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**INFLUENCE OF HEALTH MANAGEMENT INFORMATION SYSTEMS ON DECISION-
MAKING IN A LEVEL 5 PUBLIC HOSPITAL IN THARAKA NITHI COUNTY, KENYA.**

GRACE. W. GICHOHI

MBA-HCM/077201/2023



**A RESEARCH THESIS SUBMITTED TO STRATHMORE BUSINESS SCHOOL IN
PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE AWARD OF MASTER OF BUSINESS
ADMINISTRATION IN HEALTHCARE**

MANAGEMENT OF STRATHMORE UNIVERSITY

DECLARATION

I confirm that this thesis has not been submitted or accepted for the award of a degree at this or any other university. To the best of my knowledge and understanding, it contains no content that has been published or authored by someone else, except where proper acknowledgment has been provided within the thesis.

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Sign:  Date: 19/11/2025

GRACE. W. GICHOHI
MBA-HCM/077201/2023

Approval

This project has been submitted for examination with my approval as a University Supervisor.



Sign: Date: 19/11/2025

DR. JACKLINE ARIDI

ABSTRACT

The effective utilization of Health Management Information Systems (HMIS) plays a pivotal role in evidence-based decision-making in healthcare. In Kenya, the rollout of digital platforms such as Afya Kenya, under the Digital Health Act 2023, underscores the government's commitment to improving data-driven planning and service delivery. However, limited evidence exists on how healthcare workers, particularly in public facilities, use HMIS for operational and strategic decisions. The study examined the influence of HMIS on decision-making among healthcare workers at Chuka County Referral Hospital, a Level 5 public hospital in Tharaka Nithi County, Kenya. The objectives were to evaluate the technical, behavioral, organizational, and environmental factors influencing the use of HMIS data for decision-making. It was anchored on the PRISM Framework and Theory of planned behavior, which together provided a structured approach to understanding the enablers of data-driven decision-making in healthcare. A descriptive cross-sectional design was employed. The study adopted a census method, targeting all 250 departmental heads and clinical staff involved in data management and decision-making within the facility. Data were collected using semi-structured questionnaires and analyzed using descriptive statistics, Pearson correlation, and multiple linear regression. Correlation results showed, organizational factors had the strongest correlation ($r = 0.682$), followed by behavioral ($r = 0.634$), technical ($r = 0.501$), and environmental ($r = 0.372$) factors. However, regression analysis revealed a more nuanced picture by identifying which factors significantly predict actual HMIS data use. It showed that organizational factors were most statistically significant predictors ($\beta = 0.476$, $p < 0.05$) in strategic and ($\beta = 0.521$, $p < 0.05$) in operational decision making. The study concluded that while technical infrastructure and staff attitudes are important, organizational leadership, policies, and governance structures are the most critical drivers of effective HMIS data utilization. Recommendations made include strengthening internal leadership and accountability mechanisms, enhancing system interoperability, providing regular staff training, and developing policy frameworks that decentralize data-driven decision-making. These findings offer practical guidance for healthcare managers and policymakers seeking to optimize HMIS adoption for improved healthcare delivery.

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ABBREVIATIONS AND ACRONYMS

DHIS2- District Health Information System 2

HIS-Health Information System

HIE- Health Information Exchange

HMIS- Health Management Information System

KHIS- Kenya Health Information System

LMICs- Low- and Middle-Income Countries

MOH- Ministry of Health

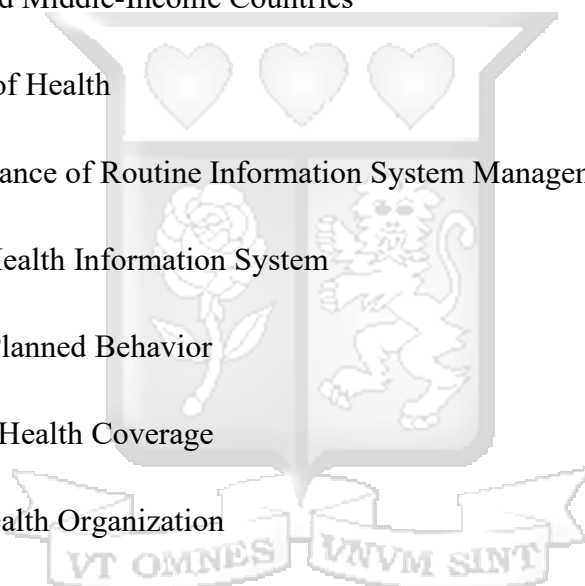
PRISM- Performance of Routine Information System Management

RHIS- Routine Health Information System

TPB-Theory of Planned Behavior

UHC- Universal Health Coverage

WHO- World Health Organization



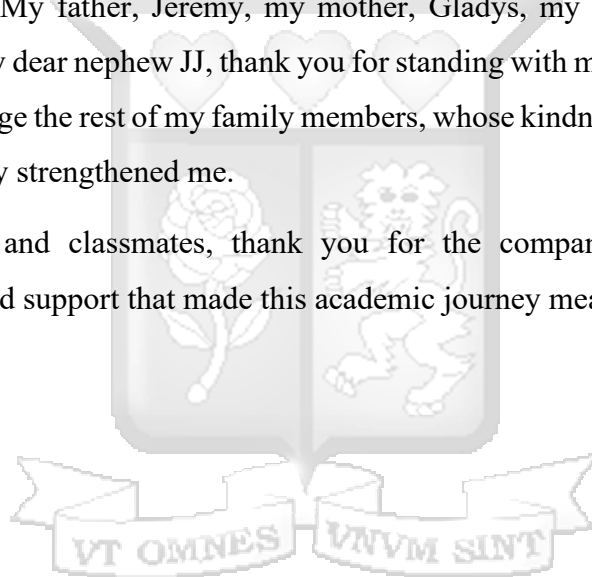
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DEDICATION

I dedicate this project to my family and friends for their steadfast support, encouragement, and prayers throughout my academic journey and the completion of this work. I also give special honorary mention to my late mother Lucy and my late grandmother Edith, whose values, love, and legacy shaped who I am today. Their memory continues to inspire my resolve, resilience, and determination.



CHAPTER ONE

INTRODUCTION

1.1 Background of the study

In an era where data is considered the new currency, healthcare systems increasingly rely on timely, accurate, and reliable information to guide decisions on policy, resource allocation, and service delivery (Cheruiyot, 2018). As Clive Humby famously stated, “Data is the new oil,” yet like oil, its value lies in proper processing, refinement, and use (Freitas, 2024). Transforming raw health data into actionable insights is now a key driver of efficient, equitable, and responsive healthcare (Isak, 2023). For data to create real value, it must be trustworthy, comprehensive, accessible, and most importantly, utilized in decision-making.

1.1.1 Health Management Information Systems (HMIS)

Modern health systems rely heavily on Health Management Information Systems (HMIS), which facilitate efficient data collection, storage, analysis, and utilization for well-informed decision-making (Endriyas et al., 2020). HMIS is widely recognized as an essential facilitator of evidence-based decision-making and is consistent with the Sustainable Development Goals (SDGs), especially SDG 17.18, which emphasizes the need for timely and accurate data to monitor service delivery and improve health outcomes (Meghani et al., 2021; UNCTAD, 2016). HMIS supports workforce planning, medication access, financing, and governance as a component of the larger Health Information System (HIS), which is a fundamental component of healthcare (Andersen, 2023).

In Low and Middle-Income Countries (LMICs), the demand for robust HMIS is especially critical. Countries have implemented systems to track disease trends, monitor services, and detect public health threats (Isak, 2023; Mboera et al., 2021). Yet, challenges such as poor data quality, lack of standardization, and fragmented digital systems hinder the full impact of HMIS (Bagyendera et al., 2023; Dakika & Saronga, 2024). While data collection is often emphasized, its translation into actionable insights is weak, limiting health systems’ responsiveness (Chanyalew et al., 2023; Abajebel et al., 2011).

In Africa, HMIS supports disease surveillance and health planning, but problems like reporting inaccuracies and limited system interoperability persist (Mboera et al., 2021). A functioning HMIS must collect data and ensure its analysis and communication to support timely decisions (Kyalo & Otieno, 2017; USAID et al., 2010). Without effective use, health data remains underutilized, contributing to the misallocation of resources and service inefficiencies (Isak, 2023). In Kenya, initiatives such as KHIS and Afya Kenya aim to improve data use through digital platforms (MOH, 2024). However, persistent issues like poor data quality and fragmented reporting continue to limit HMIS's potential for transformative decision-making (Isak, 2023; WHO, 2025).

1.1.2 Data-Driven Decision-Making

Attaining Universal Health Coverage (UHC) and the SDGs requires a strong Health Information System (HIS) that supports decision-making in health financing, governance, workforce planning, service delivery, and access to medicines (WHO, 2025; MOH, 2020). The global shift toward data-driven decision-making in healthcare has accelerated, mirroring other sectors that generate and utilize large volumes of data from lab tests, electronic medical records, clinical trials, and administrative records. This wealth of information, when properly utilized, can significantly improve diagnosis accuracy, treatment planning, and patient outcomes at all healthcare system levels (Freitas, 2024).

Globally, health systems invest heavily in collecting routine healthcare data (Sebsbie et al., 2022). In the COVID-19 pandemic period, HMIS proved vital in monitoring disease progression, assessing facility readiness, managing resources, and facilitating real-time response (Dahiya et al., 2022). Health data supported not just clinical care, but also pandemic preparedness and efficient supply chain management. Healthcare decision-making operates on three levels: strategic, tactical, and operational (Masic, 2022). Strategic decisions are long-term and policy-oriented, typically handled by senior managers. Tactical decisions involve resource planning and performance monitoring, while operational decisions are made by frontline workers such as clinicians, nurses, and managers using real-time data to guide service delivery (Bello et al., 2022; Isak, 2023).

Public health decision-making now demands data-informed strategies at all levels. Globally, data is used to estimate disease burdens and track development goals. Locally,

it guides targeted interventions to meet community needs (Panhuis et al., 2014). In Sub-Saharan Africa, HMIS supports strategic and operational decisions across planning, supply management, resource allocation, and performance evaluation (Mboera et al., 2021).

For instance, Tanzania's health system uses HMIS data for planning, identifying service gaps, resource mobilization, and drug management (Kessy et al., 2024). In Kenya, a study in Kitui County found that HMIS data guided program management, budgeting, HR planning, policy monitoring, and epidemic response (Karijo et al., 2021). These examples underscore HMIS's value in supporting evidence-based healthcare decisions.

Effective data management improves data quality and enhances clinical and administrative decision-making (Malahleha, 2024). HMIS facilitates streamlined workflows and access to patient data, enabling timely, efficient care while supporting data-driven decisions that improve accuracy, efficiency, cost control, and innovation (Abdul-Azeez et al., 2024; Kitaba, 2015).

Despite its potential, many healthcare decisions remain uninformed by data. Decision-makers often rely on intuition or outdated information due to pressure and lack of access to quality data. (Matube & Fosa, 2023; Mboera et al., 2021). Studies reveal low HMIS use in health management across Africa: 39.9% in Nigeria, 42% in Tanzania, 59% in Uganda, and 65% in South Africa (Tulu et al., 2021). This gap reflects the disconnect between data collection and its application. In Kenya, the devolved health system grants counties decision-making authority, but many public hospitals struggle to fully utilize HMIS data. Barriers include poor data quality, limited technical capacity, and fragmented systems, which hinder the integration of data into planning and service delivery (Karijo et al., 2021).

Globally and locally, health experts agree that data should be used not only centrally but also at the point of generation. Decentralized data use supports context-specific decisions and promotes accountability (Wagenaar et al., 2017; WHO, 2008). However, effective use of HMIS requires overcoming challenges in data quality, infrastructure, and staff training to ensure the system's full benefits are realized. As countries strive for Universal Health

Coverage (UHC) and resilient health systems, investing in the capacity for HMIS data use is essential.

1.1.3 Factors Influencing Use of HMIS

Routine health information systems in many low and middle-income nations usually struggle to support strategic planning, data-driven decision-making, and efficient resource allocation. These difficulties are largely attributed to issues such as low-quality data, inadequate data analysis capabilities, a weak culture of information use, insufficiently trained staff, and the widespread view that health information system responsibilities add to an already heavy workload in health facilities (Mboera et al., 2021; Njeru & Mathai, 2024). System quality, information quality, system utilization, user happiness, individual impact, and organizational effect are further key barriers (Cheruiyot, 2018).

HMIS in Africa is unable to realize its full potential due to several obstacles. The effectiveness and dependability of HMIS data for decision-making are directly impacted by institutional, technological, human, and logistical restrictions, which are often categorized as technical, behavioral, and organizational (Endriyas et al., 2019). According to the PRISM framework, organizational factors include institutional policies, leadership, resource availability, and structured governance; technical factors refer to usability, system integration, and digital infrastructure; behavioral factors address user skills, motivation, and engagement in data-related processes (Yusuph et al., 2024). Environmental elements such as policies, guidelines, and stakeholder support also play a role in shaping data use (Morike, 2023).

In Ethiopia, a study identified enablers of data use, including technical, individual, organizational, political, environmental, and economic influences (Chanyalew et al., 2023). Similarly, another study explored financial, human, and environmental factors, noting that political shifts, investment priorities, policy changes, and bureaucratic flexibility impact HMIS-based decisions (Wijayati & Achadi, 2019). Using poor-quality data leads to flawed decisions, which health systems must urgently address (Yusuph et al., 2024)

Despite Kenya's progress in strengthening HMIS, significant challenges persist, especially at the facility level, due to technical, behavioral, and organizational limitations (Mucee, 2016; Thurania, 2020). There remains a pressing need to study HMIS utilization to identify enablers that support better data use for resource planning and healthcare delivery (Dakika & Saronga, 2024). While earlier studies highlight data quality issues, they often fail to examine how these directly impact decision-making. Environmental factors remain underexplored, and inconsistent findings across regions point to a lack of uniformity in HMIS use, limiting the generalizability of research outcomes in Kenya (Ngusie et al., 2022).

1.1.4 Study Context

The Government of Kenya has significantly invested in digital health, especially in public hospitals, following the introduction of the Digital Health Act 2023. In 2024, the Ministry of Health launched *Afya Kenya*, a digital health platform designed to address barriers to effective data use. *Afya Kenya* integrates HMIS systems from various counties to standardize data, promote interoperability, and enable real-time health information exchange within similar health systems (Ministry of Health Kenya, 2024). The platform was piloted in five counties, namely Muranga, Kajiado, Tharaka Nithi, Nyamira, and Nairobi. In Muranga, the integrated HMIS system enhanced documentation and improved patient care efficiency (Muranga County Government, 2024).

Tharaka Nithi County was one of the first to implement *Afya Kenya* in its Level 4 and Level 5 public hospitals. The county has consistently been recognized for prioritizing quality healthcare and leading digital health adoption (Peak, 2023; *Tharaka Nithi County Government*, 2024). Initial reports from the county suggest that the system has improved data security, credibility, and completeness, and has contributed to better service delivery and operational efficiency.

Public hospitals in Tharaka Nithi, particularly Level 5 facilities, play a critical role by offering specialized and referral services to a wide catchment area. The integration of *Afya Kenya* presents an opportunity to explore how healthcare workers and administrators utilize HMIS data in decision-making and what factors hinder or facilitate its use. Public hospitals were chosen for this study due to their wide service coverage and reliance on

government-supported HMIS, unlike private facilities, which may have access to proprietary systems.

Despite these advancements, there is limited research on how public hospitals in Tharaka Nithi are leveraging *Afya Kenya* to support decision-making. This study will assess the extent of HMIS data use by healthcare professionals, identify influencing factors, and propose strategies to improve data utilization. By addressing these knowledge gaps, the research aims to inform policy and practice, ultimately enhancing the effectiveness of digital health systems and contributing to better healthcare delivery in Kenya.

1.2 Problem Statement

Globally, HMIS is fundamental in supporting evidence-based decision-making in healthcare. As emphasized by the World Health Organization (WHO) and various scholars, high-quality health information is crucial for rational and effective decision-making, enabling healthcare providers and managers to align services with patient needs, monitor performance, and improve accountability (Bogale, 2021; Gesicho & Babic, 2022; WHO, 2008). However, a Global Digital Health Monitor report surveying 67 WHO member states found that less than 5% of health data is used in decision-making, highlighting a global gap in health data utilization (WHO, 2023). Particularly in LMICs, where robust data collection does not necessarily translate into actionable insights (Abajebel et al., 2011; Chanyalew et al., 2023). This underutilization of health data has far-reaching consequences, including inefficient resource allocation, compromised healthcare quality, and poor operational efficiency (Karijo et al., 2021).

