemed ethically sound. Ethical oversight by an established committee demonstrates a commitment to upholding ethical standards in research.

Legal Compliance: A study permit was acquired from the National Commission for Science, Technology, and Innovation (NACOSTI). This legal requirement ensures that the research complies with national regulations and guidelines governing research activities. It reflects the researcher's commitment to adhering to legal and ethical norms. Minimizing Harm and Risks: Ethical approval ensures that the research design and procedures were carefully reviewed to minimize potential harm and risks to participants. This includes assessing and mitigating any potential physical, psychological, or social risks associated with the study.

Permissions from Relevant Authorities: Research permissions were diligently sought from both the Mombasa County Ministry of Health and the respective health facilities involved in the study. This step demonstrates respect for the authority and policies of the entities within which the research is conducted. It also helps prevent disruptions and ensures that the research is conducted with the cooperation of relevant stakeholders. Voluntary Participation: The study explicitly states that study participation was wholly voluntary. This underscores the importance of respecting participants' autonomy and their right to choose whether or not to participate without coercion or pressure. Voluntary participation aligns with ethical principles of research conduct.

In summary, ethical approval for this study is justified as it reflects a comprehensive commitment to ethical principles and standards in research. It demonstrates adherence to informed consent, ethical oversight, legal compliance, permissions from relevant authorities, confidentiality, voluntary participation, and minimizing harm and risks. These ethical considerations are essential for conducting research that is both morally sound and methodologically rigorous.

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

4.1 Introduction

The section encompasses the examination of data, the unveiling of research discoveries, and comprehensive discussions. The revealed findings encompass a variety of aspects, including respondents' background information, outcomes derived from pilot testing, descriptive outcomes that encompass percentages and frequencies, as well as the assessment of regression assumptions. The ensuing dialogue surrounding the findings encompasses a convergence of the current study's discoveries with those of prior research as deliberated upon within the literature review section.

4.2 Demographic Characteristics

In order to comprehend the composition, qualifications, and experience related to quality data driven decision making, the investigator gathered background info regarding participants of this survey. This information encompassed details such as the respondents' age, professional cadre, educational attainment, duration of employment, and their respective work sections. The outcomes revealed that 109 individuals (65%) were below the age of 40, 54 respondents (32%) belonged to the clinician cadre, 60 participants (35.7%) held degrees, 60 individuals (35.7%) had accumulated over 4 years of employment, and 58 respondents (34.5%) were associated with the OPD section. The demographic findings are presented in Table 4.1. As proposed by Stinchcombe (2020), a 50% response rate is deemed adequate, whereas 60% is considered good, while 70% or more is rated as very well. In alignment with this guideline, the substantial response rate of 98% achieved in this case is exceedingly high, signifying a very well-rated and satisfactory level of participation to draw conclusions for this research.

Table 4.1: Demographic Information

Characteristic		**F**	**%**
Age of respondents	20-30 years	63	38
	30-40 years	46	27
	40-50 years	28	16.5
	>50 years	31	18.5
Response Rate	Responses	168	98%
	Non responses	4	2%
Respondents' Cadre	CLINICIANS	54	32
	HRIO	36	21
	MLO	18	11
	NURSE	32	19
	Pharm/Tech	28	17
Respondents' Education Level	Certificate	25	14.9
	Diploma	49	29.2
	Degree	60	35.7
	Postgraduate	34	20.2
Respondents' Employment Duration	< 1 year	21	12.5
	1-2 years	36	21.4
	3-4 years	51	30.4
	>4 years	60	35.7

Respondents' Section of Work	OPD GENERAL	58	34.5
	MCH	43	25.6
	SPECIAL CLINIC	26	15.5
	LAB	21	12.5
	HMIS	20	11.9

4.4 Descriptive Statistics

This segment provides an overview of the descriptive findings. The analysis involved utilizing percentages, frequencies, means, and standard deviations. The outcomes illustrate how the participants' responses were distributed across a range of statements in the questionnaires, using a scale ranging from strongly agree (SA) to strongly disagree (SD). The disclosure of such findings is structured according to the research objectives.

4.4.1 Technical Factors and Data Driven Decision Making

In this section, the analysis aimed at investigating association between technical variables and data driven decision making among health providers in Mombasa County. Table 4.2 has summarized subjects' agreement level regarding how technical variables are influencing quality data use in decision-making within Mombasa County. The outcomes highlighted in Table 4.2 indicate that a significant respondent’s majority, comprising 96.2%, acknowledged that the existence of technically qualified human resources is pivotal in backing effective data management. Similarly, 96.1% of the participants concurred that the development of skills in analyzing, interpreting, and decision-making is essential in facilitating the use of information. A notable 87.4% of respondents affirmed that health providers prioritize patient care over data collection, and 83.3% expressed that decentralizing RHIS management could improve the local utilization of health information data. Moreover, 83.9% of the respondents agreed that training in data management at facilities level could foster the use of high-quality data in processes of decision-making. Additionally, 79.1% of the participants indicated that technical determinant factors are connected to specialized expertise in quality data management.

The outcomes are aligned with Iddi (2020), who highlights the association between technical determinant factors and specific know-how required in developing, managing, and enhancing HIS performance and processes. Chen and Hsieh (2014) assert that under the PRISM framework, irrelevant indicators, complex data collection forms, and user-unfriendly computer software can undermine HIS implementers' motivation and confidence. Equally, inadequate data processing by software can lead to ineffective analysis and hinder significant conclusions for decision-making, consequently impacting information use (Harrison & Moreland, 2019).

Furthermore, the outcomes of this study align with Bhattacherjee and Hikmet (2016), who underscore that enhancing skills in analysing, and interpreting, as well as decision-making encourages information use. Chorongo (2016) revealed that a properly designed HMIS, coupled with appropriate training in accordance with internationally recognized practices, contributes to data quality necessary for informed decisions. Chen and Hsieh (2014) emphasize the importance of data utilization training to empower health workers at local and district levels to effectively leverage health data for improved service delivery and management. Janssen et al. (2017) expand on this by explaining that the capability of interpreting health information (HI) as well as applying HI to policy and programmatic contexts necessitates a skill set, often overlooked in the pre- and post-service training of healthcare practitioners.

Table 4.2: Technical Factors and Data Driven Decision Making

Statement	1	2	3	4	5	Mean	Std Dev
Availability of technically qualified human resource is key in supporting data management	0.0%	0.0%	3.8%	65.2%	31.0%	4.27	0.52
Developing skills in analyzing, interpreting and decision-making promote information use	0.0%	0.0%	3.8%	67.9%	28.2%	4.24	0.51
Health providers value the care of patients over data collection	0.0%	0.0%	12.6%	49.8%	37.6%	4.42	3.02
Routine health information systems management should be decentralized to improve local use of health information data	0.0%	0.0%	16.7%	34.5%	48.8%	4.32	0.74
Training in data management at facility level may promote good quality data to be used in decision making processes	0.0%	0.0%	16.1%	43.9%	40.0%	4.24	0.71
Technical determinant factors are related to the specialized know-how on quality data management	0.0%	0.0%	20.9%	39.7%	39.4%	4.18	0.76

4.4.3 Behavioural Factors and Data Driven Decision Making

This research aimed to evaluate the correlation between data driven decision-making and behavioral factors among health providers in Mombasa County. Table 4.3 offers a summarized representation of respondents' agreement levels concerning the impact of behavioral aspects on the use of quality data in making decisions within Mombasa County. Notably, 93.3% of participants acknowledged that the perceptions and attitudes of senior management towards data significantly impact the utilization of health information. The majority of respondents, accounting for 95.4%, concurred that a positive attitude prevails towards data collection and usage. Additionally, 85.7% expressed that perceptions of HIS processes and associated tasks contribute to improved quality data driven decision making. A significant proportion of 73.5% indicated that managers of health facilities often gather data devoid of comprehending their utilities. Moreover, 63% of respondents revealed that the absence of incentives for data gathering affects the quality of data driven decision making, while 71.5% agreed that reinforcing health workers' sense of data ownership is necessary.