Although significant investments have been made to improve HMIS, many countries still face challenges in managing routine health facility data. These challenges include inconsistent data quality, fragmented data management systems, lack of standardized operating procedures, and insufficient capacity for data analysis and utilization at both the facility and district levels (WHO, 2019). The decentralization of health systems in LMICs has shifted decision-making responsibilities to local levels, including health facilities and district administrations (Dwicaksono & Fox, 2018). However, studies indicate that routine health information system (RHIS) data use remains low, as many countries struggle to

move beyond data collection to effective analysis and decision-making (Hazel et al., 2017; Hoxha et al., 2022).

In sub-Saharan Africa, routine health data utilization rates remain significantly low. Studies show that Tanzania (42%), Liberia (58%), Angola(<50%), Ethiopia (33-78%), and South Africa (65%) have lower data utilization rates compared to high-income countries, where health data is systematically used for planning and continuous improvement (Asemahagn, 2017; Chanyalew et al., 2023; Isak, 2023; Mary & Otieno, 2023; Sanjuluca et al., 2022). Kenya faces similar challenges, with variations of data use in different counties ranging from 34-74% despite multiple HMIS initiatives aimed at improving data use in decision-making (Aila, 2021; Karijo et al., 2021; Morike, 2023; Mumo, 2016). Some key barriers include insufficient ICT infrastructure, inadequate staff training, and limited managerial support, all of which hinder the effective use of health data for evidence-based decision-making (Chaulagai et al., 2005; Thurairara, 2020). Additionally, the lack of integration between different health information systems leads to data fragmentation, making it difficult to ensure data accuracy, improve data accessibility, and maintain high-quality records for decision-making (Malahleha, 2024).

Furthermore, many health facilities experience what has been termed “mailbox syndrome”, where health data is collected and forwarded to higher administrative levels but is not actively utilized at the local level to support decision-making (Abajebel et al., 2011; Nicol et al., 2017). Even when healthcare workers receive training in data collection and analysis, there is often a disconnect between data reporting and its application in strategy formulation and policy-making (Endriyas et al., 2020; Lippeveld, 2017; Osterman et al., 2021). This underutilization of health data is particularly significant in secondary and tertiary public healthcare facilities, where the complexity of healthcare services and large patient volumes necessitate well-informed decision-making processes.

In Tharaka Nithi County, the recent introduction of *Afya Kenya* represents a critical step toward addressing some of these data utilization challenges. However, its impact on decision-making in secondary-level hospitals, particularly Level 5 facilities, remains largely unexplored. Secondary healthcare facilities are expected to leverage HMIS for

operational efficiency, resource optimization, and service quality improvement. However, studies have not sufficiently examined how healthcare workers at these facilities use HMIS data in their decision-making processes. The Tharaka Nithi County Integrated Development Plan (CIDP) 2023 reports that health facilities in the county collect extensive health data, but little is known about how individual facilities analyze, report, and disseminate this information at the facility level.

Existing research has primarily focused on the technical, organizational, and behavioral determinants of HMIS utilization, but environmental factors such as policies, legislative frameworks, and external support have received limited attention. Additionally, there remains a contextual gap in understanding how digital health systems, such as Afya Kenya, are utilized at secondary healthcare facilities in Tharaka Nithi County. Given that public hospitals play a critical role in service delivery, handling high patient volumes, and implementing national health policies, it is essential to examine the extent to which HMIS supports decision-making in these facilities.

This study, therefore, sought to explore the factors influencing the utilization of HMIS data in decision-making in Tharaka Nithi County's secondary public healthcare facility.

1.3 Research Objectives

1.3.1 General Objective

To assess the factors influencing data use for decision-making using HMIS amongst healthcare workers working at a public health facility in Tharaka Nithi County.

1.3.2 Specific Objectives

- i. To evaluate the technical factors influencing data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County
- ii. To evaluate the behavioral factors influencing data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County.

- iii. To evaluate the organizational factors influencing data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County.
- iv. To evaluate the environmental factors influencing data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County.

1.4 Research Questions

The following research questions guided the study;

- i. What technical factors influence data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County?
- ii. What behavioral factors influence data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County?
- iii. What organizational factors influence data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County?
- iv. What environmental factors influence data use of routine health information for decision-making among healthcare workers at a public health facility in Tharaka Nithi County?

1.5 Scope of the Study

This study focused on a Level 5 public health facility in Tharaka Nithi County, specifically examining the utilization of HMIS in decision-making processes. It assessed the factors influencing effective HMIS data use and its role in evidence-based decision-making in public healthcare, particularly within secondary facilities such as Chuka County Referral Hospital, with a focus on evidence-based decision-making for service delivery, resource planning, and healthcare management. The study did not cover all aspects of HMIS use. Still, it concentrated on its role in supporting operational and strategic decision-making within secondary-level facilities, which play a pivotal role in bridging primary care and

higher-level referral services. The study adopted a quantitative approach using semi-structured questionnaires that included both closed and open-ended questions, with the latter analyzed thematically to provide deeper insights. Eligible participants were healthcare workers available during data collection who were willing to provide informed consent. Those on leave or unwilling to participate were excluded.

1.6 Significance of the Study

Utilizing HMIS is essential for healthcare facilities aiming to enhance their decision-making processes and gain a competitive advantage. HMIS can significantly improve organizational value by enabling healthcare providers and managers to make informed decisions that directly impact service delivery and patient outcomes (Kithinji, 2018). The findings offer policymakers and healthcare managers practical guidance for strengthening RHIS integration into routine decision-making. In resource-constrained settings like public hospitals, understanding the role of leadership, infrastructure, and data culture will support evidence-based practices, transparency, and accountability. Private and faith-based facilities may also adopt the identified best practices to improve their own data utilization efforts.

Academically, the study contributes to the body of knowledge on HMIS and its role in data-driven healthcare. It highlights key enablers and barriers and proposes strategies to optimize HMIS use. The insights generated will support the Ministry of Health and other stakeholders in evaluating and scaling digital platforms like Afya Kenya to improve health system performance across Kenya.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews key literature on how healthcare workers across various settings utilize HMIS, focusing on understanding how routine health information is utilized in decision-making. Exploring the factors shaping data use in healthcare facilities. The chapter critically examines existing gaps in the literature, particularly the limited exploration of how these factors impact data utilization in secondary healthcare facilities, and positions the current study as an effort to bridge these gaps. The review aligns with the study's specific objectives.

2.2 Theoretical review

A theoretical review analyzes existing theories and models relevant to a study, helping to establish the foundation for understanding key concepts, relationships, and frameworks that guide the research. The PRISM Framework and Theory of Planned Behavior guide this study.

2.2.1 Prism Framework

The Performance of Routine Information System Management (PRISM) framework was developed to address RHIS's shortcomings in improving health system performance. It emerged in response to documented weaknesses in RHIS, such as poor data quality, information underutilization, and limited integration within health systems (Aqil et al., 2009). Unlike earlier approaches that predominantly focused mainly on technical aspects, the PRISM framework introduces a paradigm shift by emphasizing the overall performance of RHIS and incorporating three key categories of determinants: technical, behavioral, and organizational/environmental. According to the PRISM framework, organizational, technical, and behavioral factors (inputs) affect how data is collected, transmitted, processed, and presented (processes), which in turn affect how well the data is used and its quality (outputs), how well the health system performs (outcomes), and eventually how health outcomes (impact) turn out (Hotchkiss et al., 2010).

In addition, the PRISM framework also acknowledges the role of environmental factors, which, although not always under the direct control of the RHIS, significantly influence its performance and outcomes. Environmental factors include the broader socioeconomic, political, and infrastructural context within which RHIS operates. All these factors shape the system's ability to collect, analyze, and use data effectively (Aqil et al., 2009). Measure Evaluation (2011) stated that PRISM is a standardized tool that measures the full spectrum of the use of data to enhance decision-making. PRISM has been adapted for this thesis as its scope can be modified to fit, and its focus mirrors that of this research. It has already been applied in similar contexts (Andersen, 2023).

In the context of this study, the PRISM framework offers valuable insights into assessing and improving the use of HMIS for decision-making in healthcare facilities. By employing PRISM, the study can identify and analyze the behavioral factors (such as staff competencies and attitudes towards data use), technical factors (including data collection tools and processes), organizational factors (like leadership support and resource allocation) and environmental factors (such as government funding and external infrastructure) that affect the performance of to enhance data utilization and promote HMIS. This comprehensive analysis facilitates the development of targeted interventions aimed at enhancing data utilization and promoting a culture of information use within healthcare organizations.

Furthermore, the PRISM framework's emphasis on continuous improvement aligns with the study's objective to foster an information-rich environment where data-driven decisions lead to improved health outcomes. By integrating PRISM into the research methodology, the study can systematically evaluate current HMIS practices, identify gaps, and implement strategies that strengthen the overall health information system, ultimately contributing to more effective healthcare delivery.

2.2.2 Theory of Planned Behavior

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991) as an extension of Fishbein and Ajzen's Theory of Reasoned Action, has become one of the most dominant frameworks for predicting and explaining human behavior across health, education, consumer, and environmental contexts (Ajzen, 1991; Chen et al., 2024). According to

TPB, behavior is determined by intention, which is shaped by three key constructs: attitudes toward the behavior (beliefs about expected outcomes), subjective norms (perceptions of social expectations), and perceived behavioral control (PBC) (perceived ability and access to resources). Intention is considered the most immediate antecedent of behavior, while perceived behavioral control may also have a direct impact on actual behavior. This framework assumes that individuals are rational and make planned decisions based on the evaluation of outcomes, social pressures, and their perceived control over the behavior (Ajzen, 1991; Seong & Hong, 2021).

Applied to this study, TPB provides a lens for understanding both the factors influencing HMIS data use and the behavior of different respondents within public health facilities. For example, healthcare workers' attitudes toward HMIS reflect whether they perceive it as useful and reliable for improving patient care and planning. Subjective norms represent the influence of colleagues, supervisors, and institutional culture in encouraging or discouraging the use of routine health data. Perceived behavioral control reflects whether staff feel equipped with the technical skills, infrastructure, and organizational support to utilize HMIS effectively.

Importantly, TPB also helps explain why some cadres or respondents behave differently (Ajzen, 1991). Lower-level staff may have weaker perceived behavioral control due to limited training, while younger staff may have more positive attitudes due to digital fluency. Senior staff, on the other hand, may respond more strongly to subjective norms because of leadership expectations. Thus, the theory accounts not only for the determinants of intention but also for the variation in data-use behavior across different categories of health workers.

The strengths of TPB in this study include its ability to integrate individual, social, and organizational factors into a single explanatory model, which is particularly relevant in examining HMIS data utilization (Chen et al., 2024). It has strong empirical validation in diverse health-related behaviors, such as vaccination, rehabilitation, and treatment adherence (Antonopoulou et al., 2022; Hsu et al., 2023). However, the theory also has limitations: the intention-behavior gap means intentions may not always translate into actual practice, especially where systemic barriers exist; PBC may not always represent

true control in contexts with infrastructural or policy gaps; and the model assumes rational, planned behavior, underplaying emotional or habitual influences (Ajzen, 1991; Seong & Hong, 2021). Despite these weaknesses, TPB is highly suitable for this study, as it explains both the determinants of HMIS data use and the behavioral differences among respondents, making it a robust theoretical foundation for investigating decision-making in secondary public healthcare facilities.

2.3 Empirical Review

An empirical literature review involves analyzing studies that provide direct evidence based on observations, expert opinions, or real-world data. Health data plays a crucial role in shaping decisions at all levels of healthcare. Data-driven decision-making ensures that healthcare policies and clinical decisions are informed by empirical evidence rather than intuition. This review explores the role of health data in decision-making and how its utilization influences healthcare outcomes.

2.3.1 Technical Factors Influencing Data Use

Technical factors in healthcare decision-making involve both technology and human infrastructure, as they are essential resources that enable effective health system management. The success of a health institution depends on how well it aligns health workers' knowledge and skills with the tools and systems available to them. When healthcare workers are properly trained and equipped with user-friendly digital tools, they can streamline processes and improve efficiency (Kyalo et al., 2018).

In LMICs, technical challenges are more pronounced due to resource constraints and infrastructural limitations. Adane et al. (2017) and Asemahagn (2017) emphasize that technical support, computer availability, data management knowledge, and computer skills are critical for enhancing HMIS utilization. However, many facilities in LMICs struggle with systemic issues such as outdated hardware, inadequate ICT infrastructure, and limited training opportunities (Dhadho et al., 2024). System instability, including frequent crashes and slow response times, further undermines the reliability of HMIS data, impeding its usability for health facility planning (Dakika & Saronga, 2024). The fragmentation of systems and tools adds another layer of complexity, limiting

interoperability and hindering the effective exchange of health information (Bagyendera et al., 2023).

Kenya faces similar challenges, including fragmented HMIS tools, insufficient staff competence, and inadequate ICT infrastructure (Kyalo & Odhiambo-Otieno, 2019). A study in Kiambu County recommended developing standardized guidelines to address these technical issues and ensure a unified system (Njeri, 2018). Integrated HMIS has been identified as a potential solution to enhance system efficiency through features such as data validation, multi-level security, and streamlined data processing (Musa, 2023).

In Tharaka Nithi county, adopting Afya Kenya in a level 5 facility marks a significant step toward addressing these technical challenges. The integrated HMIS is expected to reduce the fragmentation of existing systems and enhance interoperability and health information exchange across the county. This integration promises to increase data collection, analysis, and utilization efficiency, ultimately improving healthcare delivery. However, the extent to which this new system has addressed technical barriers and enhanced data-driven decision-making in higher-tier facilities remains unclear. Previous studies, such as Mucee 2016, have largely focused on technical gaps in lower-tier facilities, leaving a gap in understanding the impact of integrated HMIS on higher-tier facilities' more complex decision-making processes.

2.3.2 Behavioral Factors Influencing Data Use

Behavioral factors focus on the human aspect of data use and can be improved to enhance data quality and reduce inconsistencies. One of the most effective ways to achieve this is through capacity building and training for personnel handling health information (Malahleha, 2024). In Tharaka Nithi County, the CIPD 2023 reports inadequate ICT skills among healthcare workers. According to Aqil et al. (2009), when HIS personnel feel more confident in their skills, their data collection and use approach also improves. The PRISM framework supports this idea by showing that training enhances technical skills and boosts confidence, leading to better data management practices, reduced errors, and improved overall data reliability.

Behavioral factors critically influence how health workers collect, process, and use data within HMIS. As LaFond and Fields (2003) point out, the primary roles of most health workers revolve around clinical care and managing health services, with secondary duties such as disease surveillance, stock-keeping, and evidence-based planning often being deprioritized. When expectations regarding data collection and use are unclear, the motivation and commitment of health workers to manage data suffer. Even when technical aspects such as well-designed data collection tools, clear indicators, and adequate training are in place, they do not automatically lead to consistent data utilization in healthcare decision-making. The same study has shown that health workers may still underuse data due to low motivation, lack of feedback, and staff competencies that do not prioritize evidence-based actions.

This lack of clarity, coupled with the absence of feedback on routine reporting, demotivates staff and leads to poor data recording, underreporting, and minimal data use in decision-making. Interventions to strengthen HMIS that do not address these behavioral factors, such as attitudes, motivation, and incentives, risk resulting in poor-quality data and infrequent data use (Mairanga et al., 2020). Competence, attitudes, and motivation among staff are central behavioral factors influencing HMIS performance (Chanyalew et al., 2023).

In LMICs, findings suggest that behavioral challenges such as poor attitude, lack of motivation, and inadequate knowledge and skills influence the use of data (Dakika & Saronga, 2024). In Ethiopia, a study by Ngusie et al. (2022) reported that 55.1% of health professionals demonstrated good knowledge of HMIS, while 64.3% showed strong motivation to use it. However, only 46.7% of respondents reported a positive culture of health information use, and an equal proportion (46.7%) expressed confidence in their ability to perform RHIS-related tasks. A study previously done in some of the primary public healthcare facilities in Tharaka Nithi County showed behavioral factors such as lack of staff motivation at 97.3 % and lack of recognition for well-done jobs at 98.7% (Mucee, 2016).