These findings align with Karisa and Wainaina (2020), who in their study unveiled the detrimental impact of the insufficient incentives for data gathering and the limited understanding of data utilities on HIS performance. The results further underscore that managers frequently fail to integrate the generated information into their managerial activities, a behavior that ultimately influences the utilization of health information. Consequently, comprehending collective values linked to HIS processes and related tasks is crucial for promoting values that foster the utilization of Routine -HIS (RHIS). This, in turn, can augment the efficacy of health information utilization in processes of making decision.

Furthermore, such outcomes are consistent with Abajebel et al. (2017), who assert that perceptions as well as attitudes of senior management towards data significantly shape the utilization of HI. When senior management does not prioritize evidence-based decision-making alongside information utilization for transparency and accountability, it becomes unlikely that an information-oriented culture will be cultivated. Janssen et al. (2017) emphasize the importance of scrutinizing the values, attitudes, and perceptions of senior management and additional organizational employees regarding information-centric functions. To enhance HI utilization in developing nations, it is imperative to strengthen sense of data ownership among health workers and eradicate the discernment that their role concludes with data collection and transmission (Karisa & Wainaina, 2020).

Table 4.3: Behavioural Factors and Data Driven Decision Making

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
Perceptions and attitudes of senior management towards data have an influence on the use of health information	0.0	0.0	6.6	68.3	25.1	4.18	0.53
There is positive attitude towards data collection and use	0.0	0.0	4.5	70.7	24.7	4.20	0.50
Perception on HIS processes and related tasks improves quality data driven decision making	0.0	0.0	14.3	68.2	17.5	4.03	0.56
Health facility managers gather data without understanding its utility	0.0	0.0	18.5	37.3	36.2	4.10	0.79
Quality data driven decision making is affected by lack of incentives towards data collection	0.0	0.7	36.4	42.7	20.3	3.83	0.75
There is need to strengthen health workers' sense of data ownership	0.0	0.0	28.6	29.3	42.2	4.14	0.83

4.4.4 Organizational Factors and Data Driven Decision Making

The study aimed as ascertaining the linkage between organizational variables and quality data usage in decision-making among Mombasa County's health providers. Table 4.4 provides a summarized overview of respondents' agreement levels regarding the organizational factors' effects on quality data-led decision making within Mombasa County. An overwhelming majority of respondents, comprising 95.8%, indicated the presence of structures and processes designed to enhance collaboration between data users and producers. Furthermore, 93.4% agreed that roles and responsibilities relating to data usage for informed decision making are well-defined. In addition, 81.9% concurred that recognition and reward systems are established for commendable data system performance. A considerable percentage of 57.1% affirmed the sharing of best practices in Health Information System (HIS) utilization. Moreover, 75.3% expressed the availability of sufficient resource allocation for support supervision of data systems, and 89.9% acknowledged the existence of feedback mechanisms for health information data utilization.

These findings align with Mboro (2017), whose research indicated that the presence of organizational systems supporting a data-led decision-making culture, results in enhanced data quality, improved communication and sharing of data throughout the health system, ultimately leading to its effective utilization in decision making. Conversely, the absence of consistent systems for Monitoring and Evaluation activities undesirably influences the supposed significance and quality of data gathering and usage. Transforming an organization into an information-oriented culture poses challenges, necessitating sustained behavioral interventions over the long term (Ajuwon, 2017).

Seitio-Kgokwe et al. (2015) similarly concluded that missing mechanisms for feedback deprives sub-counties the opportunity to employ HI for service enhancement. The generated information should benefit healthcare management and facilities by providing them with feedback for informed decision-making. In their study, though reports' submission is done to the MOH, no established measures guaranteeing that the info from these reports remained relayed back to the submitting facilities, thus emphasizing the significance of feedback to complete the data reporting cycle. The availability of feedback notably influences how health facilities utilize health information to inform their decisions (Teklegiorgis, Tadesse, Terefe & Mirutse, 2016).

Table 4.4: Organizational Factors and Data Driven Decision Making

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
There are feedback mechanisms on health information data utilization	0.0	0.3	9.8	59.6	30.3	4.20	0.61
We have structures and processes for improving the interaction of data users and producers	0.0	0.3	3.8	69.7	26.1	4.22	0.52
We define roles and responsibilities related to using data to improve data informed decision making	0.0	0.0	6.6	51.6	41.8	4.35	0.60
There is recognition and reward systems for good performance of data systems	0.0	0.0	18.1	33.8	48.1	4.30	0.76
There is sharing of best practices on HIS utilization	0.0	1.0	41.8	33.4	23.7	3.80	0.81
There is adequate resource allocation for support supervision on data systems	0.0	1.0	23.7	48.1	27.2	4.01	0.74

4.4.5 Data Driven Decision Making

This section provides descriptive insights into the dependent variable, focusing on decision making propelled by data. The mean score for the statement emphasizing the prominence of data completeness for decision-making was 4.19. Around 63.5% of respondents expressed that data completeness is crucial for effective decision-making. Similarly, 82.5% highlighted the significance of data consistency in the decision-making process. Furthermore, 68.1% indicated that the submitted data encompasses all requisite dataset reports. Regarding the assertion about taking prompt corrective actions to address data reporting issues, 39.8% agreed, while 41.5% maintained a neutral standpoint. In contrast, 6.7% disagreed with this statement. For the statement concerning the existence of procedures for data distribution and reporting, 50.3% concurred, whereas 42.1% maintained a neutral stance, and 6.7% disagreed. Notably, 89.9% acknowledged the presence of criteria for verifying the completeness and consistency of collected data.

These findings resonate with those of Ogondi et al. (2019), who identified data quality across 4 dimensions: completeness, accuracy, consistency, alongside timeliness. Completeness pertains to not solely the proper completion of all data facets in report forms of the facilities, but also to the percentage of facilities submitting reports within a given an area of administration like a district. Timeliness evaluates whether reports are submitted according to established deadlines. Karisa and Wainaina (2020) further emphasized that data accuracy is evaluated through comparisons between reports and records of facilities, as well as between facility databases and reports within administrative areas. The concept of consistency addresses the level of correspondence between patient data on patient cards alongside registers. Timeliness, meanwhile, assesses if health facilities adhere to the specified schedule for reporting to higher administrative levels.

Table 4.5: Data Driven Decision Making

Statement	**1 %**	**2 %**	**3 %**	**4 %**	**5 %**	**Mean**	**Std Dev**
Completeness of reported data is essential for decision-making	0.4	14.4	21.8	38.9	24.6	3.73	1.00
Consistency is essential for decision-making	0.0	1.1	16.5	35.1	47.4	4.29	0.77
Reported data includes all the necessary dataset reports	0.4	2.8	28.8	33.0	35.1	4.00	0.89
Corrective actions are always taken within reasonable time to address data reporting issues	1.1	17.6	41.5	35.6	4.2	3.24	0.83
There is a procedure for distributing and reporting data	0.7	6.7	42.1	44.2	6.3	3.49	0.74
There is criteria for verification of completeness and consistency of data collected	0.0	0.3	9.8	59.6	30.3	4.20	0.61

4.4.6 Government Policy and Data Driven Decision Making

This part is dedicated to investigating the interplay between the moderating influence of government policy and data driven decision making among Mombasa County's health providers. Table 4.6 succinctly presents subjects' perspectives on how government policy (as the moderating variable) impacts data driven decision making within the county. Additionally, respondents were requested to assess government policy.