In Tharaka Nithi County, behavioral factors present challenges and opportunities with adopting an integrated HMIS. While the new system aims to reduce fragmentation and

enhance interoperability, its success depends on addressing behavioral gaps, such as improving staff motivation, building competence, and fostering positive attitudes toward data use. However, there is limited research on how these behavioral factors influence the data utilization of the integrated HMIS in level 5 facilities.

2.3.3 Organizational Factors Influencing Data Use

Organizational factors significantly shape HMIS performance; they focus on internal elements such as governance, leadership, and workflows. These factors are closely tied to health facilities' structure, culture, and processes that support HMIS. Governance, leadership, human resources, training, supervision, and communication workflows are critical in data collection, processing, and utilization. Aila (2021) emphasizes that data's potential impact on decision-making is only realized when it is promptly processed and communicated to the relevant individuals. Without clear procedures and roles for those involved in data management, HMIS cannot effectively support evidence-based decision-making. Organizational culture is another critical factor (Hlaing & Zin, 2020). Many health projects focus on training and technical aspects rather than improving organizational culture (Kessy et al., 2024). In Tharaka Nithi County, Mucee (2016) reported that most respondents indicated a lack of information use culture promotion.

Another key organizational factor identified was the absence of clearly defined roles and responsibilities for HMIS implementers, leading to job insecurity. In response, HMIS authorities in LMICs developed a national HMIS policy outlining critical components such as data security, confidentiality, information exchange and usage, interoperability standards, and explicit job descriptions for HMIS personnel (Hlaing & Zin, 2020). Supportive supervision and feedback mechanisms are also essential for enhancing HMIS performance. Moloko and Ramukumba (2022) found that regular supervision, adequate human resources, and decision-making power are critical for improving data quality. The power that different actors in healthcare facilities wield can have a significant impact on how data is used for decisions and whether some information is weighed more than others (Isak, 2023).

Similarly, studies in Kenya and Ethiopia demonstrated that consistent mentorship and feedback positively influence data quality and utilization (Dagnew et al., 2018; Mairanga

et al., 2020). Mumo (2016) found that while 55% of respondents at Malindi Sub County Hospital acknowledged receiving feedback from their managers about the quality of data collected and its consumption, facility policies and guidelines on data use were provided. In Makueni County, the county's feedback on data use and management support was found to be low. This was confirmed by a related study that found supportive supervision to be low at 44.4% and hospital funding for HMIS activities to be much lower at 7.2% (Mary & Otieno, 2023).

Resource allocation is a key organizational factor affecting data utilization in public health. Limited financial, human, and technological resources restrict planning and implementation, making developing, improving, and sustaining data-driven health programs difficult. Without adequate investment, data collection, analysis, and use remain inefficient, limiting evidence-based decision-making (Isak, 2023). However, many facilities in resource-limited settings lack these critical organizational supports, further undermining HMIS effectiveness (Hlaing & Zin, 2020).

2.3.4 Environmental Factors Influencing Data Use

Environmental factors address the broader external health system and policy environment that influences HMIS operations. These are external elements such as policies, infrastructure, and resource allocation that shape HMIS performance. LaFond and Fields (2003) describe these factors as including the wider health system and policy environment, such as ministries and management units. Another study under the PRISM framework considered competition, regulatory environment, and community resources to be environmental factors (Feldstein, & Glasgow, 2008) while another study focused on external environmental factors such as the distribution of resources, policy, social system structure, and coverage (Fort et al., 2023).

Constraints such as poor road networks, limited telecommunications infrastructure, and inadequate human resources create significant challenges for timely and accurate data reporting. Poor HMIS performance has been linked to unclear and inequitable allocation of national budgets for HMIS-related activities. In Lesotho, the HMIS is overseen by the statistics unit within the Department of Planning at the Ministry of Health (MOH) and is lacking sufficient government funds; however, it has received more external funding over

the last decade (Matube & Fosa, 2023). Additionally, a systematic review of LMICs reports that insufficient government funding for system implementation, equipment maintenance, staff training, and data documentation directly impacts data quality and overall system efficiency (Hlaing & Zin, 2020).

In Kenya, government legislation, such as the Digital Health Act, has been pivotal in streamlining the management and security of digital health data and facilitating integration, standardization, and interoperability of HMIS across healthcare facilities (Digital Health Act, 2023). Policies such as the Kenya Health Sector Strategic and Investment Plan (KHSSP) and initiatives supporting Universal Health Coverage (UHC) further emphasize the importance of robust health information systems for equitable healthcare delivery and data-driven decision-making. However, challenges such as limited stakeholder training and inadequate alignment of policies with HMIS implementation persist, hindering the realization of these objectives.

In Tharaka Nithi County, adopting Afya Kenya in level 5 facilities represents progress toward addressing these challenges. However, while organizational factors such as low culture of information use and limited supervision have been studied in the primary health facilities in the county (Mucee, 2016). Environmental factors, including the impact of national policies, resource allocation, and infrastructure, remain underexplored.

2.4 Summary of Research Gaps

Despite the growing recognition of HMIS in enhancing data-driven decision-making, several gaps persist in the existing literature. Empirically, there has been limited attention to environmental influences such as infrastructure, funding, and policy frameworks, which significantly impact HMIS performance (Fort et al., 2023; Matube & Fosa, 2023; Mumo, 2016). Furthermore, while Kenya has made strides in digital health through initiatives such as Afya Kenya, there is a lack of research exploring how its integration has influenced data utilization in healthcare decision-making. Many studies have also focused primarily on operational decision-making, such as patient care and routine data reporting, rather than strategic decision-making, which is essential for long-term planning, resource allocation, and policy formulation (Karijo et al., 2021; Morike, 2023).

Also, there is a gap in understanding the role of HMIS at different levels of decision-making in healthcare. While HMIS is designed to support evidence-based decision-making, there is insufficient research on how national policies, governance structures, and institutional frameworks influence its utilization and effectiveness. Many studies have emphasized system functionality rather than its impact on managerial decision-making at higher levels.

From a contextual perspective, most studies on HMIS utilization in Kenya have been conducted in primary healthcare facilities, with limited research focusing on secondary and tertiary public healthcare institutions (Mucee, 2016). In particular, there is limited research investigating higher-tier healthcare facilities in Tharaka Nithi County, where challenges such as infrastructure limitations, policy implementation gaps, and resource constraints may differ significantly from those in urban settings or primary care facilities. The unique challenges and enablers of HMIS utilization in this region remain underexplored, limiting the generalizability of findings from other regions to this specific context. Conceptually, there has been insufficient differentiation between strategic and operational decision-making in HMIS research. Most studies do not account for the distinct needs and perspectives of departmental heads, senior management, and frontline healthcare workers when using HMIS for decision-making.

To address these gaps, this study will employ a quantitative approach and will be guided by the PRISM framework and the Theory of Planned Behavior to assess both strategic and operational decision-making. It will investigate the impact of environmental factors, Afya Kenya integration, and organizational structures on data utilization, with a particular focus on secondary public healthcare facilities in Tharaka Nithi County. By bridging these methodological, empirical, theoretical, contextual, and conceptual gaps, the study aims to provide actionable policy recommendations for strengthening HMIS adoption and utilization in healthcare management

Table 2.1 Summary of Study Gaps

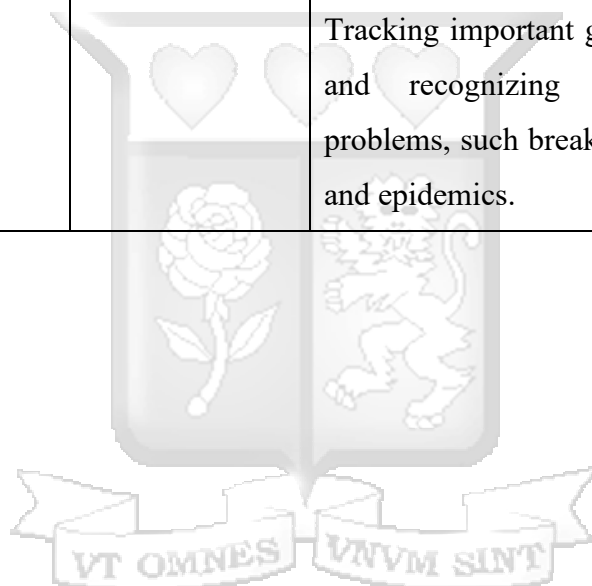
Objective	Authors and year	Country	Findings	Gap
Technical Factors	(Dakika & Saronga, 2024) (Mucee, 2016) (J. Mumo et al., 2024)	Uganda Kenya (Tharaka Nithi, Machakos, Kisumu, Nyeri, Isiolo County)	-Limited Staff Competence & Infrastructure gaps due to inadequate training and multiple uncoordinated HIS tools. -Dashboards, computers, and internet access support data visualization, but software availability and hardware adequacy remain concerns. -Data Security risks& outdated infrastructure, and frequent technical disruptions affect HMIS's effectiveness	-Few studies have assessed technical factors affecting HMIS in higher-tier facilities Most studies are in lower Level facilities.
Organizational	(Andersen, 2023) (Hoxha et al., 2022) (Morike, 2023) (Sahota et al., 2024) (Kessy et al., 2024), (Otieno et al., 2020) (Cheruiyot, 2018)	India Dodoma, Tanzania Kenya (Kisumu, Mombasa, Narok, Machakos, Kisumu, Nyeri, Isiolo County)	-Limited Organizational Support & Resources hinder data use - Strong leadership, participation in monitoring data, regular data reviews, and feedback mechanisms improve data utilization, while lack of policies and poor supervisory support hinder progress	-Studies rarely focus on the specific resource gaps in secondary public hospitals. -Limited research on how organizational factors influence data use in Level 5 hospitals with HMIS.

	(J. Mumo et al., 2024)			
Behavioral	(Chanyalew et al., 2023) (Hoxha et al., 2022) (Sahota et al., 2024) (Dakika & Saronga, 2024) (J. Mumo et al., 2024)	Ethiopia India Uganda Kenya (Machakos, Kisumu, Nyeri, Isiolo County)	-Poor attitude and limited value for data hinder HMIS use, and resistance to new technologies affects usage. -Encouraging training-seeking behavior, role clarity, and recognition programs can improve confidence, skills, and motivation in using HMIS data.	Limited research on how behavioral factors influence HMIS data use in higher tier Facilities.
Environmental	(Global Health Science and Practice, 2022) (J. M. Mumo, 2016) (Fort et al., 2023) (Matube & Fosa, 2023) (Hlaing & Zin, 2020)	Ethiopia, Ghana, and Mozambique -Kenya (Makueni County)	-External policies, resource allocation, and social system structures affect the use of HMIS data. -Reliable internet, computers, and supportive facilities are essential for efficient data sharing, retrieval, and utilization. - Insufficient government funding for system implementation and maintenance affects data quality and overall HMIS efficiency.	Limited research on how national policies influence data use at Level 5 facilities. -The impact of infrastructure and funding gaps on HMIS utilization in Level 5 hospitals are underexplored.

Decision Making	(Sanjuluca et al., 2022)	Angola	More than 50% of hospital managers have rarely or never used the health information system to support clinical and administrative decision-making.	-Focused on top management -Contextual gap
	(Karijo et al., 2021)	Kenya (Kilifi County)	34% of healthcare workers used data for operational decision-making such as medical supply and drug management, reviewing financial statements, human resources management, and monitoring key objectives and policy.	-Looked at more operational than strategic decision making -Contextual gap
	(Morike, 2023)	Kenya (Kisumu County)	This study revealed 73.6% use of routine health information for decision-making, with the majority using it for formulation of planning, identification of emerging epidemics, and medical supply & drug management	-Contextual gap -No assessment of Environmental factors
	(Tulu, Demie, & Tessema, 2021)	Oromia Regional State, Ethiopia	The level of RHI use for decision-making was 71.6% in clinical service,	-Contextual gap

			service improvement, resource allocation, policy development, and advocacy.	
	(Kessy et al., 2024)	Dodoma, Tanzania	In decision-making processes like quality improvement, patient safety monitoring, performance reviews, dashboard creation, and report generation, 41% of health managers said they used data generated.	-Contextual gap -No environmental factors -Focuses on EMR not HMIS.
	(Abdul-Azeez et al., 2024)	USA, UK, Canada, South Africa	Businesses can find opportunities, reduce risks, and streamline procedures by using data to obtain insightful knowledge about their operations, clients, and market trends.	-Does not look at factors influencing data use. -Contextual gap
	(Matube & Fosa, 2023)	South Africa	According to a study, 40–59% of HMIS data is utilized for strategic decision-making, including establishing performance metrics, establishing goals to meet within a fiscal year based on baselines, Creating	-Contextual gap

			reports to track performance	
	(J. M. Mumo, 2016)	Kenya (Makueni County)	Sixty-seven percent of data was used to make decisions about the management of medical supplies and drugs, create strategies, create budgets, allocate funds, and manage human resources. Tracking important goals and recognizing new problems, such breakouts and epidemics.	-Contextual gap -Doesn't consider environmental factors



2.5 Conceptual Framework

The conceptual framework shows expected interaction between the independent variables and data use in decision making. Figure 2.1 below illustrates the conceptual framework

Independent variables

Dependent variable

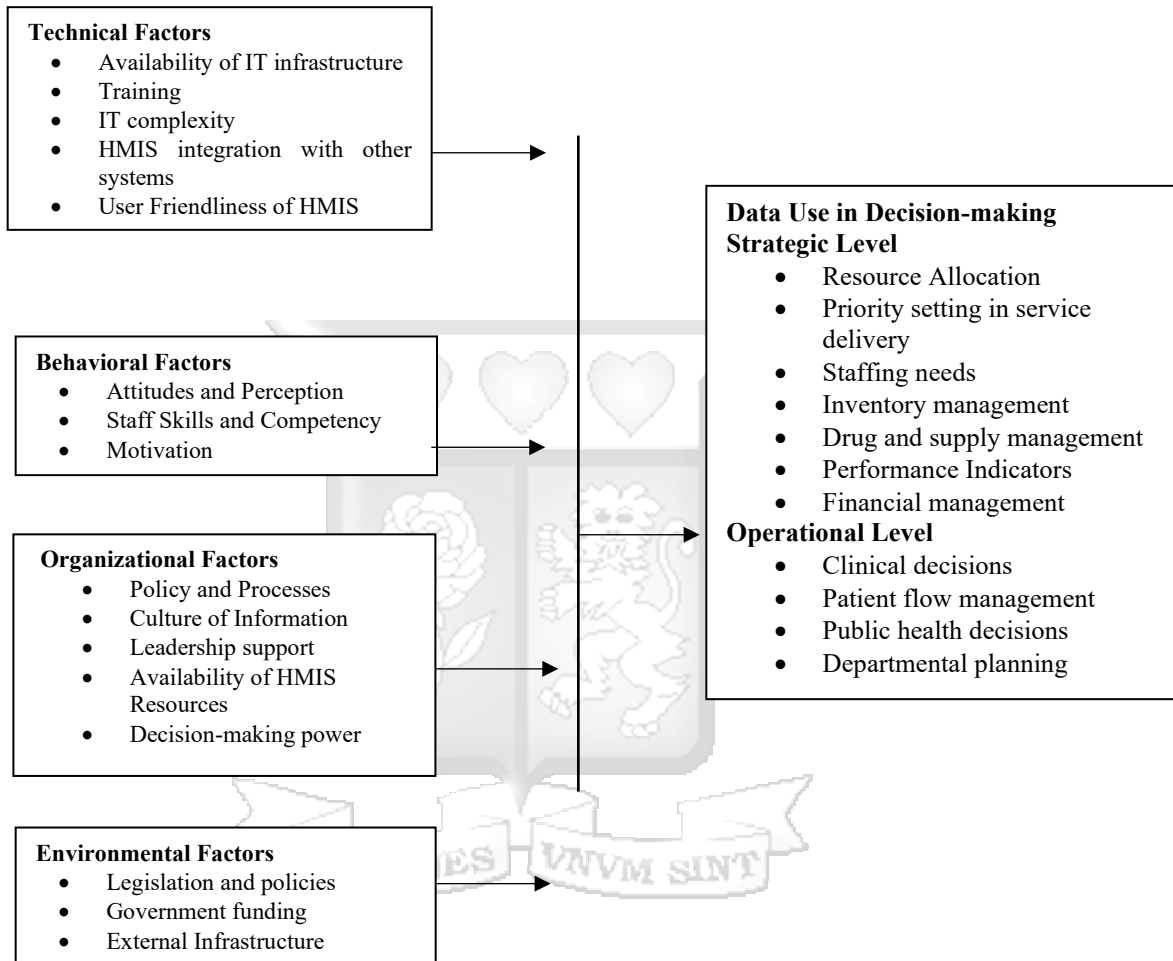


Figure 2.1 Conceptual Framework

2.5.1 Operationalization of Variables

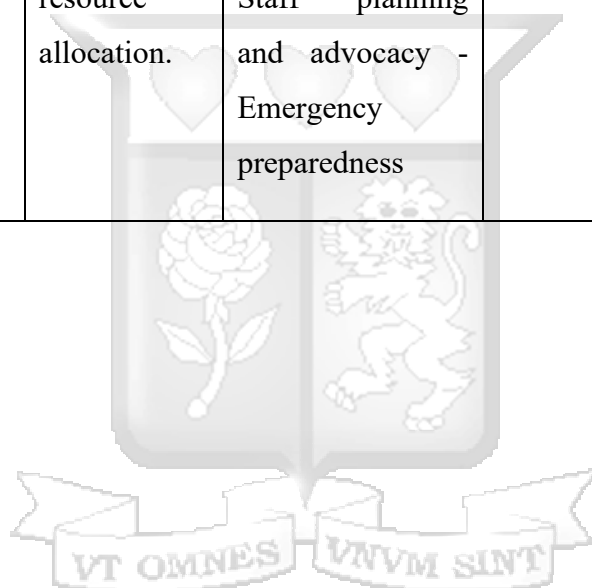
The operationalization of the study variables is covered in this section. The dependent variable was Data use in decision-making. The independent variables were technical factors, behavioral factors, organizational factors and environmental factors. Table 2.2 below illustrates how these variables were operationalized

Table 2.2 Operationalization of variables

Variable	Definition	Indicators	Measurement Method	Citation
Technical Factors	The technological systems, tools, and IT environment supporting or hinder HMIS data use.	- Availability of internet, computers, printers - HMIS user-friendliness - System complexity - Integration with other systems	Survey using a 5-point Likert scale on technical capacity and usability (1 = Strongly Disagree to 5 = Strongly Agree)	(Chorongo, 2016; Matube & Fosa, 2023; MEASURE EVALUATION & USAID, 2012)
Organizational Factors	Internal policies and processes, leadership, resources, and culture that influence HMIS data use.	- Leadership support - Policy and Processes - Culture of information - Availability of resources - Decision-making power	Survey using 5-point Likert scale across enablers/barriers within facility structure	(Matube & Fosa, 2023; MEASURE EVALUATION & USAID, 2012)
Behavioral Factors	Health workers' individual competence	- Competency and skill in data retrieval, analysis, and	Survey using 5-point Likert scale on personal	(Kitaba, 2015; MEASURE EVALUATION & USAID, 2012)

	s, motivation, attitudes, and self-efficacy related to HMIS data use.	interpretation - - Attitude and perceptions toward data use in decision making - Motivation - Confidence in using data for planning and reporting	behavior and competence indicators	2012; Tulu, Demie, & Teshome, 2021)
Environmental Factors	External policies, infrastructur e, and funding environment that enable or limit HMIS effectiveness .	- Government funding - Internet/electricit y reliability - External partner/donor policies - Political and social influences	Survey using a 5-point Likert scale measuring perceived external support/barriers	(Fort et al., 2023; Hlaing & Zin, 2020; MEASURE EVALUATIO N & USAID, 2012)
Operational Decision- Making	Day-to-day use of HMIS data by departments and clinical units to manage	- Use of data in patient care - Drug/supplies management - Daily planning - Monitoring KPIs - Staff feedback	Survey based on a 5-point Likert scale measuring different use of various operational decisions.	(Dagnew et al., 2018; Mary & Otieno, 2023; MEASURE EVALUATIO N, 2011;

	health services.	and performance tracking		Sahota et al., 2024)
Strategic Decision-Making	Use of HMIS data by top-level leadership for long-term planning, policy, and resource allocation.	- Strategic planning - Budgeting and resource mobilization - Policy development - Staff planning and advocacy - Emergency preparedness	Survey based on a 5-point Likert scale measuring different use of various strategic decisions.	(Malahleha, 2024; MEASURE EVALUATION, 2011; Mugendi, 2015; Sahota et al., 2024)



CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the research methodologies utilized in the study, providing an in-depth explanation of the research philosophy, design, study population, data collection tools, data collection techniques, approaches to data analysis, and ethical principles adhered to throughout the research.

3.2 Research Philosophy

This study adopted a post-positivist research philosophy, which aligns closely with the quantitative cross-sectional design employed. Post-positivism, sometimes referred to as the scientific method or empirical science, recognizes the existence of an objective reality but acknowledges that our understanding of it is imperfect, fallible, and subject to revision (Creswell, 2018). Knowledge claims are considered probabilistic rather than absolute, making this worldview particularly suitable for studying complex social and organizational behaviors, such as health workers' use of HMIS data.

The choice of post-positivism was also guided by the nature of the study objectives. The research aimed to determine the correlational relationships between independent factors, technical, organizational, behavioral, and environmental and the dependent outcome, which is the utilization of HMIS data for decision-making. Such objectives are inherently explanatory and require a philosophical stance that emphasizes measurement, hypothesis testing, and statistical inference. Post-positivism supports this by allowing researchers to use structured tools, apply statistical models such as chi-square tests and multiple regression, and interpret findings as generalizable patterns rather than absolute truths.

By adopting this stance, the study could systematically quantify perceptions, behaviors, and contextual influences while remaining open to the possibility that results are provisional and may be refined with further evidence. This balanced orientation offered a robust philosophical foundation for investigating how HMIS contributes to evidence-based decision-making at a Level 5 public health facility in Kenya. It ensured that the inquiry remained objective, structured, and empirically grounded, consistent with the

study's overall goal of generating actionable insights for health policy and facility management.

3.3 Research Design

This study adopted a descriptive cross-sectional research design. A quantitative approach was undertaken to examine the influence of HMIS on decision-making in Chuka Level 5 Hospital, Tharaka Nithi County. A cross-sectional design was appropriate as it allowed for the collection of data at a single point in time, offering a snapshot of current HMIS practices and healthcare workers' perceptions of HMIS data utilization (Indeed, 2024; Wang & Cheng, 2020). This design was particularly suited for identifying patterns and relationships among variables without manipulating the study environment. The quantitative design allowed for statistical analysis of associations and predictive relationships, offering a data-driven understanding of how HMIS influences decision-making in a level-five public hospital context.

3.4 Population and Sampling

The unit of analysis for this study was Chuka Level 5 Hospital, a public referral facility offering primary, secondary, and tertiary healthcare services in Tharaka Nithi County. Within this facility, the study focused on healthcare workers directly involved in health data generation, reporting, and utilization for decision-making.

The target population was stratified into two main categories to reflect the different levels of interaction with HMIS. Departmental Heads, including Senior administrators and officers in charge of specific units (e.g., Medical Superintendent, Hospital Administrator, Head of Pharmacy, Head of Laboratory, Nursing Officer in Charge, and others). These individuals primarily engage in strategic decision-making, such as resource allocation, staffing, budgeting, and performance monitoring.

Healthcare Cadres, including clinical and technical staff such as nurses, medical officers, consultants, laboratory officers, clinical officers, nutrition officers, and others. These cadres interact with HMIS at the operational level, using data for patient care, treatment planning, surveillance, and reporting.

This distinction is illustrated in Table 3.1, which presents the staff distribution at Chuka Level 5 Hospital. The table is organized into two parts: the first showing the 27

departmental heads across key functional areas, and the second detailing the 223 healthcare cadres engaged in routine clinical and technical service delivery. Together, these groups constitute the entire population of 250 staff members who interact with HMIS either for clinical decision-making or for administrative and strategic functions.

Table 3.1 Distribution of Healthcare Workers in Chuka Level 5 Hospital

Cadres	Chuka Level 5 Hospital
Medical Superintendent	1
Hospital Administrator	1
Nursing Officer in Charge	1
Accountant	1
Health Records Department in Charge	1
Procurement in Charge	1
Head of Human Resource Department	1
Laboratory Department in Charge	1
Radiology Department in Charge	1
Pharmacy in Charge	1
Ward in Charge	10
Other departments in charge	7
Subtotal Departmental Heads	27
Nurses	100
Consultants	14

Cadres	Chuka Level 5 Hospital
Medical Officer	11
Pharmacist	2
Health Records officers	14
Public Health Officer	4
Clinical Officer	12
Nutrition Officer	8
Pharmaceutical Technician	8
Laboratory Officer	40
Anesthetist	10
Subtotal Healthcare Cadres	223
Grand Total	250

The study employed a census approach, targeting all 250 staff members. This decision was guided by two considerations. First, the population size was manageable, making it feasible to conduct a full enumeration without the need for sampling. Second, since both departmental heads and healthcare cadres play complementary roles in HMIS use ranging from data entry and reporting to resource allocation and strategic planning excluding any subgroup could risk omitting critical insights into the decision-making process. Thus, all staff directly involved in data management and utilization were included in the study. Only non-clinical support staff (e.g., cleaning, catering, and maintenance personnel) were excluded, as their roles do not involve HMIS use or decision-making based on health data. This comprehensive census ensured that the study captured the full spectrum of perspectives across strategic and operational levels of decision-making, allowing for a nuanced assessment of how HMIS influences healthcare delivery in a Level 5 public hospital setting.

3.5 Data Collection Methods

The primary quantitative data was collected using a semi-structured survey questionnaire with open-ended questions. The researcher developed the survey instrument based on a thorough review of HMIS literature and expert consultations and is adapted from tools by MEASURE Evaluation and USAID (2008) focused on data demand and use in the healthcare sector. The questionnaire was aligned with the study objectives and is designed to capture data across all study variables. It included questions categorized under the four independent variables: technical, behavioral, organizational, and environmental factors, as well as the dependent variable, which is decision-making.

The survey included 5-point Likert scale items to assess the level of agreement or frequency of actions and behaviors, with response options ranging from Strongly Disagree (1) to Strongly Agree (5). Questions under technical factors assess the availability and adequacy of IT infrastructure, the integration of HMIS with other systems, and user-friendliness. Behavioral factors were evaluated through questions on individual competencies, attitudes, and motivations regarding HMIS use. Organizational factors were measured by examining leadership support, availability of resources, supervision, training, and the existence of policies promoting data use. Environmental factors focused on external influences such as government funding, electricity and internet reliability, and national legislation that may support or hinder data use.

The survey was designed with a skip logic mechanism to ensure data relevance to the respondents' roles. This allowed for targeted questioning based on the respondent's position and responsibilities. Top management and departmental heads (such as the Medical Superintendent, Hospital Administrator, Human Resource and Finance heads, and heads of technical departments) were guided to complete survey sections focusing on strategic decision-making such as planning, budgeting, policy development, human resource allocation, and performance monitoring. On the other hand, frontline healthcare workers and mid-level supervisors (including nurses, clinical officers, medical officers, and lab officers) were directed to sections focusing on operational decision-making such as patient care, daily departmental planning, service improvement, and drug or supply management. The design and administration of the tool ensured robust data collection,

enabling rigorous quantitative analysis of HMIS influence on healthcare decision-making at both strategic and operational levels.

3.6 Data analysis

The study adopted a quantitative data analysis approach using both descriptive and inferential statistical methods to examine the influence of HMIS on decision-making processes at Chuka Level 5 Hospital. Data collected through the structured Likert-scale survey was entered, cleaned, and analyzed using SPSS. Qualitative aspects were analyzed using thematic analysis. Descriptive statistics, including frequencies, percentages and means, were used to summarize the characteristics of the respondents and to describe the distribution of responses across the variables of interest. These results provided a general understanding of how healthcare workers perceive technical, behavioral, organizational, and environmental factors affecting HMIS use. The results were presented in the form of tables for clarity and easy interpretation.

For inferential analysis, the study applied Chi-square tests, Pearson correlation, and Multiple linear regression. The Chi-square test assessed the association between categorical variables, such as the age of respondents, working experience, and their perception towards use of HMIS data. This made it easier to ascertain if respondent characteristics and HMIS data consumption patterns were statistically related. Pearson correlation was used to assess the strength and direction of the linear relationships between key independent variables and HMIS data use. It helped identify which factors are most strongly associated with operational and strategic data utilization. Multiple regression analysis was further used to determine the strength and nature of the relationship between the independent variables (technical, behavioral, organizational, and environmental factors) and the dependent variable (HMIS data use in strategic/operational decision-making). This approach allowed the study to identify which factors significantly predict the use of HMIS data in both strategic and operational decision-making contexts.

The regression model typically yielded this equation

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon$$

Where:

Y = Data Use in Decision-Making

β_0 = Intercept (constant term)

$\beta_1, \beta_2, \beta_3, \beta_4$ = Regression coefficients for each independent variable

X_1 = Technical Factors

X_2 = Behavioral Factors

X_3 = Organizational Factors

X_4 = Environmental Factors

ε = Error term

This model helped identify which factors are significant predictors of HMIS data utilization and to what extent they influence strategic and operational decision-making in the facility. The results from this analysis guided evidence-based recommendations for strengthening HMIS use in public hospitals in Tharaka Nithi County.

3.7 Research Quality

3.7.1 Validity

Validity refers to the extent to which an instrument's scores provide meaningful and useful inferences (Creswell, 2018). It refers to the extent to which the research accurately captures what it intends to measure (Andersson et al., 2024). To enhance the validity of this study, the survey instrument was carefully designed using standardized questions and a 5-point Likert scale, which promotes consistency in data collection and interpretation across all respondents. The instrument was adapted from validated tools used in previous HMIS literature (MEASURE EVALUATION, 2011; MEASURE EVALUATION & USAID, 2012) and aligns directly with the study objectives and conceptual framework.

A pilot survey test was conducted at a level five public hospital in the neighboring Embu County, involving a small group of clinical and administrative healthcare workers. This

pilot helped to assess whether respondents interpret the questions as intended and whether any ambiguity or inconsistencies exist in the wording or flow of the survey. Revisions were made based on the pilot results to ensure that questions are uniformly understood, thereby minimizing the risk of inconsistent responses. To further support validity, research assistants conducting the survey underwent training to standardize the administration of the instrument. This training covered question delivery, clarification techniques, and ethical considerations, ensuring that the data collection process was uniform and that researcher-induced variability was minimized.

The internal validity was ensured by assessing whether survey items specifically align with the study's objectives, covering technical, behavioral, organizational, environmental, and individual factors that impact HMIS utilization. The External validity was considered by evaluating the extent to which the study's findings in Tharaka Nithi County level 5 public hospitals would be generalized to similar healthcare settings in Kenya and beyond.

3.7.2 Reliability

Reliability is the consistency of results over time and across different groups (Andersson et al., 2024). Statistical reliability was assessed using Cronbach's alpha, a commonly used measure of internal consistency reliability in the social and organizational sciences. Cronbach's alpha was calculated for each of the main constructs: technical, behavioral, organizational, and environmental factors and decision-making variables. A Cronbach's alpha value of between 0.70 to 0.90 was considered acceptable, indicating high internal consistency among the items within each scale (Creswell, 2018). Through statistical reliability testing, this study ensured that the data collected was reliable and robust, forming a strong basis for valid conclusions about the influence of HMIS on decision-making in level five public hospitals.

3.8 Ethical Considerations

Ensuring the ethical integrity of this research involves respecting participants' rights and safeguarding their well-being. This study upheld strict ethical standards to protect participant rights and confidentiality. Ethical clearance was granted by the Strathmore University Institutional Scientific and Ethical Review Committee (SU-IERC) and the National Commission for Science, Technology, and Innovation (NACOSTI) gave its

permission. Before starting any investigation, permission was also acquired from the administration of Tharaka Nithi County's Chuka Level 5 Hospital.