The findings reveal that 47.9% and 43.1% of participants conveyed the necessity of a regulatory framework to ensure comprehensive reporting from all health service delivery sources. Regarding the reuse of standardized data forms for future decisions, 46.5% strongly agreed and 41.3% agreed with this notion. Similarly, 45.5% and 42.7% of participants respectively strongly agreed and agreed with the notion that the Ministry of Health can motivate public health facilities to report health data through incentives or penalties for compliance and noncompliance. On the subject of implementing support systems for a common data architecture, 43.1% strongly agreed, while 46.5% expressed agreement. Pertaining to ensuring accuracy and reliability through periodic reviews of data collection methods, 43.8% strongly agreed, and 47.6% agreed. In terms of the availability of a legal and regulatory framework governing the National Health Information System (NHIS), 28.2% strongly agreed, and 67.9% expressed agreement.

These findings mirror those of previous research that underscore the critical role of government policy in shaping the landscape of data-led decision making. The data emphasizes the significance of standardization, incentives, penalties, and supportive structures in fostering effective data use. It also highlights the significance of legal frameworks in governing the National Health Information System, which can ultimately influence data utilization practices.

Table 4.6: Government Policy

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
Regulatory framework is necessary to ensure complete reporting from all sources of health service delivery	2.8	2.8	3.5	47.9	43.1	4.26	0.87
Data forms are standardized and then reused for future decisions	4.2	4.2	3.8	41.3	46.5	4.22	0.96
The Ministry of Health can compel public health facilities to report health data by creating incentives or penalties for compliance and noncompliance	4.2	3.8	3.8	42.7	45.5	4.22	0.99
Support systems have been put in place to establish a common data architecture	2.8	3.1	4.5	46.5	43.1	4.24	0.89
Accuracy and reliability expectations is ensured through periodic review of data collection methods	2.4	3.5	2.8	47.6	43.8	4.27	0.87
There is legal and regulatory framework governing NHIS	0.0	0.0	3.8	67.9	28.2	4.24	0.51

These findings align with the perspective presented by Senkubuge et al. (2016), who contend that a fundamental characteristic of data-driven policymaking entails transparent decision-making, wherein data is openly shared, and choices are elucidated. Within the context of budgetary processes, this underscores the need for several reforms. However, as highlighted by Ahanhanzo et al. (2014), it's important to acknowledge that data-driven policymaking doesn't offer a comprehensive solution to complexities of quality data-propelled decision making. Data, in and of itself, cannot singularly unveil the optimal policy selection or guide us on which issues to prioritize and how to allocate resources. Policy choices inherently blend facts, analysis, judgment, and values (Omambia et al., 2016).

These findings resonate with those of Ogondi et al. (2019), who reached the conclusion that mechanisms for establishing a shared data architecture, exemplified by the Kenya HIS comprising elements like Health Commodity Information System (HCIS) and Community Health System (CHS, have been instituted. Additionally, data clinic forums alongside Nutrition Information Technical Working Groups (NITWGs) have been established and reinforced nationally and county-wise. These platforms validate and disseminate data and statistics.

Furthermore, Iddi (2020) also validates these findings by unveiling that performance enhancement is achieved through quarterly monitoring and review processes at the county level, coupled with monthly assessments at health facilities as well as communities' tiers. Such evaluations stay conducted via reassuring supervision, data reviews, and periodic quality and data reviews. Routinely engaging communities in action days and dialogues enables people to scrutinize data. To increase communities' involvement, findings are broadcasted through community radio as part of a comprehensive community health strategy.

Echoing these sentiments, Chorongo (2016) proposes the necessity of a regulatory authority to ensure comprehensive reporting across all health service delivery sources, encompassing both public and private domains. The Ministry of Health can enforce data submission from publicly owned health facilities through incentives or penalties, which can be a particularly potent motivator. Conversely, the Ministry's influence over private providers is constrained, emphasizing the significance of regulatory authority in compelling reporting, especially within the private sector (Iddi, 2020).

4.5 Inferential Statistics

4.5.1 Correlation Analysis between Study Variables

The researcher conducted a correlation examination to establish the potential relationships among the variables. Pearson correlation was employed for this analysis, utilizing the (r) coefficient to assess the linear connection between the study variables. As noted by Mugenda et al. (2012), the correlation coefficient generates a statistic spanning from negative1.0 (denoting ideal negative correlation) to 1.0 (reflecting ideal positive correlation), offering insights into the strength of the connection between 2 variables. The magnitude of the coefficient of correlation value indicates the robustness of the association between these variables. A value of zero for (r) signifies the absence of any connection between the variables. The computation of correlation coefficients was undertaken for each pair of variables, with the outcomes tabulated in the correlation matrix (Table 4.7).

The outcomes indicated that quality data driven decision making exhibited a substantial correlation with technical factors ($r = .642$, p-value = 0.000). This observation signifies that positive alterations in technical factors were linked with enhanced quality data driven decision making. Furthermore, the findings highlighted a significant correlation between quality data driven decision making and behavioural factors (r = .821, p-value = 0.000). This underscores the notion that favorable shifts in behavioural factors were associated with heightened data-led decision making. Additionally, the study's results revealed a marked correlation between quality data-propelled decision-making alongside organizational factors (r = .819, p-value = 0.000). This indicates that favorable modifications in organizational factors were linked to improved quality data driven decision making.

Table 4.7: Correlation Analysis Results for Study Variables

		Y	X_1	X_2	X_3	M
Y	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	168				
X_1	Pearson Correlation	.642**	1			
	Sig. (2-tailed)	.000				
	N	168	168			
X_2	Pearson Correlation	.821**	.614**	1		
	Sig. (2-tailed)	.000	.000			
	N	168	168	168		
X_3	Pearson Correlation	.819**	.555**	.880**	1	
	Sig. (2-tailed)	.000	.000	.000		
	N	168	168	168	168	
M	Pearson Correlation	.563**	.410**	.491**	.521**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	168	168	168	168	168

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

Key: Y= Data Driven Decision Making; X_1 = Technical Factors; X_2 = Behavioural Factors; X_3 = Organizational Factors; M=Government Policy.

4.5.2 Logistic Regression Analysis

In assessing the exogenous variables' impact on endogenous variable, the researcher utilized multinomial logistic regression analysis. As outlined by Bell, Bryman, and Harley (2018), this analytical technique is employed to anticipate the categorization or the likelihood of belonging to specific categories within a dependent variable, contingent on several independent variables. The outcomes of this analysis are expounded upon in the ensuing subsections.

4.5.2.1 Model Fitting Information

The table containing information about the fitting of model includes a Likelihood Ratio chi-square test, which compares the complete model (comprising all predictors) with a null model (only containing an intercept/no predictors). The statistical significance of this test demonstrates whether the full model's fit is notably better than that of the null model. As presented in Table 4.8, it is evident that the final model significantly enhances the fit over the null model [X^2 (36) = 86.051, $p < 0.05$. This establishes a substantial connection between the dependent variable (quality data driven decision making) and independent variables (technical, organizational, alongside behavioral factors) in the final model.

Table 4.8: Model Fitting Information

	Model Fitting Criteria			Likelihood Ratio Tests		
Model	**AIC**	**BIC**	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	384.956	422.444	360.956			
Final	370.906	520.856	274.906	86.051	36	.000

4.5.2.2 Goodness-of-fit Test

The table displaying goodness of fit encompasses the Pearson Chi-square and Deviance tests, employed to evaluate the extent to which a model corresponds with data. When the test outcomes are not statistically significant, it suggests that the model aligns well with the data. In this case, the two tests reveal that model conforms suitably to the data, signifying a favorable fit. The computed p-value surpassed the predefined significance level ($p > 0.05$), showcasing that this model effectively aligns with data. These findings are provided in Table 4.9.

Table 4.9: Goodness-of-fit Test

	Chi-Square	df	Sig.
Pearson	211.603	432	1.000
Deviance	173.749	432	1.000

4.5.2.3 Pseudo R-Square

These Pseudo R-square values serve as approximate counterparts to R-square value within ordinary least squares (OLS) regression. It's important to note that their interpretation differs from the proportion of variance explained in OLS regression. According to McFadden's assessment, the complete model incorporating the predictors accounts for around 13.4% of the variance, which indicates substantial and meaningful effects.

Table 4:10: Pseudo R-Square

Cox and Snell	.401
Nagelkerke	.410
McFadden	.134

4.5.2.4 Likelihood Ratio Tests

The outcomes encompass likelihood ratio tests that evaluate the combined impact of each exogenous variable on the model (when a variable becomes introduced as a factor, its outcome signifies an overall test of that factor). Applying the conventional threshold of p = .05, both technical factors and organizational factors remained significant statistically with $p < 0.05$, signifying their significance as predictors within the model. Hence, they stand as the primary determinants of quality data driven decision making among health providers in Mombasa County. However, behavioural factors exhibited statistical insignificance with $p > 0.05$.

Table 4.11: Likelihood Ratio Tests

	Model Fitting Criteria			Likelihood Ratio Tests		
Effect	**AIC of Reduced Model**	**BIC of Reduced Model**	**-2 Log Likelihood of Reduced Model**	**Chi-Square**	**df**	**Sig.**
Intercept	394.098	506.561	322.098	47.192	12	.000
Technical Factors	395.371	507.833	323.371	48.465	12	.000
Behavioural Factors	364.542	477.005	292.542	17.636	12	.127
Organizational Factors	367.614	480.076	295.614	20.708	12	.055

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

4.5.2.5 Contribution of the Moderating Variable to the Model

Every independent variable's statistical significance was assessed via Wald test with a 0.05 significant level. The outcomes indicated organizational factors ($p < 0.05$), that technical factors ($p < 0.05$), and government policy ($p < 0.05$) exhibited significant contributions to the model and consequently made substantial contributions to the model's predictive capability. However, behavioral factors ($p > 0.05$) did not demonstrate a statistically significant effect to prediction or model.

Table 4.12: Contribution of Moderating Variable in the Model

	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I. for Exp(B)**	
							Lower	**Upper**
Technical Factors	-1.074	.250	18.462	1	.000	.342	.209	.558
Behavioural Factors	-.510	.263	3.775	1	.052	.600	.359	1.005
Organizational Factors	-.035	.232	30.365	1	.000	.965	.953	.978
Government Policy	2.501	.167	224.279	1	.000	12.192	8.789	16.913
Constant	1.243	.321	14.965	1	.000	3.465		

a. Variable(s) entered on step 1: Technical Factors, Behavioural Factors, Organizational Factors, Data Driven Decision Making, Government Policy

Mboro (2017) proposes that when organizational structures are established to endorse a data-driven decision-making culture, individuals responsible for data creation and consumers are properly equipped to comprehend the significance of data within health system. Consequently, higher quality data and effective data communication via health system tend to occur, leading to its utilization in decision-making. Conversely, the absence of regular supportive systems for data activities negatively impacted the perceived value and quality of data collection and utilization. Organizational factors, such as culture, play a role in either encouraging or discouraging information use. A robust information culture is marked by consistent data usage, visual representation of data for the public and workforce, and information dissemination to decision-makers, public, and providers across various societal and health sector segments. For the HIS's sustainability, fostering a culture supportive of info use in processes of decision-making is just as crucial as having adequate technical resources (Kihuba et al., 2014).

This observation aligns with the findings of Iddi (2020), who emphasizes that technical determinant factors encompass specialized expertise and technology necessary for the development, management, and enhancement of HIS performance and processes. Furthermore, the outcomes of this study corroborate those of Bhattacherjee and Hikmet (2016), who posit that cultivating skills in analysis, interpretation, and decision-making fosters information utilization. Chorongo (2016) also discovers that a well-designed Health Management Information System, coupled with training adhering to international practices, enhances the quality of data needed to support informed decisions. The proficiency in interpreting and applying HI within programmatic and policy contexts requires often overlooked skill set in the training of health professionals before or after service.

In line with Senkubuge et al. (2016), this finding concurs that a key characteristic of data-driven policy-making is conducting decision-making transparently. However, Ahanhanzo et al. (2014) underscore the necessity of acknowledging upfront that data-driven policymaking may not offer all solutions to the quality data-led decision-making challenges. Data, in isolation, does not unveil the optimal policy choice, nor does it exclusively guide problem prioritization or resource allocation. Successful policy decisions are invariably influenced by a blend of factual insights, analysis, judgment, and values (Omambia et al., 2016).

4.6 The Joint Moderation Effect

4.6.1 Joint Moderation Effect of Government Policy and Determinants of Data Driven Decision Making

This section encompassed the outcomes of a comprehensive moderated linear regression examination. Within this model, exogenous variables (X3, X2, X1), the moderating variable (M), as well as interaction variables (X1M, X2M, X3*M) were collectively integrated into a single regression analysis.

The results from the summary of comprehensive model, as visualized in Table 4.14, demonstrated that the initial R-squared value was 0.744, excluding the interaction and moderating variables. Subsequently, with the inclusion of the moderating variable (M), the R-squared value increased to 0.758. Upon further introduction of the interaction variables (X1M, X2M, X3*M), the R-squared value expanded to 0.828. These findings indicated that the moderating variable of government policy (M) wielded a substantial influence on data-driven decision-making determinants among health providers in Mombasa County.

Table 4.13: Overall Model Summary for Moderated Effect of Government Policy

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.862[a]	.744	.739	.12533
2	.870[b]	.758	.752	.12222
3	.910[c]	.828	.820	.10396

a. Predictors: (Constant), X_1, X_2, X_3
b. Predictors: (Constant), X_1, X_2, X_3, M
c. Predictors: (Constant), X_1, X_2, X_3, M, X_1*M, X_2*M, X_3*M

The outcomes of the analysis unveiled that the models assessing the connections between the independent variables (X1, X2, X3) and data-driven decision-making among health providers yielded significant results. The first model displayed an F-statistic of 158.644, with a p-value of 0.000 (<0.05 significance level). Similarly, the second model, which linked the independent variables (X1, X2, X3), government policy (M), and quality data-driven decision-making among health providers, exhibited an F-statistic of 127.467 and a 0.000 p-value, also indicating significance. Lastly, the third model, encompassing the independent variables (X1, X2, X3), government policy (M), interaction variables (X1M, X2M, X3*M), and quality data-driven decision-making among health providers, revealed an F-statistic of 110.002 and a 0.000 p-value, underscoring its significance. These findings implied that the interplay of the exogenous variables (X3, X2, X1), government policy (M), and interaction variables (X1M, X2M, X3*M) collectively had a considerable and significant influence on the quality of data-driven decision-making among health providers. The detailed outcomes are meticulously visualized in Table 4.14.