Informed consent was obtained from all survey participants and interview informants after clearly explaining the study's purpose, the voluntary nature of their participation, and their right to withdraw at any stage. They were assured that their responses would remain confidential and anonymous. Survey data and observation notes were anonymized to safeguard privacy, with only aggregated findings being reported. Additionally, all collected data was securely stored on password-protected computers, accessible only to authorized personnel, ensuring strict confidentiality



CHAPTER FOUR

PRESENTATION OF RESULTS

4.1 Introduction

Data presentation, analysis, and findings discussions are included in this chapter. The analysis was conducted in compliance with the study's variables and research objectives. The chapter reports the findings derived from the data analysis conducted using both statistical and thematic procedures. Although the study employed a quantitative research design, it also included open-ended questions to capture additional qualitative insights. The quantitative data were analyzed using SPSS, whereas the qualitative responses were examined through a content analysis approach.

4.2 Socio-demographic Factors

To provide context for the study findings, the sociodemographic profile of the respondents was analyzed across key variables, including age, gender, education level, professional background, and work experience. The summarized distribution is presented in Table 4.1, which highlights the composition of the study sample.

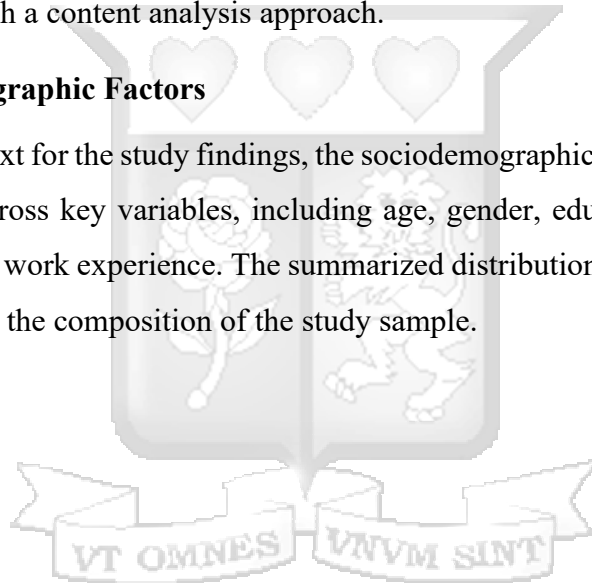


Table 4.1 Socio-demographic Factors

Variable	Category	Frequency (n)	Percentage (%)
Age	18-25 years	32	26.7
	26-35 years	49	40.8
	36-45 years	28	23.3
	46+ years	11	9.2
Gender	Male	59	49.2
	Female	61	50.8
Education Level	Certificate	15	12.5
	Diploma	50	41.7
	Undergraduate	40	33.3
	Postgraduate	15	12.5
Work Experience	< 1 year	20	16.7
	1-2 years	33	27.5
	> 2 years	67	55.8

From the data, the majority of the respondents (67.9%) were within the age range of 18 to 35 years, indicating that the study primarily captured views from a younger demographic. A smaller proportion, 29.3%, fell within the 36 to 50-year age group, representing middle-aged participants. Only 2.8% of the respondents were aged between 51 and 60 years.

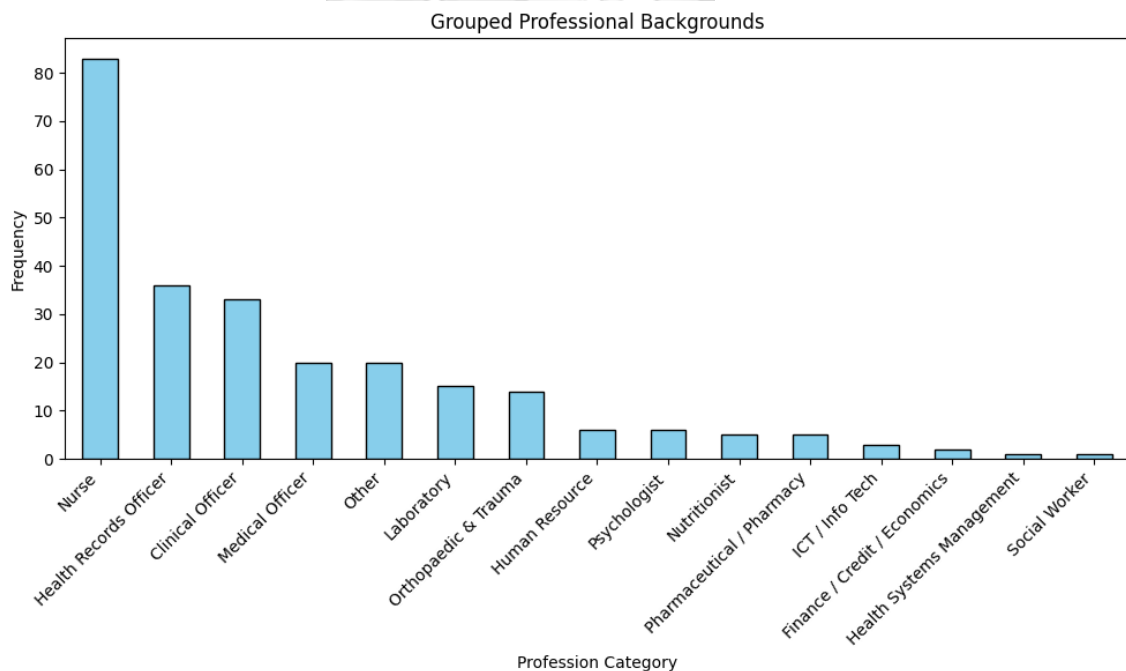
The gender composition of the respondents was relatively balanced. Female participants constituted a slight majority at 51.0%, while male respondents accounted for 49.0%. This near-equal representation suggests that the study achieved a fairly equitable gender balance, minimizing gender-related bias in the findings. The data on educational attainment indicate that a significant portion of respondents held a Diploma (41.4%), followed by those with an undergraduate Degree qualification (33.7%). Respondents with a Higher Diploma made up 9.2% of the sample, while 8.4% reported having attained a master's degree. A smaller proportion held a Certificate (4.8%), and only 0.4% of respondents had reached the Doctorate level.

The majority of respondents (55.8%) reported having worked in the healthcare facility for more than two years. This was followed by 18.9% who had been employed for 6 to 12 months, 14.9% for 1 to 6 months, and 10.4% for 1 to 2 years. These results indicate that most participants had substantial experience in their roles, which enhances the credibility and depth of their responses regarding healthcare operations and workplace dynamics.

4.2.1 Professional Background

A total of multiple healthcare professional cadres was represented in the survey, with responses grouped into various departments to allow for meaningful interpretation. The bar chart above illustrates the frequency distribution of the various professional backgrounds among the respondents. Nurses represent the largest group, followed by Health Records Officers, Clinical Officers, and Medical Officers. Professions such as Social Workers, Health Systems Management, and Finance/Economics are the least represented. This suggests that frontline clinical and records staff make up the majority of the workforce involved in the study.

Figure 4.1 Distribution of Professional Backgrounds of Respondents



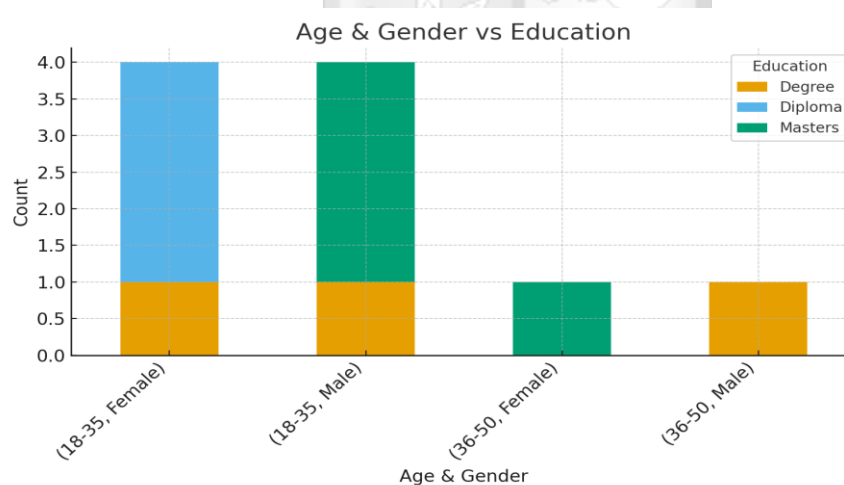
4.2.2 Sociodemographic Factors with Cross-Tabulation Charts

In addition to descriptive statistics, cross-tabulations were used to visualize relationships between key demographic variables. Stacked bar charts illustrate how categories overlap, providing a clearer understanding of patterns within the data.

4.2.2.1 Cross-tabulation of Age and Gender vs Education

The analysis shows that the 18-35 age group dominated across all education levels, particularly at the Diploma and Degree levels, highlighting their strong presence in the workforce. Within this age bracket, female respondents were mostly concentrated at the Diploma level, while male respondents were more evenly spread across Degree and Master's qualifications, suggesting greater diversity in their educational attainment. In contrast, respondents aged 36-50 were more represented at the Master's level, reflecting advanced qualifications that align with seniority and professional progression. The results are in Figure 4.2 below

Figure 4.2 Cross-tabulation of Age & Gender vs Education

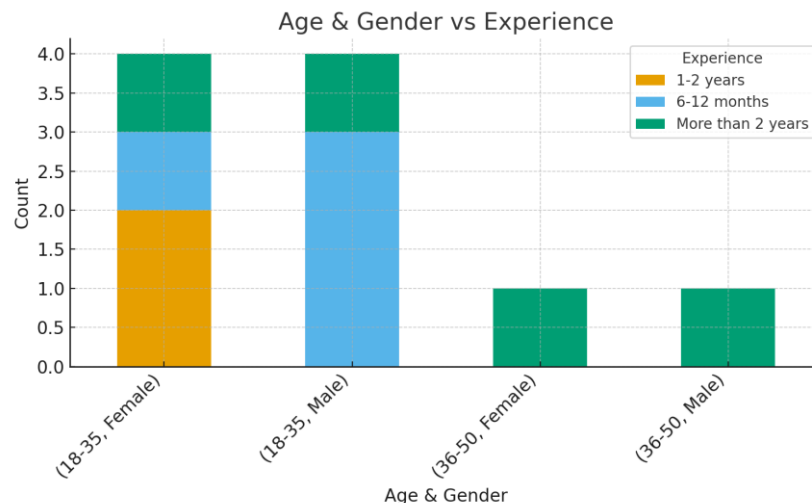


4.2.2.2 Cross-tabulation of Age & Gender vs Experience

The findings revealed that most respondents in the 18-35 age group had between 6 months and 2 years of experience, indicating that they are relatively new in their roles. In contrast, the 36-50 age group was characterized by longer work experience of more than 2 years, which is consistent with seniority and leadership responsibilities. Additionally, females in the 18-35 age group tended to have shorter experience compared to their male

counterparts, suggesting possible gender differences in career progression or entry into these roles. The results are in figure 4.3 below

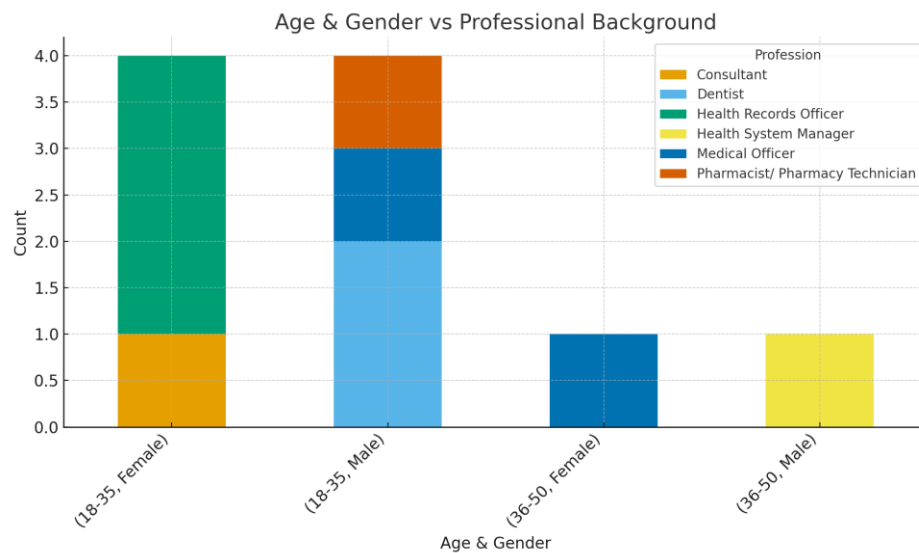
Figure 4.3 Cross-tabulation of Age & Gender vs Experience



4.2.2.3 Cross-tabulation of Age & Gender vs Professional Background

This chart examines the distribution of professional backgrounds across age and gender categories. Health Records Officers dominated across most age and gender categories, particularly among younger respondents. Male respondents showed more variation in professions, including Medical Officers, Dentists, and Pharmacists, while females were heavily concentrated in Health Records Officer roles, with fewer represented in clinical professions. The 36-50 age group included professionals in managerial and multi-cadre roles, which reflected career progression.

Figure 4.4 Cross-tabulation of Age & Gender vs Professional Background



4.3 Descriptive Statistics

The descriptive statistics for both the independent and dependent variables were computed. This section presents the descriptive statistics, which include the mean values and standard deviations of each variable

4.3.1 Organizational Factors Influencing HMIS Use

This section presents the respondents' perceptions regarding organizational influences on the utilization of HMIS. The analysis draws on survey responses using a 5-point Likert scale, ranging from *Strongly Disagree* (1) to *Strongly Agree* (5), with the mean values and standard deviations illustrated in Table 4.2 Below

Table 4.2 Organizational Factors

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
The hospital has clear and standardized policies and guidelines for using HMIS and follows well-defined processes for data collection, analysis, and reporting.	5	12	18	40	25	4.00	1.03
The facility encourages staff to regularly review and use data to monitor health service indicators and promotes a culture of accountability by documenting and following up on data-driven decisions.	10	15	20	30	25	3.85	1.12
Facility leadership actively supports and encourages using HMIS data for evidence-based decision-making, and supervisors provide constructive feedback on improving data collection and utilization.	8	10	22	35	25	3.92	1.03
The facility has sufficient IT resources (e.g., computers, internet access, data collection tools) and provides adequate training opportunities to improve staff data management skills.	12	14	30	25	19	3.51	1.27
I have the authority to use HMIS data to make decisions related to patient care, resource allocation, and service improvement.	9	16	19	33	23	3.35	1.52
I can make HMIS-based decisions without unnecessary external influence or interference.	7	11	25	32	25	3.18	1.34

The analysis of organizational factors influencing the use of HMIS reveals important insights into the strengths and gaps within the hospital environment. From the table, the hospital had clear and standardized policies and guidelines for using HMIS and followed well-defined processes for data collection, analysis, and reporting. This statement attracted the highest support within the organizational factor category, with 65% of respondents agreeing or strongly agreeing and a mean value of 4.00, suggesting that HMIS processes were generally well-structured. On the other hand, the facility had sufficient IT resources such as computers, internet access, and data collection tools, and provided adequate training opportunities to improve staff data management skills received much lower agreement, as only 44% of the respondents agreed or strongly agreed, with a mean of 3.51, indicating challenges in resources and staff capacity.

Facility leadership actively supported and encouraged using HMIS data for evidence-based decision-making, and supervisors provided constructive feedback on improving data collection and utilization. This statement recorded the strongest support under organizational culture, with 60% of respondents agreeing or strongly agreeing and a mean of 3.92, pointing to effective leadership involvement. In contrast, the facility encouraged staff to regularly review and use data to monitor health service indicators and promoted a culture of accountability by documenting and following up on data-driven decisions received slightly less support, as 55% agreed with a mean of 3.85, reflecting that routine staff engagement in data use was not consistent.

The statement that I had the authority to use HMIS data to make decisions related to patient care, resource allocation, and service improvement. This statement attracted moderate support, with 56% of respondents agreeing or strongly agreeing and a mean of 3.35, though variation was considerable. Similarly, I could make HMIS-based decisions without unnecessary external influence or interference, also received moderate support, with 57% of respondents agreeing or strongly agreeing, but a relatively lower mean of 3.18, highlighting that many staff members still experienced external constraints in their decision-making autonomy.