Table 4.14: Overall ANOVA Summary for Moderated Effect of Government Policy

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.476	3	2.492	158.644	.000[b]
	Residual	2.576	164	.016		
	Total	10.052	167			
2	Regression	7.617	4	1.904	127.467	.000[c]
	Residual	2.435	163	.015		
	Total	10.052	167			
3	Regression	8.323	7	1.189	110.002	.000[d]
	Residual	1.729	160	.011		
	Total	10.052	167			

a. Dependent Variable: Data Driven Decision Making

b. Predictors: (Constant), X_1, X_2, X_3

c. Predictors: (Constant), X_1, X_2, X_3, M

d. Predictors: (Constant), X_1, X_2, X_3, M, X_1*M, X_2*M, X_3*M

The comprehensive beta coefficient outcomes indicated that across Model 1, the variables X1 (β=0.165, p=0.000), X2 (β=0.276, p=0.000), and X3 (β=0.386, p=0.000) exhibited substantial and positively significant influences on data-driven decision-making among health providers. Correspondingly, in Model 2, the variables X1 (β=0.146, p=0.000), X2 (β=0.270, p=0.000), and X3 (β=0.335, p=0.000), as well as the moderating variable M (β=0.100, p=0.002), demonstrated noteworthy and positive effects on data-driven decision-making among health providers (Y). Moreover, the findings of Model 3 elaborated that the independent variables X1 (β=0.196, p=0.000), X2 (β=7.702, p=0.000), and X3 (β=8.726, p=0.000), along with the moderating variable M (β=0.621, p=0.035), and interaction variables X2M (β=1.948, p=0.000) and X3M (β=2.049, p=0.000), exhibited significant influences on data driven decision making among health providers (Y), except for X1*M (β=0.016, p=0.775) which did not yield a significant effect. These outcomes accentuated the considerable positive contributions of the independent variables, moderating variable, and interaction variables on the enhancement of data-driven decision-making among health providers.

Table 4.15: Overall Beta for Moderated Effect of Government Policy

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.744	.163		4.574	.000
	X_1	.165	.039	.212	4.240	.000
	X_2	.276	.074	.328	3.725	.000
	X_3	.386	.078	.413	4.949	.000
2	(Constant)	.637	.162		3.927	.000
	X_1	.146	.038	.189	3.823	.000
	X_2	.270	.072	.321	3.738	.000
	X_3	.335	.078	.358	4.305	.000
	M	.100	.033	.141	3.073	.002
3	(Constant)	1.453	1.231		1.181	.239
	X_1	.196	.247	.253	.794	.428
	X_2	7.702	1.034	9.154	7.446	.000
	X_3	8.726	1.041	9.333	8.381	.000
	M	.621	.292	.871	2.127	.035
	X_1*M	.016	.056	.152	.286	.775
	X_2*M	1.948	.251	18.070	7.752	.000
	X_3*M	2.049	.254	18.375	8.075	.000

a. Dependent Variable: Data Driven Decision Making

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This section encapsulates a concise overview of the outcomes derived from the analysis, the resultant conclusions, as well as recommendations. This was carried out in alignment with stipulated study objectives, which encompassed the examination of the correlation between technical factors and data-led decision-making among health providers in Mombasa County, the assessment of the connection between behavioral factors and data-centric decision-making among health providers in the same region, the establishment of the nexus between organizational factors and data-led decision-making among health providers, and lastly, the exploration of the influence of government policy moderation on data-centric decision-making among health providers in Mombasa County.

5.2 Summary of Major Findings

The primary aim encompassed scanning connection between data-driven decision-making and technical factors within the cohort of health providers operating in Mombasa County. The analysis indicated that technical factors exhibited a satisfactory level of explanatory power concerning data-driven decision-making among the health providers. Moreover, the outcomes highlighted that technical factors serve as a robust predictor of data-driven decision-making in this context. Through correlation analysis, it was discerned that technical factors exhibited a statistically and positive significant association with data-driven decision-making among health providers. The application of multinomial logistic regression analysis confirmed that technical factors held statistical significance with a $p < 0.05$ significance level, thus establishing their significance as a predictor within the model.

This implies that an enhancement in technical factors can lead to the promotion of quality data-propelled decision-making.

The second core study objective was to assess the correlation between behavioral factors and data-driven decision-making among health providers in Mombasa County. However, the multinomial logistic regression analysis of behavioral factors yielded statistically insignificant results with a p-value greater than 0.05. Consequently, behavioral factors were considered to be an inconsequential predictor within the model.

The third primary objective centered on elucidating the relationship between organizational factors and data-driven decision-making among health providers in the specified county. The findings indicated that organizational factors demonstrated a satisfactory capacity to elucidate the phenomenon of data-driven decision-making among the health providers. Moreover, the results underscored the efficacy of organizational factors as a substantial predictor for the quality of data-driven decision-making within the health provider context.

5.3 Conclusions

From the outcomes of this investigation, the researcher arrived at the determination of an existence of a constructive and robust association between technical variables and the practice of data-driven decision-making within health provider domain. Specifically, the study found that the technically adept human resources' availability plays a pivotal role in bolstering data management among health providers. Furthermore, the cultivation of skills in analysis, interpretation, and decision-making contributes significantly to the utilization of information. It was also deduced that decentralizing the RHIS management enhances the local usage of HI data. Additionally, providing training in managing data at level of facility emerged as a prospective avenue to improve data quality employed in process of making decision. This underscores that the technical determinants are intrinsically linked to the specialized knowledge requisite for ensuring quality data management within the health provider context.

Furthermore, the study's results culminated in researchers concluding that a substantial and positive correlation exists between behavioral factors and the caliber of data-driven decision-making executed by health providers. Notably, behavioral determinants such as the demand of Health Information System (HIS) users, their competence, motivation, and confidence in HIS activities directly influence performance and HIS processes. The study highlighted that an enhanced perception of HIS processes and related responsibilities augments data-driven decision-making quality. On the contrary, the study observed that an absence of incentives for data collection could impede effective data-driven decision-making. The recommendation emerged that reinforcing the sense of data ownership among health workers can enhance the practice. Additionally, the study's outcomes demonstrated that managers of health facilities sometimes collect data but do not grasp their utilities.

In a parallel vein, based on the empirical evidence, the study confirmed a substantial and affirmative relationship between organizational factors and the practice of data-driven decision-making within the realm of health workers operating in Mombasa County. Concretely, the study deduced that a facility that establishes processes and structures to enhance interaction between data producers and users, offers lucid guidelines for maintaining data quality, and demarcates responsibilities and roles tied to data usage can serve to fortify other interventions directed at advancing data-informed decision-making. The study further noted that the absence of regular monitoring and evaluation-support systems can adversely influence the supposed significance of data collection and utilization.

5.4 Recommendations

5.4.1 Technical Factors

The study offers several recommendations for enhancing data-driven decision-making within the healthcare sector. It is advised that the establishment of a well-structured Health Management Information System (HMIS) should be prioritized. Within this framework, comprehensive training initiatives should be implemented to empower healthcare workers, particularly at the county level. These training programs should be designed to augment the analytical, interpretative, and decision-making skills of healthcare professionals, thereby fostering a culture of information utilization. Additionally, the study underscores the significance of training endeavors at the facility level, emphasizing that such initiatives can contribute to the high-quality data generation that remains conducive to effective decision-making processes. This highlights the essential connection between technical factors and the specialized expertise required for proficient data management within the health provider domain. Furthermore, it is recommended that efforts be made to decentralize the management of RHIS. By facilitating localized processes for managing data, this approach can enhance the HI data usage within the community, thus promoting a more contextually relevant approach to decision-making. This recommendations can be justified below:

Establishment of a Well-Structured Health Management Information System (HMIS): This recommendation is vital because a robust HMIS serves as the backbone for effective data-driven decision-making. A well-structured HMIS ensures the systematic collection, storage, and retrieval of healthcare data. It facilitates the availability of accurate and timely information for decision-makers. By prioritizing the establishment of such a system, the healthcare sector can overcome the challenges associated with fragmented or inadequate data infrastructure.

Comprehensive Training Initiatives: Training healthcare workers, both at the county and facility levels, is essential to build the technical skills necessary for proficient data management. In an era of rapidly evolving data technologies, continuous training ensures that healthcare professionals remain competent in data analysis and interpretation. Empowering healthcare workers with these skills fosters a culture of information utilization, leading to more informed decision-making. Decentralization of RHIS Management: Decentralization is recommended because it brings data management closer to the community level. This approach recognizes that healthcare decisions often need to be contextually relevant. By involving local management teams in data management, healthcare providers can tailor their decision-making processes to the specific needs of their communities, leading to more effective and locally responsive healthcare services.

In summary, the study's recommendations encompass the cultivation of technical skills through comprehensive training initiatives, the decentralization of RHIS management, and the creation of a well-designed Health Management Information System. These measures collectively aim to augment data-driven decision-making practices within the healthcare landscape.

5.4.2 Behavioral Factors

Efforts aimed at fortifying the health information system should take into account the significance of shaping perceptions and attitudes pertaining to the HI use. This strategic approach is essential in mitigating the risks associated with subpar data quality, instances of underreporting, infrequent engagement with information, and the potential for suboptimal decision-making outcomes. Moreover, a concerted endeavor should be made to enhance the sense of data ownership among healthcare workers, thereby fostering a stronger commitment to the data management process. Also, it is noteworthy that this study's results illuminate the fact that health facility managers often collect data without a comprehensive grasp of its practical utility. This underscores the importance of enhancing their understanding of the broader implications of data utilization, aligning their actions with the overarching objectives of effective decision-making processes. Furthermore, the study accentuates the role of behavioral factors in influencing Health Information System (HIS) users' engagement with data-driven decision-making practices. Elements such as user demand, motivation, competency, alongside confidence unswervingly impact the functioning and effectiveness of HIS processes. A positive shift in the perception of HIS processes and associated tasks contributes to the enhancement of quality data-propelled decision-making practices. This recommendation is justified below based on the following points:

Shaping Perceptions and Attitudes: The recommendation to shape perceptions and attitudes toward Health Information (HI) use is critical because these factors influence how healthcare workers engage with data. Negative perceptions or attitudes can lead to underreporting, reluctance to use data, and suboptimal decision-making. Addressing these behavioral aspects is essential for improving data quality and decision-making outcomes.

Enhancing Data Ownership: Fostering a sense of data ownership among healthcare workers encourages them to take responsibility for the data management process. When individuals feel a personal connection to the data, they are more likely to ensure its accuracy and relevance. This, in turn, contributes to higher data quality and better decision-making.

Managerial Understanding of Data Value: The recommendation to enhance the understanding of data's practical utility among health facility managers is crucial. Managers play a pivotal role in data collection and utilization. When they grasp the broader implications of data use, they can align their actions with the objectives of effective decision-making. This alignment is essential for ensuring that data-driven practices are integrated into daily operations.

Acknowledging Behavioral Determinants: Recognizing the influence of behavioral determinants, such as user demand, motivation, competency, and confidence, is essential. These factors directly impact the effectiveness of Health Information System (HIS) processes. Positive shifts in these determinants can lead to more engaged and competent healthcare workers, resulting in improved data-driven decision-making practices.

In conclusion, addressing perceptions and attitudes, reinforcing the sense of data ownership among healthcare workers, fostering managers' comprehension of data's value, and acknowledging the influence of behavioral determinants are critical considerations for interventions aiming at strengthening the HIS and elevate data-driven decision-making capabilities.

5.4.3 Organizational Factors

The study's recommendations emphasize the establishment of well-defined structures and systematic processes that foster enhanced collaboration between data producers as well as users. By introducing transparent guidelines governing data quality processes and clarifying the delineation of roles and responsibilities associated with data utilization, the effectiveness of existing interventions aimed at enhancing data-driven decision-making can be substantially reinforced. A crucial recommendation centers on the implementation of consistent systems designed to support M&E activities. This strategic move is poised to exert a positive influence on the perceived significance and the overall quality of data gathering as well as utilization. Furthermore, it is imperative for health facility managers to ensure the comprehensive involvement of all healthcare providers in the sphere of quality data management, recognizing the vital role each member plays in this endeavor. The study also underscores the importance of integrating feedback mechanisms into the realm of health information data utilization. By doing so, an avenue is created for information flow and exchange, thus fostering a deeper engagement with data-driven decision-making processes. Moreover, an appropriate allocation of resources towards the support and supervision of data systems is highly recommended. This allocation will not only enhance the efficiency of data-related operations but also contribute to the overall effectiveness of health information management processes. The specific implications from this recommendations include:

Establishment of Well-Defined Structures: Clear organizational structures and processes are recommended because they promote collaboration between data producers and users. When roles and responsibilities are well-defined, healthcare teams can work more cohesively toward data-driven decision-making. This clarity reduces confusion and enhances the effectiveness of data-related interventions.

Implementation of Consistent Systems for M&E: Monitoring and evaluation (M&E) activities are essential for assessing the impact of healthcare interventions. By implementing consistent systems for M&E, the healthcare sector can ensure that data gathering and utilization align with the goals of improving healthcare outcomes. This, in turn, enhances the perceived significance of data-driven decision-making.

Comprehensive Involvement of Healthcare Providers: Involving all healthcare providers in quality data management is crucial because each member plays a unique role in this endeavor. By recognizing the contributions of every team member, healthcare facilities can ensure that data is collected accurately and comprehensively. This collaborative approach strengthens data-driven decision-making.

Integration of Feedback Mechanisms: Feedback mechanisms are recommended to facilitate information flow and exchange. When healthcare workers have access to feedback, they can make more informed decisions. This continuous loop of feedback fosters deeper engagement with data-driven decision-making processes and leads to ongoing improvements in healthcare services.

Allocation of Resources for Support and Supervision: Allocating resources for the support and supervision of data systems is essential for optimizing data-related operations.

Adequate resources ensure that data processes are efficient and effective. This investment contributes to the overall quality of health information management.

5.4.4 Government Policy

To guarantee comprehensive reporting from all sources of health service deliveries, the implementation of a regulatory framework is imperative. The Ministry of Health ought to possess the authority to enforce compliance with health data reporting within public health facilities. This enforcement can be accomplished by introducing incentives or penalties to incentivize adherence to reporting protocols. Furthermore, it is advisable to institute mechanisms that assure data accuracy and reliability. This might be effectively attained via the periodic assessment and review of methods of collecting data. This practice ensures that the data collected remains consistent and dependable over time. Lastly, a prudent recommendation involves the standardization of data forms, which can subsequently be repurposed for future decision-making endeavors. This approach not only streamlines the data collection process but also fosters consistency and coherence in the data use for various decision-making processes. The insights from these recommendations include:

Regulatory Framework for Comprehensive Reporting: Implementing a regulatory framework is necessary to ensure that all health service providers comply with data reporting protocols. By introducing incentives or penalties, the government can incentivize adherence to reporting requirements. This regulatory approach promotes data accuracy and completeness, which are fundamental for data-driven decision-making.