4.3.2 Qualitative Findings on Organizational Factors

The qualitative insights into organizational factors highlighted a mix of progress and persistent challenges in the use of HMIS within healthcare institutions. Positive developments included efforts to involve health records officers in decision-making and promote a multidisciplinary approach, which enhances accountability and data ownership. In the departments with strong leadership support, staff were more receptive to digitization, aided by improved infrastructure and training. The active engagement of various departments was identified as essential to sustaining HMIS use and fostering a data-driven culture.

However, many respondents pointed out significant institutional barriers that undermine HMIS effectiveness. Frontline workers are often excluded from key decisions, leading to diminished ownership and motivation. Governance issues, including unclear guidelines and weak accountability structures, further limited data use. Cultural resistance to evidence-based practices, coupled with political interference, was reported to distort data integrity and reduce trust in the system. Additionally, poor data quality, inadequate standardization across platforms like KHIS, and weak infrastructure, such as unreliable systems and a lack of regular audits, were cited as major obstacles. These systemic inefficiencies continue to hinder the timely, accurate, and effective use of HMIS for decision-making within the institution.

4.3.3 Behavioral Factors Influencing HMIS Use

Behavioral dimensions assessed in the study captured individual competencies, perceptions, motivations, and organizational influences that affect the use of HMIS in healthcare settings. The table 4.3 below presents the descriptive statistic distribution of Likert scale responses across several behavioral indicators, offering valuable insight into staff attitudes and engagement levels.

Table 4.3 Behavioral Factors

Statement	1	2	3	4	5	Mean	Std
	%	%	%	%	%		Dev
I have the necessary skills to retrieve, analyze, and interpret HMIS data, including calculating percentages, rates, and trends for decision-making.	5	8	16	40	31	3.41	1.26
I can effectively plot health data by months or years and use the trends for informed decision-making.	10	14	32	22	22	3.45	1.26
Collecting and using HMIS data is meaningful, contributes to better health service delivery, and helps identify gaps to improve patient care.	3	4	9	30	54	4.25	1.02
In my facility, data collection is often done as a routine activity rather than for actual decision-making.	10	12	23	32	23	3.76	1.19
I feel motivated to use HMIS data because my colleagues, supervisors, and management appreciate and encourage its use in decision-making.	5	10	21	30	34	3.73	1.20
Lack of incentives and recognition discourages staff from actively using HMIS data for decision-making.	8	8	23	38	23	3.73	1.20

The analysis of behavioral factors influencing HMIS data use revealed a generally positive attitude among staff regarding the value of data in improving healthcare delivery. The statement that I had the necessary skills to retrieve, analyze, and interpret HMIS data, including calculating percentages, rates, and trends for decision-making, was moderately supported, as 71% of respondents selected options 3, 4, or 5, and the mean score was 3.41. This indicated that while basic analytical skills were present, proficiency was not evenly

distributed. Similarly, the statement I could effectively plot health data by months or years and use the trends for informed decision-making was moderately endorsed, with 76% selecting 3, 4, or 5 and a mean of 3.45, showing that competence in trend analysis was only partly achieved.

Further, collecting and using HMIS data is meaningful, contributes to better health service delivery, and helps identify gaps to improve patient care received the strongest support, with 84% of respondents agreeing or strongly agreeing and a mean of 4.25. This demonstrated that the usefulness of HMIS data in improving service outcomes was widely acknowledged. By contrast, the statement that In my facility, data collection is often done as a routine activity rather than for actual decision-making was less positively rated, with 55% agreeing or strongly agreeing and a mean of 3.76, suggesting that collected data was not consistently translated into actionable insights.

The statement that I felt motivated to use HMIS data because my colleagues, supervisors, and management appreciated and encouraged its use in decision-making was supported by 64% of respondents, with a mean of 3.73, reflecting that some encouragement for data use was provided. However, the statement Lack of incentives and recognition discourages staff from actively using HMIS data for decision-making was also affirmed, with 61% agreeing or strongly agreeing and a mean of 3.73, indicating that the absence of structured rewards was a barrier to sustained data utilization.

4.3.3.1 Qualitative Findings on Behavioral Factors

The qualitative insights on behavioral factors indicate that staffing shortages, heavy workloads, and inadequate task standardization significantly undermine effective HMIS use, leading to staff burnout and poor data quality. Resistance to change was also a recurring theme, with many healthcare workers struggling to adapt to new systems or frequent HMIS updates, often due to limited digital literacy and lack of involvement in the change process. However, respondents also noted that regular supervision, refresher training, and inclusive departmental engagement could help mitigate these challenges. A supportive work environment that encourages and values data use was identified as essential for fostering a positive data culture and sustaining meaningful HMIS adoption.

4.3.4 Technical Factors Influencing HMIS Use

An assessment of technical determinants influencing the utilization of HMIS revealed generally positive perceptions across various infrastructural and usability dimensions. The results are illustrated in Table 4.4 below

Table 4.4 Technical Factors

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
My facility has adequate IT infrastructure, including computers, internet access, printers, and backup systems, and provides technical support for troubleshooting HMIS-related IT issues.	12	14	30	25	19	3.52	1.28
The IT equipment in my facility is well-maintained and regularly serviced to support smooth HMIS operations.	8	17	19	33	23	3.38	1.27
I have received formal training on data management and the use of HMIS tools, which has improved my ability to handle and utilize HMIS data effectively	9	16	17	35	23	3.22	1.38
The HMIS system is user-friendly, easy to navigate, and does not hinder efficient data entry, retrieval, or analysis	8	14	23	32	23	3.68	1.13
The complexity of the HMIS system makes it difficult for staff to efficiently enter, retrieve, and analyze data	9	16	22	35	18	3.12	1.32
The HMIS is well integrated with other health information systems (e.g., laboratory, pharmacy, patient records), allowing for seamless data exchange and decision-making.	3	4	9	34	50	3.98	1.18

On technical factors, the statement that My facility has adequate IT infrastructure, including computers, internet access, printers, and backup systems, and provides technical support for troubleshooting HMIS-related IT issues was moderately supported, with 44% of respondents agreeing or strongly agreeing and a mean of 3.52. This suggested that while some facilities had adequate infrastructure, gaps in IT resources and technical support were still evident.

The statement that the IT equipment in my facility is well-maintained and regularly serviced to support smooth HMIS operations was supported by 56% of respondents, with a mean of 3.38, reflecting that equipment maintenance was inconsistent across facilities. Similarly, the statement I have received formal training on data management and the use of HMIS tools, which has improved my ability to handle and utilize HMIS data effectively, received lower support, with only 58% of respondents agreeing or strongly agreeing and a mean of 3.22, indicating that training opportunities were insufficient or unevenly provided.

The HMIS system's user-friendliness, navigation, and efficiency in data entry, retrieval, and analysis was more positively perceived, with 55% of respondents agreeing or strongly agreeing and a mean of 3.68, suggesting that usability was relatively strong compared to other technical factors. By contrast, the statement that the complexity of the HMIS system makes it difficult for staff to efficiently enter, retrieve, and analyze data was endorsed by only 53% of respondents, with a mean of 3.12, highlighting concerns about system design challenges.

Lastly, the statement that the HMIS is well integrated with other health information systems (e.g., laboratory, pharmacy, patient records), allowing for seamless data exchange and decision-making, received the strongest support, as 84% of respondents agreed or strongly agreed, with a mean of 3.98. This showed that integration across systems was widely recognized as a positive technical feature in supporting decision-making.

4.3.4.1 Qualitative Findings on Technical Factors

The qualitative insights on technical factors revealed that infrastructure deficiencies remain a major impediment to effective HMIS use across many health facilities.

Respondents reported challenges such as inadequate access to computers, unstable internet connections, and unreliable power backup systems. These infrastructure gaps are especially pronounced in specific departments, leading to unequal integration of HMIS into routine operations. While some members of the facility acknowledged receiving support from county governments in the form of equipment and training, widespread underinvestment continues to limit the scalability and efficiency of digital health solutions. Additionally, system performance issues, such as incompatibility between platforms like Afyake and KHIS, frequent and poorly communicated software updates, and the simultaneous use of multiple EMRs, have led to confusion, inefficiencies, and fragmented data records.

Training and technical capacity were also identified as critical gaps hindering HMIS optimization. Many staff members use the system without formal training, resulting in inconsistent data entry and a lack of standardized practices. Limited digital literacy and inadequate understanding of data management were particularly noted among general healthcare workers, even though some departments benefit from trained HRIOs and data clerks. Furthermore, concerns about data security and patient confidentiality though less frequently raised highlight the need for robust data protection protocols and secure system design. Together, these technical shortcomings underscore the urgency of investing in infrastructure, user-friendly systems, staff capacity building, and data governance to enhance the overall performance and trustworthiness of HMIS.

4.3.5 Environmental Factors Influencing HMIS Use

The environmental context in which HMIS is implemented plays a critical role in determining its successful adoption and sustainability.

4.3.5.1 Extended Environmental Factors for Administrative Staff

To capture system-level insights into HMIS use, a specialized module targeting administrative personnel (n = 27) was incorporated. This section explored broader environmental enablers and policy mechanisms influencing HMIS utilization for decision-making. The findings reflect structural, procedural, and policy-related dimensions reported by facility leadership and administrative stakeholders.

Table 4.5 Environmental Factors (Administration Staff)

Statement	1	2	3	4	5	Mean	Std Dev
	%	%	%	%	%		
Government funding and budget allocations are sufficient to support HMIS infrastructure, operations, and staff capacity-building in my facility.	9	35	20	22	14	2.52	1.12
National and county-level health information policies provide clear guidance and support for effective HMIS data collection, analysis, and use	7	20	25	35	13	3.00	1.30
External regulations, reporting demands from development partners, and the broader political environment influence how HMIS data is prioritized and used in decision-making	12	14	30	25	19	3.52	1.01

The environmental factors provided insight into the broader context shaping HMIS adoption and use in facilities. They reflected the extent to which funding, policies, and external pressures supported or hindered the effectiveness of data systems. Government funding and budget allocations were reported as the weakest factor. Government funding and budget allocations were sufficient to support HMIS infrastructure, operations, and staff capacity-building in my facility was supported by only 36% of respondents (22% agreed, 14% strongly agreed). A higher proportion, 44%, either disagreed or strongly disagreed, with a mean of 2.52, suggesting that resource constraints were a persistent challenge.

Policy guidance was perceived more positively. National and county-level health information policies provided clear guidance and support for effective HMIS data collection, analysis, and use was affirmed by 48% (35% agreed, 13% strongly agreed), although 27% disagreed or strongly disagreed. This yielded a mean of 3.00, pointing to moderate confidence in policy clarity and support. External pressures were seen as the

strongest driver among environmental factors. External regulations, reporting demands from development partners, and the broader political environment influenced how HMIS data was prioritized and used in decision-making was endorsed by 44% of respondents (25% agreed, 19% strongly agreed), with a smaller proportion of 26% in disagreement. This statement recorded the highest mean of 3.52, reflecting the significant role of external stakeholders and regulatory demands in shaping data use practices.

These findings suggested that while policy and external regulations provided moderate support and incentives for HMIS use, inadequate funding remained the most critical environmental limitation.

4.3.5.2 Extended Environmental Factors for Routine Staff

Table 4.6 Environmental Factors (Routine Staff)

Statement	1	2	3	4	5	Mean	Std Dev
	%	%	%	%	%		
My facility has reliable internet access, and power outages rarely disrupt the consistent use of HMIS for decision-making	10	16	23	32	23	3.67	1.23
The current infrastructure (e.g., workspace, power backup, and server access) supports effective HMIS data entry and utilization.	8	18	25	28	21	3.67	1.14
Limited budget allocations hinder the effective implementation and sustainability of HMIS activities in my facility	8	10	18	36	28	4.02	1.04

The environmental factors for routine staff provided an understanding of how infrastructure, connectivity, and budgetary support influenced the functionality and sustainability of HMIS within facilities. Internet access and power stability were rated moderately. My facility had reliable internet access, and power outages rarely disrupted

the consistent use of HMIS for decision-making was supported by 55% of respondents (32% agreed, 23% strongly agreed). However, 26% either disagreed or strongly disagreed. The mean score was 3.67, indicating that while connectivity was relatively reliable, it was not without occasional disruptions.

Similarly, the current infrastructure was viewed as moderately supportive. The current infrastructure (e.g., workspace, power backup, and server access) supported effective HMIS data entry and utilization, as affirmed by 49% (28% agreed, 21% strongly agreed), whereas 26% disagreed or strongly disagreed. This resulted in a mean of 3.67, suggesting that infrastructural provisions were adequate but still required strengthening in some facilities. Budgetary limitations emerged as the strongest concern. Limited budget allocations hindered the effective implementation and sustainability of HMIS activities in my facility was acknowledged by 64% of respondents (36% agreed, 28% strongly agreed). Only 18% expressed disagreement. This yielded the highest mean of 4.02, highlighting that financial constraints were consistently perceived as the most critical barrier to effective HMIS use. The results suggested that although connectivity and infrastructure moderately supported HMIS operations, persistent funding limitations posed the greatest challenge to sustainable system utilization among routine staff.

4.3.5.3 Qualitative Findings on Environmental Factors

A strong theme emerging from the qualitative data on environmental factors was the role of county governments in allocating adequate resources to support HMIS, especially for staffing, infrastructure development, and ensuring reliable network backup. Respondents stressed the importance of engaging development partners and ensuring a coordinated stakeholder approach to address emerging gaps in real time.

4.3.6 Use of HMIS Data

4.3.6.1 Strategic Use of HMIS Data

Table 4.7 Strategic Decision Making

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
HMIS data has been used to conduct a situation analysis to assess the status of various health services in my facility/district	12	14	30	25	19	3.52	1.09
HMIS data is used to prioritize resource allocation based on the most prevalent diseases or pressing public health needs.	9	17	32	23	19	3.26	1.23
HMIS data is used to evaluate hospital performance indicators and address service delivery gaps	7	10	16	37	30	3.89	1.04
HMIS data is used to assess staff workload, recruitment needs, and performance monitoring	6	8	18	38	30	4.00	1.22
HMIS data is utilized in developing multi-year strategic plans (e.g., 3–5-year plans) at the facility level.	5	21	32	23	19	3.22	1.14
HMIS data is used to share evidence with partners, inform policy formulation, and support decision-making in executive meetings.	9	11	38	20	22	3.28	1.40

The results on strategic decision-making showed that HMIS data plays a moderate role in strategic decision-making, with varying levels of use across key functions such as service evaluation, human resource planning, and policy influence. The strategic application of HMIS data was assessed to determine how facilities employed information for planning, resource allocation, and performance monitoring. The highest-rated statement was that

HMIS data was used to assess staff workload, recruitment needs, and performance monitoring. This view was supported by 68% of respondents (38% agreed, 30% strongly agreed), while only 14% expressed disagreement. The mean score was 4.00, showing that staff management decisions were strongly guided by HMIS data.

Similarly, HMIS data was perceived as important for evaluating hospital performance indicators and addressing service delivery gaps. This was endorsed by 67% of participants (37% agreed, 30% strongly agreed), with a mean of 3.89. These findings suggested that HMIS played a key role in continuous quality improvement within facilities. In contrast, the lowest-rated statement was the use of HMIS data in developing multi-year strategic plans. Only 42% agreed or strongly agreed, compared to 26% who disagreed. The mean was 3.22, showing that while some planning functions utilized HMIS data, long-term strategic integration remained limited.

A similar pattern was observed for resource allocation, where 42% supported that HMIS data guided prioritization of resources, while 26% disagreed. This resulted in a mean of 3.26, indicating moderate application in aligning resources to health priorities. The use of HMIS data for sharing evidence with partners, informing policy, and guiding executive-level decisions was also relatively weak. Only 42% agreed or strongly agreed, while 20% disagreed. The mean score stood at 3.28, highlighting that broader policy and partnership applications of HMIS were not consistently emphasized.