Periodic Assessment and Review of Data Collection Methods: Periodic assessment and review of data collection methods are essential to maintain data consistency and reliability over time. By continuously evaluating data collection practices, the healthcare sector can adapt to changing needs and technologies, ensuring that data remains dependable for decision-making.

Standardization of Data Forms: Standardizing data forms streamlines the data collection process and fosters consistency and coherence in data use. Standardized forms can be repurposed for various decision-making processes, reducing redundancy and errors in data collection. This approach improves the efficiency and effectiveness of data utilization.

In summary, these recommendations are justified because they address key technical, behavioral, organizational, and policy-related aspects that impact data-driven decision-making in the healthcare sector. Implementing these recommendations can lead to more effective, efficient, and informed healthcare practices, ultimately benefiting both healthcare providers and the communities they serve.

5.5 Areas for Further Research

The research aimed to explore the variables impacting data-driven decision-making among health providers within Mombasa County. Given the study's focus on Mombasa County exclusively, future research endeavors could encompass additional counties to facilitate a comparative analysis of outcomes, thereby enhancing the comprehensiveness of findings. The outcomes of this investigation have illuminated that the variables investigated in this study do not comprehensively elucidate the enhancements observed in quality data-driven decision-making within Mombasa County's health provider landscape. Consequently, there is a recommendation for subsequent research endeavors to explore other factors influencing data-driven decision-making among health providers, thereby contributing to a more holistic understanding of the subject. The proposal for further research in the identified areas can be justified based on several key considerations:

Generalizability: The current study focuses exclusively on Mombasa County. While it provides valuable insights into data-driven decision-making within this specific context, it may not capture the full spectrum of variations and determinants that exist across different counties or regions. Conducting research in additional counties allows for a more comprehensive understanding of the factors influencing data-driven decision-making and whether these factors vary between regions. This can contribute to the generalizability of findings to a broader geographical context.

Comparative Analysis: By extending the research to multiple counties, future studies can facilitate a comparative analysis of outcomes. This approach enables researchers to identify similarities and differences in the determinants of data-driven decision-making across different regions. Comparative research can uncover patterns, trends, and variations that may not be apparent when studying a single location in isolation. Such insights can inform more targeted and region-specific strategies for improving data-driven decision-making.

Completeness of Understanding: The acknowledgment that the variables investigated in the current study do not comprehensively explain the enhancements observed in data-driven decision-making suggests that there may be additional, unexplored factors at play. To gain a more holistic understanding of this complex phenomenon, it is essential to delve into other potential factors that may influence data-driven decision-making among health providers. This pursuit of a more comprehensive understanding aligns with the spirit of continuous improvement in research and practice.

Policy and Practice Implications: Research that explores a broader range of factors influencing data-driven decision-making can have direct implications for policy development and healthcare practice. Policymakers and healthcare leaders may benefit from insights into regional variations and the identification of specific determinants that require targeted interventions. This can lead to more effective strategies for promoting data-driven decision-making, ultimately improving healthcare outcomes.

Advancing Knowledge: The field of data-driven decision-making in healthcare is dynamic and evolving. Continuous research is essential for advancing knowledge in this area. By exploring additional variables and regions, researchers can contribute to the ongoing development of theory and best practices. This not only benefits the academic community but also enhances the capacity of healthcare professionals to leverage data effectively for decision-making.

In summary, proposing further research in additional counties and exploring other factors influencing data-driven decision-making among health providers is justified because it enhances generalizability, enables comparative analysis, contributes to a more complete understanding of the subject, has practical implications for policy and practice, and advances the knowledge base in this important area of healthcare management and decision-making.

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APPENDICES

Appendix I: Letter of Introduction

Dear Respondent

RE: <u>REQUEST FOR FILLING QUESTIONNAIRES</u>

I am a student enrolled at Mount Kenya University's Mombasa CBD campus, pursuing a Master's program in Public Health. Currently, I am conducting research on the topic "**DETERMINANTS OF DATA DRIVEN DECISION MAKING AMONG HEALTH PROVIDERS IN MOMBASA-COUNTY**," which is a mandatory component of my Master's curriculum. Due to your distinguished position within the organization and your valuable expertise, I have been directed to approach you as a potential participant for this research. Your involvement in this study will solely entail participating in an interview. It is essential to emphasize that this research serves purely academic purposes, and there are no tangible benefits associated with your participation. However, the insights gained from this study will play a significant role in enhancing the adoption of Universal Health Coverage (UHC) within the county. Your participation is entirely voluntary, and I assure you that any information you share will be treated with the utmost confidentiality. Therefore, I kindly request your willingness to allocate some of your time to engage in this research endeavor.

Yours faithfully,

Wangige Muhula Sally.

Appendix II: Informed Consent Form

TITLE OF THE STUDY: DETERMINANTS OF DATA DRIVEN DECISION MAKING AMONG HEALTH PROVIDERS IN MOMBASA COUNTY

I..willingly agree to take part in this research study. I comprehend that my participation is entirely voluntary, and I have the option to withdraw or decline to answer any questions without facing any consequences. I am aware that I can revoke my consent for the use of data from my interview within a two-week period after the interview, leading to the removal of the material. I acknowledge that there will be no direct personal benefits resulting from my involvement in this research. I am aware that any information I provide for this study will be treated with confidentiality. I understand that portions of my interview, with identifying details removed, may be cited in a dissertation, presented at conferences, and included in published papers. I acknowledge that I am free to reach out to any of the individuals involved in the research if I need more clarification or information.

Signature of research participant

……………………………… ………………………………………….

Signature of participant Date

Signature of Researcher

I am of the opinion that the participant is providing knowledgeable agreement to engage in this research project.

……… ……………... ……………

Signature of researcher Date

Appendix II: Research Questionnaire

Kindly complete this questionnaire with transparency and truthfulness. Your responses will be treated with strict confidentiality, and neither your personal name nor your agency will be disclosed. Please furnish the requested information below:

CONFIDENTIALITY AGREEMENT:

The information you provide is intended for academic research purposes only. Your responses will remain confidential and will be handled in an ethical manner.

SECTION A: BASIC INFORMATION

1. What is your highest level of education attained?

No.	Level of Education	Tick appropriate Answer
A	Certificate	
B	Diploma	
C	Degree	
D	Postgraduate	

2. What is your working experience?

No.	Work Experience	Tick appropriate Answer
A	Less than 1 year	
B	1 to 2 years	
C	3 to 4 years	
E	Over 5 years	

3. Please select your age range

No.	Age	Tick appropriate Answer
A	20-30 years	
B	30 to 40 years	
C	40 to 50 years	
E	Over 50 years	

4. Please select your Cadre

No.	Cadre	Tick appropriate Answer
A	CLINICIANS	
B	HRIO	
C	MLO	
E	NURSE	
F	Pharm/Tech	

5. Please select your section of work

No.	Section of Work	Tick appropriate Answer
A	OPD GENERAL	
B	MCH	
C	SPECIAL CLINIC	
E	LAB	
F	HMIS	

SECTION B: TECHNICAL FACTORS

Kindly use the scale provided below to mark the level of agreement you have with the following statements.