Finally, HMIS data use for situation analysis was rated moderately. It was supported by 44% of respondents, while 26% disagreed. This yielded a mean of 3.52, showing that although data was somewhat used to assess the status of services, it was not fully leveraged for comprehensive situational reviews. Overall, the findings suggested that HMIS data was strategically applied more strongly in areas of staff management and performance monitoring, while its use in long-term planning, resource prioritization, and external policy engagement was less consistent.

4.3.6.2 Operational Use of HMIS Data

Table 4.8 Operational Decision Making

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
HMIS data is used to support patient treatment, follow-ups, and referrals.	11	6	16	30	37	4.01	1.09
HMIS data is used to monitor medicine consumption, predict stock needs, and reduce stockouts	12	10	19	40	30	3.84	1.23
HMIS data is used to track staff workload, set targets, and evaluate departmental performance	9	8	16	37	34	3.87	1.04
HMIS data is used to plan and conduct health outreach programs and disease surveillance activities	13	10	10	42	25	3.51	1.22
HMIS data is used to identify service gaps, allocate resources, and improve department operations.	7	4	20	42	25	3.68	1.25
HMIS data is used during departmental meetings for planning, reporting, and strategy discussions	9	12	14	39	26	3.73	1.13

The findings on operational decision-making reveal a generally positive trend in the use of HMIS data across key functional areas within the health facility. The highest-rated statement was that HMIS data was used to support patient treatment, follow-ups, and referrals. A total of 67% of respondents (30% agreed, 37% strongly agreed) affirmed this, while only 17% disagreed. The mean was 4.01, showing that HMIS data played a strong role in guiding patient management decisions. Closely following was the use of HMIS data to track staff workload, set targets, and evaluate departmental performance. This was endorsed by 71% of respondents (37% agreed, 34% strongly agreed), with only 17%

expressing disagreement. The mean stood at 3.87, highlighting the importance of HMIS data in supporting performance monitoring and workload management.

Similarly, 70% of participants (40% agreed, 30% strongly agreed) reported that HMIS data was used to monitor medicine consumption, predict stock needs, and reduce stockouts. The mean score of 3.84 suggested that operational data use was essential for ensuring continuous medicine supply and avoiding shortages. The use of HMIS data during departmental meetings for planning, reporting, and strategy discussions was moderately supported. 65% of respondents (39% agreed, 26% strongly agreed) endorsed this practice, giving a mean of 3.73. This indicated that data-driven discussions were fairly common at departmental levels.

The identification of service gaps, resource allocation, and operational improvements through HMIS data was also recognized. 67% of respondents (42% agreed, 25% strongly agreed) supported this, resulting in a mean of 3.68. This showed that HMIS data was moderately used for operational planning and improvement. The lowest-rated statement was the use of HMIS data to plan and conduct health outreach programs and disease surveillance activities. Although 67% of respondents agreed or strongly agreed, 23% disagreed. The mean was 3.51, suggesting that while HMIS data contributed to outreach and surveillance, its application in this area was relatively weaker compared to patient care and medicine management. Overall, operational use of HMIS data was strongest in patient treatment and workload tracking, while its contribution to outreach and surveillance activities was less emphasized.

4.4 Diagnostic Tests

4.4.1 Chi-Square Tests

The Chi-square (χ^2) test is a non-parametric statistical method used to assess whether there is a significant association between two categorical variables. Developed by Karl Pearson (1900), it compares observed frequencies in a contingency table with those expected if the variables were independent. It is especially useful for cross-tabulated survey data, such as Likert-scale responses across demographic groups.

There are two main types of Chi-square tests: the Test of Independence, which assesses the association between two categorical variables, and the Goodness-of-Fit Test, which evaluates whether a single categorical variable follows a specified distribution. This study primarily utilized the Chi-square Test of Independence.

In this research on HMIS utilization, Chi-square tests were applied to evaluate whether demographic factors such as gender, professional background, age group, education level, and years of experience were significantly associated with perceptions and reported use of HMIS across key domains like strategic and operational decision-making.

Key uses of the Chi-square test in this study included: Assessing if professional roles (e.g., nurses vs. clinical officers) influenced HMIS use, determining whether gender affects engagement with HMIS data, evaluating the influence of educational background on HMIS usage, and examining the impact of experience length on interaction with HMIS.

The statistical significance derived from these tests (e.g., p-values < 0.05) supports or rejects hypotheses of independence. This is critical in understanding whether targeted interventions should be customized for specific subgroups.

4.4.2 Chi-square Test Results for Demographic Variables and HMIS Use

Table 4.8 below summarizes the results of Chi-square tests assessing associations between selected demographic variables and the utilization of HMIS for decision-making. The significance threshold was set at $p < 0.05$.

Table 4.8 Chi Square Tests

Demographic	Chi ² Statistic	Degrees of Freedom	p-value	Significant (p < 0.05)
Professional Background	111.13	124	0.7895	No
Gender	1.92	4	0.75	No
Education	41.11	20	0.0036	Yes
Years Worked	11.62	12	0.4763	No
Age Group	18.38	8	0.0185	Yes

A Chi-square test of independence was conducted to assess whether there was a statistically significant association between respondents' professional background and other categorical variables in the study. The results indicated that the association was not statistically significant, $\chi^2(124) = 111.13$, $p = 0.7895$. This p-value is well above the conventional alpha level of 0.05, suggesting that there is no evidence of a meaningful relationship between professional background and the examined outcome(s). Therefore, the differences in HMIS use or perceptions across various professional groups (e.g., clinicians, nurses, HRIOs, administrative staff) are likely to be due to chance rather than a systematic pattern.

Gender did not show a statistically significant relationship with HMIS usage patterns ($p = 0.7500$), indicating that male and female staff responded similarly across the HMIS Likert items. Education Level was significantly associated with HMIS use ($\chi^2 = 41.11$, $p = 0.0036$), suggesting that respondents with different educational backgrounds had varied perceptions or usage of HMIS. This may imply that educational attainment influences familiarity, confidence, or motivation to use HMIS tools effectively.

Years worked in the facility was not a significant predictor ($p = 0.4763$), indicating that duration of employment did not substantially affect how staff reported their HMIS use. Age Group showed a statistically significant association ($\chi^2 = 18.38$, $p = 0.0185$), suggesting that age may influence HMIS interaction. Younger or older staff may differ in technology adoption rates or attitudes toward data-driven decision-making. These findings highlight the importance of tailoring HMIS capacity-building efforts based on education level and age-related needs. While gender and years of experience did not significantly influence HMIS engagement, differences across education and age suggest potential gaps in training effectiveness, tool accessibility, or motivation.

4.4.3 Reliability Test

This study used Cronbach's alpha to measure the level of reliability of the research variables. Table 4.9 shows the outcomes. Reliability in terms of the instrument is determined by the extent that it assesses what it was designed for. It is also important to note that the reliability of the instrument, as determined by Cronbach's alpha was used for an internal consistency measure in the present study. Of the items developed in the

questionnaire, data collected from its application was entered into SPSS and Cronbach's alpha. Any item with a Cronbach's alpha more than 0.7 would show the reliability of the instrument.

Table 4.9 Reliability Test Results

Variables	Cronbach's Alpha	Critical Value	Conclusion
Organizational Factors	0.721	0.7	Reliable
Behavioral Factors	0.799	0.7	Reliable
Technical Factors	0.701	0.7	Reliable
Environmental Factors	0.749	0.7	Reliable
Strategic data usage	0.721	0.7	Reliable
Operational data usage	0.703	0.7	Reliable

The variables were higher than 0.7 Cronbach's alpha, as shown in Table 4.6. This indicated that the research instrument used in the study was very coherent internally.

4.5 Inferential Statistics

Inferential analysis is performed to determine the relationship between variables in a research investigation. For this study, the Pearson correlation was used to determine the magnitude and direction of the variables, while the multiple linear regression analysis was used to determine the relationship between the independent and dependent variables. The correlation was analyzed based on the two dependent variables which were use of HMIS for strategic decision-making and the use of HMIS for operational decision-making

4.5.1 Correlation Analysis

The correlation analysis sheds light on the relationship between the study's independent variables of interest and the dependent variable. For this analysis, the Pearson Correlation test from SPSS software was used in this determination. Results are in Table 4.10 below

Table 4.10 Correlation Analysis (Operational Data Usage)

		Organizational Factors	Behavioral Factors	Technical Factors	Environmental Factors	Operational Use
Organizational Factors	Pearson					
	Correlation	1				
	Sig. (2-tailed)					
Behavioral Factors	Pearson					
	Correlation	.563**	1			
	Sig. (2-tailed)	.000				
Technical Factors	Pearson					
	Correlation	.592**	.462**	1		
	Sig. (2-tailed)	.000	.000			
Environmental Factors	Pearson					
	Correlation	.528**	.323**	.597**	1	
	Sig. (2-tailed)	.000	.000	.000		
Operational Use	Pearson					
	Correlation	.681**	.477**	.584**	.585**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

The correlation analysis demonstrated significant positive correlations between operational use of HMIS data and the four key influencing factors: organizational, behavioral, technical, and environmental. The strongest correlation was observed between organizational factors and operational use ($r = 0.681$, $p < 0.05$), indicating that when facilities have clear policies, leadership support, accountability mechanisms, and resources for data management, there is a substantial increase in the effective use of HMIS data for decision-making. This highlights the crucial role of organizational commitment and structure in enabling data-driven healthcare operations.

Technical factors also showed a strong positive correlation with operational use ($r = .584$, $p < 0.05$), suggesting that adequate IT infrastructure, user-friendly systems, integration with other platforms, and technical training are key enablers of practical data usage. This implies that investments in ICT tools and user training can significantly enhance how data is applied to improve services and manage healthcare resources. Environmental factors ($r = .585$, $p < 0.05$) were also significantly associated with operational data usage, showing that external support elements such as government funding, policy clarity, and regulatory pressures contribute positively to how data is utilized within health facilities. This relationship underlines the importance of a supportive policy and funding environment in creating the conditions for routine and strategic data application.

Behavioral factors, though slightly weaker in correlation ($r = .477$, $p < 0.05$), still showed a moderate and statistically significant relationship with operational use. This suggests that while individual motivation, skills, and perceptions about HMIS are important, they must be reinforced by stronger organizational and systemic support to drive meaningful data usage in operations.

The correlation analysis confirmed that organizational, technical, environmental and behavioral factors all have a significant correlation with operational use of HMIS data. However, organizational factors stood out as the most influential, pointing to the need for structured policies, processes and a culture that values evidence-based decision-making as the foundation for effective health information system utilization.

Table 4.11 Correlation Analysis (Strategic Data Usage)

		Organizational Factors	Behavioral Factors	Technical Factors	Environmental Factors	Strategic Use
Organizational Factors	Pearson					
	Correlation	1				
Behavioral Factors	Sig. (2-tailed)					
	Pearson					
Technical Factors	Correlation	.338**	1			
	Sig. (2-tailed)	.000				
Environmental Factors	Pearson					
	Correlation	.449**	.520**	1		
Strategic Use	Sig. (2-tailed)	.000	.000			
	Pearson					
	Correlation	.445**	.436**	.576**	1	
	Sig. (2-tailed)	.000	.000	.000		
	Pearson					
	Correlation	.699**	.534**	.658**	.484**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

The correlation results in Table 4.11 indicate that all four key factors, organizational, behavioral, technical, and environmental, were significantly associated with the strategic use of HMIS data, although the strength of these relationships varied. The strongest correlation was established between operational use and organizational factors ($r = 0.699$, $p < 0.05$), reinforcing the notion that well-structured systems, leadership commitment, clear processes, and accountability mechanisms are central to enabling strategic data use in health facilities. This underscores the importance of institutionalizing data-driven decision-making through policy and leadership frameworks.

The technical factors also exhibited a strong positive relationship with operational use ($r = 0.658$, $p < 0.05$), suggesting that functional, well-maintained IT systems and adequate training are foundational for advancing from routine to strategic data application. Behavioral factors showed a moderate correlation with operational use ($r = 0.534$). This indicates that individual skills and motivation are necessary but not sufficient for strategic data use. These factors must be supported by technical infrastructure and a conducive organizational and policy environment for behavior to translate into consistent, high-level data utilization.

Environmental factors also show moderate to strong correlations with strategic use ($r = 0.484$), suggesting that external conditions such as funding adequacy, supportive policies, and regulatory environments play a facilitative role in shaping both system capabilities and staff attitudes. The data reveal that strategic use of HMIS is most powerfully influenced by organizational and technical capacities, with behavioral and environmental aspects acting as important but somewhat secondary contributors. These findings suggest that a systems-level approach, anchored in strong governance, infrastructure investment, and a supportive policy environment, is essential for driving strategic use of health data in planning, policy, and resource allocation. The consistently significant correlations also highlight that strategic data use is a multi-dimensional process, requiring simultaneous strengthening of people, systems, and environments.

4.5.2 Regression Analysis

Multiple regression analysis is a robust statistical technique employed to explore the relationship between a single dependent variable and two or more independent (predictor) variables. It extends simple linear regression by allowing for the simultaneous evaluation of multiple factors, thus offering a more nuanced understanding of the factors that influence an outcome of interest. In health systems research, this approach was particularly valuable for disentangling complex interrelationships between technical, behavioral, organizational, and environmental components that may affect both strategic and operational performance outcomes.

In the context of this study, multiple regression was utilized to examine how various categories of health information management determinants namely Technical, Behavioral, Organizational, and Environmental factors influence the Strategic and Operational use of HMIS data. Each of these categories represents a composite score derived from participants' Likert-scale responses to items assessing respective domains. The regression results are indicated below in table 4.12 for operational use of data and 4.13 for strategic use of data

Table 4.12 Regression Analysis (Operational Use)

Operational use of Data	Coef.	Std. Err.	P>t
Organizational Factors	.521	0.075	0.000
Behavioral Factors	.070	0.073	0.338
Technical Factors	.137	0.076	0.042
Environmental Factors	.201	0.048	0.000
_cons	.394	0.221	0.076
Model Summary			
R-squared	0.59		
F(4, 218)	79.04		
	0.000		
Prob > F			
Observations	223		

The regression analysis in Table 4.12 explores the influence of organizational, behavioral, technical, and environmental factors on the operational use of HMIS data. The model was statistically significant overall ($F(4, 218) = 79.04, p < 0.05$), with an R-squared value of 0.59, indicating that approximately 59% of the variability in operational use of HMIS data can be explained by the four predictor variables. This demonstrates a strong explanatory power, suggesting that the selected factors are key determinants of how effectively HMIS data is utilized in daily health operations.

Among the predictors, organizational factors emerge as the most significant and influential ($\beta = 0.521, p < 0.05$). This means that improvements in institutional structures, such as leadership support, policies, accountability practices, and resource provision, are strongly associated with increased operational use of HMIS data. This finding aligns with earlier correlation results, emphasizing the critical role of strong governance and systems thinking in enhancing data utilization at the facility level.

Environmental factors also show a moderate significant positive effect ($\beta = 0.201, p < 0.05$), indicating that external supports like funding, policy frameworks, and regulatory pressure contribute substantially to the use of data in operations. Similarly, technical factors had a moderate but statistically significant effect ($\beta = 0.137, p = 0.042$), suggesting that access to reliable IT infrastructure, tools, and technical support facilitates effective HMIS use, though to a lesser extent than organizational or environmental influences.

In contrast, behavioral factors do not significantly predict operational data use in this model ($\beta = 0.070, p = 0.338$). While individual motivation, skills, and perceived value of data are important, the finding implies that personal attributes alone are insufficient to drive operational data use unless they are backed by organizational and systemic enablers.

The results were thus modelled as follows:

$$Y = 0.394 + 0.521X_1 + 0.070X_2 + 0.137X_3 + 0.202X_4 + \varepsilon$$

Where:

Y = Operational data Use in Decision-Making

β_0 = Intercept (constant term)

$\beta_1, \beta_2, \beta_3, \beta_4$ = Regression coefficients for each independent variable

X1 Organizational Factors

X2 = Behavioral Factors

X3 =Technical Factors

X4 = Environmental Factors

ε = Error term

Table 4.13 Regression Analysis (Strategic Use)

Strategic use of Data	Coef.	Std. Err.	P>t
Organizational Factors	.481	0.154	0.005
Behavioral Factors	.342	0.207	0.014
Technical Factors	.428	0.168	0.018
Environmental Factors	-.134	0.189	0.486
_cons	-.376	0.674	0.583
Model Summary			
R-squared	0.68		
F(4, 22)	11.76		
	0.000		
Prob > F			
Observations	27		

The regression analysis in Table 4.13 assesses how organizational, behavioral, technical, and environmental factors influence the strategic use of HMIS data in healthcare decision-making. The overall model is statistically significant ($F(4, 22) = 11.76, p < 0.05$), with an R-squared of 0.68, indicating that 68% of the variance in strategic data use is explained by the four predictor variables. This high explanatory power suggests that the model captures the key elements that contribute to the strategic application of HMIS data in planning, policy formulation, and long-term decision-making.