Strongly Agree=5, Agree=4, Uncertain=3, Disagree=2, Strongly Disagree=1

	Statement	1	2	3	4	5
B.1	Availability of technically qualified human resource is key in supporting data management					
B.2	Developing skills in analyzing, interpreting and decision-making promote information use					
B.3	Health providers value the care of patients over data collection					
B.4	Routine health information systems management should be decentralized to improve local use of health information data					
B.5	Training in data management at facility level may promote good quality data to be used in decision making processes					
B.6	Technical determinant factors are related to the specialised know-how on quality data management					

SECTION C: BEHAVIORAL FACTORS

Kindly use the provided scale to mark the degree to which you agree with the statements below by placing a checkmark.

Strongly Agree=5, Agree=4, Uncertain=3, Disagree=2, Strongly Disagree=1

	Statement	1	2	3	4	5
C.1	Perceptions and attitudes of senior management towards data have an influence on the use of health information					
C.2	There is positive attitude towards data collection and use					
C.3	Perception on HIS processes and related tasks improves quality data driven decision making					
C.4	Health facility managers gather data without understanding its utility					
C.5	Quality data driven decision making is affected by lack of incentives towards data collection					
C.6	There is need to strengthen health workers' sense of data ownership					

SECTION D: ORGANIZATIONAL FACTORS

Using the provided scale, please mark the level of agreement you have with the following statements by placing a checkmark.

Strongly Agree=5, Agree=4, Uncertain=3, Disagree=2, Strongly Disagree=1

	Statement	1	2	3	4	5
D.1	There are feedback mechanisms on health information data utilization					
D.2	We have structures and processes for improving the interaction of data users and producers					
D.3	We define roles and responsibilities related to using data to improve data informed decision making					
D.4	There is recognition and reward systems for good performance of data systems					
D.5	There is sharing of best practices on HIS utilization					
D.6	There is adequate resource allocation for support supervision on data systems					

SECTION E: GOVERNMENT POLICY

Kindly express your level of agreement with the following statements by marking the appropriate extent on the provided scale below.

Strongly Agree=5, Agree=4, Uncertain=3, Disagree=2, Strongly Disagree=1

	Statement	1	2	3	4	5
E.1	Regulatory framework is necessary to ensure complete reporting from all sources of health service delivery					
E.2	Data forms are standardized and then reused for future decisions					
E.3	The Ministry of Health can compel public health facilities to report health data by creating incentives or penalties for compliance and noncompliance					
E.4	Support systems have been put in place to establish a common data architecture					
E.5	Accuracy and reliability expectations is ensured through periodic review of data collection methods					
E.6	There is legal and regulatory framework governing NHIS					

SECTION F: QUALITY DATA DRIVEN DECISION MAKING

Please use the provided scale below to mark the degree to which you agree with the statements by placing a check mark.

Strongly Agree=5, Agree=4, Uncertain=3, Disagree=2, Strongly Disagree=1

	Statement	1	2	3	4	5
F.1	Completeness of reported data is essential for decision-making					
F.2	Consistency is essential for decision-making					
F.3	Reported data includes all the necessary dataset reports					
F.4	Corrective actions are always taken within reasonable time to address data reporting issues					
F.5	There is a procedure for distributing and reporting data					
F.6	There is criteria for verification of completeness and consistency of data collected					

We appreciate your time and effort in filling out the questionnaire.

Appendix III: Authorization from Nacosti

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 840335

Date of Issue: 19/November/2021

RESEARCH LICENSE

This is to Certify that Miss.. Sally Wangigi Muhula of Mount Kenya University, has been licensed to conduct research in Mombasa on the topic: Determinants of Quality Data Driven Decision Making Among Health Providers in Mombasa County for the period ending : 19/November/2022.

License No: NACOSTI/P/21/14375

840335

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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

Appendix IV: Letter from School of Postgraduate

Mount Kenya University

MKU

Unlocking Infinite Possibilities

DIRECTORATE OF GRADUATE STUDIES

MPH/2017/73991

9th November, 2021

The Director, Research Coordination Division
National Commission for Science, Technology & Innovation
Utalii House, 8th & 9th Floor
P.O Box 30623- 00100
NAIROBI

Dear Sir/Madam,

RE: WANGIGI MUHULA SALLY – REGISTRATION NO. MPH/2017/73991

The purpose of this letter is to introduce the above named student who is pursuing **Master of Public Health** in the **Department of Epidemiology and Biostatistics** in the **School of Public Health.**

The title of her research is *"Determinants of Quality Data Driven Decision Making Among Health Providers in Mombasa County."*

She has been cleared by the University's Ethics Review Committee (Certificate attached) and now has to proceed to the field to collect data for his research between **November and January, 2022.**

Any assistance accorded to her will be highly appreciated.

Thank you.

Mount Kenya University
Box 342 - 01000, THIKA
Office of the Director
Graduate Studies

Dr. Samuel M. Karenya, Ph.D
Director, Graduate Studies
Enc.

Main Campus, General Kago Road, P.O. Box 342-01000 Thika. Tel: +254 67 2820 000,
Cell: +254 720 790 796, 0709 153 000
Email:info@mku.ac.ke, Web: www.mku.ac.ke
Chartered and ISO 9001 : 2015 Certified Institution.
Unlocking Infinite Possibilities

Appendix V: Research Proposal Approval Letter

Mount Kenya University

MKU
Unlocking Infinite Possibilities

REF: **MKU/ERC/1896**
TO: **WANGIGI MUHULA SALLY**

Date: 23 September 2021

REG: **MPH/2017/73991**

Dear Sir/Madam,

RE: DETERMINANTS OF QUALITY DATA DRIVEN DECISION MAKING AMONG HEALTH PROVIDERS IN MOMBASA COUNTY

This is to inform you that **Mount Kenya University** has reviewed and approved your above research proposal. Your application approval number is **969.** The approval period is **23/09/2021 - 22/09/2022.**

This approval is subject to compliance with the following requirements;

i. Only approved documents including informed consents, study instruments, MTA will be used
ii. All changes including amendments, deviations and violations are submitted for review and approval by **Mount Kenya University**
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to **Mount Kenya University** within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to **Mount Kenya University** within 72 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal
vii. Submission of an executive summary report within 90 days upon completion of the study to **Mount Kenya University**

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://research-portal.nacosti.go.ke and also obtain other clearances needed.

Yours sincerely,

The Chairman
Mount Kenya University
Ethics Review Committee
P. O. Box 342 - 0100, Thika

Dr. Peter G. Kirira
Chairman, Mount Kenya University IERC

Main Campus, General Kago Road, P.O. Box 342-01000 Thika. Tel: +254 67 2820 000,
Cell: +254 720 790 796, 0709 153 000

Appendix VI: Plagiarism Report

DETERMINANTS OF DATA DRIVEN DECISION MAKING AMONG HEALTH PROVIDERS IN MOMBASA COUNTY

ORIGINALITY REPORT

19%	18%	9%	12%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Mount Kenya University Student Paper	2%
2	ir.jkuat.ac.ke Internet Source	1%
3	repository.kemu.ac.ke:8080 Internet Source	1%
4	ugspace.ug.edu.gh Internet Source	1%
5	erepository.uonbi.ac.ke Internet Source	1%
6	ir-library.ku.ac.ke Internet Source	1%
7	www.iprjb.org Internet Source	1%
8	ikesra.kra.go.ke Internet Source	<1%
9	Submitted to Kenyatta University Student Paper	<1%