Among the predictors, organizational factors had the strongest and most significant influence on strategic data use ($\beta = 0.481, p = 0.05$). This reinforces the finding from the operational use model and emphasizes that institutional support structures, leadership engagement, and formalized processes are critical to embedding data into high-level decision-making. Similarly, technical factors also significantly predicted strategic use (β

= 0.428, $p = 0.018$), suggesting that adequate infrastructure, user-friendly systems, and data integration capabilities are vital to support the transition from routine to strategic use.

Behavioral factors show a significant influence as well ($\beta = 0.342$, $p = 0.014$), unlike in the operational use model. This suggests that individual competencies, motivation, and perception of data relevance become more important in strategic contexts, where higher-order data interpretation and long-term planning are involved. Strategic use often requires more complex data skills, critical thinking, and initiative, which may explain the stronger effect of behavioral factors here. In contrast, environmental factors did not significantly influence strategic data use in this model ($\beta = -0.134$, $p = 0.486$). This could indicate that while external conditions such as policies, funding, and regulatory environments may enable or constrain operations, they have less direct impact on internal strategic decision-making, which tends to depend more on internal capacity, leadership, and system readiness.

The results were modelled as follows:

$$Y = -0.376 + 0.481X_1 + 0.342X_2 + 0.428X_3 - 0.134X_4 + \varepsilon$$

Where:

Y = Strategic data Use in Decision-Making

β_0 = Intercept (constant term)

$\beta_1, \beta_2, \beta_3, \beta_4$ = Regression coefficients for each independent variable

X_1 = Technical Factors

X_2 = Behavioral Factors

X_3 = Organizational Factors

X_4 = Environmental Factors

ε = Error term

4.6 Summary of Findings

This chapter presents the findings from the data analysis. From the results, organizational, behavioral, technical, and environmental factors all significantly influence the operational and strategic use of HMIS. Quantitative findings indicated that organizational factors such as leadership support, data-driven culture, and clearly defined policies scored relatively

high, positively influencing HMIS use. Regression analysis confirmed organizational and environmental factors as significant predictors of operational data use, while for strategic use, organizational, behavioral, and technical factors were more influential. Technical factors, including system integration, infrastructure, and usability, were moderately rated, but still showed a strong positive correlation with HMIS utilization. Correlation analysis revealed strong relationships between all independent variables and both operational and strategic HMIS use, especially organizational and technical components.

The correlation results indicate that all four factors, technical, behavioral, organizational, and environmental, are positively associated with HMIS data use, meaning that improvements in any of these areas are likely to enhance how health workers utilize HMIS for decision-making. Among them, organizational factors had the strongest correlation ($r = 0.682$), followed by behavioral ($r = 0.634$), technical ($r = 0.501$), and environmental ($r = 0.372$) factors. This implies that facilities with supportive leadership, clear policies, and accountability structures are more likely to use health data consistently.

However, regression analysis revealed a more nuanced picture by identifying which factors significantly predict actual HMIS data use when controlling for others. It showed that only organizational ($\beta = 0.476$, $p < 0.05$) and technical ($\beta = 0.226$, $p < 0.05$) factors were statistically significant predictors. In contrast, behavioral and environmental factors, despite their positive correlations, were not significant predictors in the regression model. This suggests that while staff motivation and external policy support are important, they are not sufficient alone to drive consistent data use unless backed by strong internal systems and technical infrastructure.

Qualitative insights complemented these findings, shedding light on practical challenges and enablers. While some facilities demonstrated strong leadership, adequate infrastructure, and regular data use, others struggled with poor documentation, lack of feedback loops, political interference, inadequate infrastructure, and insufficient training. Behavioral challenges included resistance to change, digital literacy gaps, and understaffing, although motivation and support systems were identified as enablers. Technical limitations, such as fragmented systems, unreliable connectivity, and lack of standardization, were significant barriers. Overall, the findings underscore the need for a

holistic approach that combines leadership, capacity building, technological investment, and inclusive engagement to enhance effective HMIS use in healthcare decision-making.



CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study, summarizes its findings, draws conclusions based on the results, and provides suggestions for future research and policy interventions in line with the study's objectives. The chapter concludes with a discussion of the limitations that were encountered and recommendations for further research based on these limitations

5.2 Summary of Findings

The study aimed to assess how HMIS influences decision-making among healthcare workers at a Level 5 public hospital in Tharaka Nithi County, Kenya. Specifically, it sought to evaluate the impact of four key factors, technical, behavioral, organizational, and environmental, on HMIS data utilization for both strategic and operational decision-making within the hospital setting. A descriptive cross-sectional design was adopted using a quantitative approach. The study targeted all 250 healthcare workers and departmental heads at Chuka County Referral Hospital, making it a census study. Data was collected via semi-structured questionnaires, featuring Likert-scale items to assess perceptions related to the four independent variables. Descriptive statistics, chi-square tests, and multiple linear regression were used for quantitative data analysis. The Theory of Planned Behavior and the PRISM framework guided the conceptual and analytical approach for understanding the data.

From the descriptive results, behavioral factors were found to have the highest influence on HMIS data use, followed by strategic use, organizational, technical, and environmental factors respectively. The Chi-square analysis revealed significant associations between HMIS use and both education level and age group. The Pearson correlation analysis was conducted to assess the strength and direction of relationships between the independent variables (technical, behavioral, organizational, and environmental factors) and the dependent variable (HMIS data use in decision-making). The results showed positive correlations between all four factors and HMIS data utilization, indicating that improvements in these areas are associated with increased use of HMIS for decision-making.

The regression analysis indicated that for operational use of data, organizational, technical, and environmental factors were significant predictors of HMIS use, with organizational support being the strongest predictor for operational decisions. Only behavioural factors were not significantly associated with HMIS use. For strategic use of data, organizational, behavioral, and technical factors exhibited significant relationships with HMIS data for strategic use with the exception of environmental factors. Qualitative insights highlighted leadership involvement, infrastructure adequacy, and multidisciplinary participation as key enablers, while barriers included poor system interoperability, inconsistent training, weak feedback mechanisms, and political interference. The study concluded that HMIS usage is uneven and needs targeted investments and policy support to be fully effective in healthcare decision-making.

5.3 Discussion of the Results

5.3.1 Organizational Factors and Data Use for Decision-Making

Respondents generally agreed that leadership, governance, and internal policies support HMIS data use on analysing the organisational factors. Correlation analysis revealed a strong positive relationship between organizational factors and HMIS utilization. In the multiple regression analysis, organizational factors were the strongest and most statistically significant predictors of HMIS use for both operational and strategic use of data. This suggests that facilities with clear data-use policies, proactive leadership, and adequate internal resources are more likely to use HMIS data effectively in both strategic and operational decisions.

These findings are consistent with the empirical literature. Moloko & Ramukumba (2022) emphasized the importance of regular supervision and institutional feedback mechanisms, while Hlaing & Zin (2020) highlighted the need for defined HMIS roles, leadership engagement, and resource availability. The results also align with Isak (2023), who emphasized that data must be systematically processed and reviewed at the facility level to be impactful. In Tharaka Nithi, although leadership support and policy clarity were present, gaps in decision-making autonomy and uneven access to IT resources across

departments hampered HMIS use. These limitations suggest that institutional culture and governance remain essential levers for enhancing HMIS utilization.

5.3.2 Behavioral Factors and Data Use for Decision-Making

Behavioral factors indicated generally positive staff attitudes, motivation, and confidence in HMIS use. Correlation analysis showed a strong and statistically significant correlation between behavioral factors and HMIS data use at both the strategic and operational level. However, contrary to expectations, multiple regression results indicated that behavioral factors were not statistically significant predictors of HMIS utilization at the operational level but were significant predictors of HMIS data use at the strategic level. The findings also suggest that while behavioral factors toward HMIS are linked to higher data use overall, they do not by themselves determine whether staff use data for decision-making when other factors like infrastructure, supervision, and data quality are taken into account.

This aligns with Chanyalew et al. (2023) and Ngusie et al. (2022), who reported that staff competence and motivation were necessary but not sufficient for effective HMIS use. LaFond & Fields (2003) also noted that without structural support, such as supervision, feedback, and recognition, behavioral improvements may not translate into practice. In Tharaka Nithi, Mucee (2016) previously found that over 97% of primary health workers lacked motivation due to the absence of feedback or reward structures, reinforcing the importance of linking behavioral change with institutional reinforcement.

5.3.3 Technical Factors and Data Use for Decision-Making

The study found that technical factors had a moderate influence on HMIS utilization at both the strategic and operational levels. Correlation analysis showed a significant positive relationship between technical factors and HMIS data use for both operational and strategic data use, indicating that better technical infrastructure is associated with increased data utilization. Regression results further revealed that technical factors were a statistically significant predictor of data use for both HMIS data use at the operational and strategic levels. This suggests that the presence of integrated systems, internet access, user-friendly interfaces, and digital tools directly enhances decision-making effectiveness at the facility.

These findings are similar Adane et al. (2017) and Asemahagn (2017), who emphasized the importance of IT infrastructure and user competence in Ethiopia. The study also corroborates Bagyendera et al. (2023) and Dakika & Saronga (2024), who similarly identified system fragmentation and usability challenges as key constraints in Uganda and Tanzania specifically. Despite the implementation of Afya Kenya, which sought to address system fragmentation and enhance integration, technical gaps such as inconsistent connectivity, limited interoperability, and uneven digital literacy persist in Tharaka Nithi. These challenges indicate that, although national reforms have laid an important foundation, the absence of consistent facility-level digital infrastructure continues to limit effective HMIS utilization. As a result, data systems remain partially siloed and underused, constraining timely and evidence-based decision-making at both operational and strategic levels. This finding highlights that meaningful improvement in HMIS performance requires more than top-down policy interventions; it depends on sustained investment in local infrastructure, system integration, and continuous staff capacity-building. Strengthening these technical foundations at the facility level is therefore critical for translating national digital health reforms into tangible gains in data-driven decision-making across Tharaka Nithi County.

Despite the implementation of Afya Kenya, which aimed to resolve system fragmentation and improve integration, technical gaps such as inconsistent connectivity and uneven digital literacy persist. Even though the national initiative aimed to address system fragmentation, the lack of consistent facility-level infrastructure means that data systems remain partially siloed and underutilized. This emphasizes that meaningful improvement in HMIS performance requires more than national-level reforms; it depends on sustained investment in local digital infrastructure, system integration, and staff capacity-building. Strengthening these technical foundations at the facility level is therefore essential for translating system reforms into tangible gains in data-driven health decision-making. This finding confirms the importance of facility-level implementation of digital infrastructure for meaningful impact.

5.3.4 Environmental Factors and Data Use for Decision-Making

Environmental factors in the study reflected moderate perceptions among respondents regarding the external support systems influencing HMIS implementation. Although correlation analysis showed a positive but moderate relationship, regression results indicated that environmental factors were not statistically significant predictors of HMIS data use. Politically, external legislation and policies such as the *Digital Health Act (2023)* and the *Afya Kenya* platform demonstrate strong national commitment to digital health transformation. However, the limited translation of these policies into actionable county-level strategies within Tharaka Nithi constrains their effectiveness. Weak political prioritization and fragmented governance structures continue to hinder adequate resource allocation, technical oversight, and accountability for HMIS performance. Economically, while government and donor funding provide vital support for digital infrastructure, inconsistent financial flows and reliance on short-term external aid undermine the sustainability of HMIS operations. This economic instability limits ongoing investments in infrastructure maintenance, software upgrades, and capacity-building, consequently affecting data quality and utilization. Socially, the broader funding and partnership environment is characterized by uneven engagement among health partners, community actors, and local administrators, leading to limited ownership of HMIS processes and reduced motivation to use data in decision-making.

In the Tharaka Nithi context, these findings underscore that environmental enablers, while essential, are insufficient on their own. National legislation and funding frameworks create an enabling environment, but without strong local political commitment, sustainable economic investment, and active social collaboration, their influence on HMIS data use remains limited. These results suggest that although infrastructure, funding, and national policies indirectly support HMIS, they do not significantly determine whether healthcare workers consistently use data for decision-making at the facility level. This aligns with Fort et al. (2023) and Matube & Fosa (2023), who similarly observed that inadequate infrastructure and misalignment between national policies and facility-level needs restrict HMIS effectiveness in LMICs. In Kenya, despite the *Digital Health Act (2023)* and *Afya Kenya* reforms, the study revealed persistent challenges such as limited alignment between national initiatives and county priorities, underutilization of policy

frameworks, and inconsistent engagement from external partners. These findings support Hlaing & Zin (2020), who argue that environmental enablers must be complemented by robust organizational systems and strengthened local capacity to achieve meaningful improvements in HMIS utilization.

5.4 Conclusions

5.4.1 Organizational Factors and HMIS Data Use

The study established that organizational factors are the most critical determinant of HMIS utilization at both the strategic and operational levels. These include leadership support, standardized data policies, training opportunities, and clear governance structures. Regression results showed that organizational factors were the strongest predictors of both strategic and operational decision-making using HMIS. This highlights the importance of strong internal systems and decision-making autonomy in ensuring that health data is not just collected but actively used. Therefore, fostering a data-use culture at the facility level, supported by leadership and well-defined processes, is key to maximizing HMIS value in Tharaka Nithi County.

5.4.2 Behavioral Factors and HMIS Data Use

Behavioral factors such as staff attitudes, motivation, and competence are positively associated with HMIS data use but do not independently drive it. Although healthcare workers expressed high confidence in using HMIS and behavioral factors recorded the highest mean scores, regression results showed that behavioral factors only significantly influenced strategic decision-making and were not statistically significant predictors of operational HMIS use when controlling for other variables. This implies that positive perceptions and willingness to use data are not enough on their own to translate into routine day-to-day data use. Therefore, behavioral efforts must be reinforced with strong organizational structures, accountability mechanisms, feedback systems, and leadership support. The implication is that interventions aimed at improving data use should integrate both behavioral strengthening (motivation, skills, digital literacy) and organizational support (policies, supervision, incentives) to successfully translate positive attitudes into consistent and sustained HMIS data utilization.

5.4.3 Technical Factors and HMIS Data Use

On technical factors, the study concludes that technical factors moderately influence HMIS data use among healthcare workers at Chuka Level 5 Hospital. While most respondents acknowledged the availability of HMIS infrastructure such as internet access and digital tools, issues related to system usability, inconsistent training, and integration challenges persisted. The correlation and regression analyses confirmed a statistically significant yet moderate relationship between technical capacity and HMIS utilization, suggesting that although technical enablers are essential, they must be complemented with user-centered system design and consistent ICT support to ensure effective data use in decision-making. These findings imply that without deliberate strengthening of the technical ecosystem particularly system usability enhancements, seamless integration across platforms, and continuous structured digital capacity-building the hospital risks underutilizing the potential value of data despite having the basic infrastructure in place. Therefore, targeted investment in improving HMIS functionality, interoperability, and ongoing ICT support is not just supportive but strategically necessary to unlock meaningful, routine, and sustained data-driven decision-making at both operational and strategic levels, ensuring that technical capacity becomes a catalyst rather than a bottleneck to improved health system performance.

5.4.4 Environmental Factors and HMIS Data Use

Lastly, the study concludes that environmental factors, while positively correlated with HMIS data use, demonstrated different levels of influence across decision tiers they significantly influenced strategic HMIS use but had limited predictive power at the operational level. These environmental elements include national digital health policies, infrastructure reliability, donor support, and broader regulatory frameworks. Strategic-level respondents (primarily departmental heads, and senior managers) were more influenced by these external reforms because their decision space is more policy-oriented and aligns directly with national priorities such as Afya Kenya and the Digital Health Act. However, operational-level healthcare workers (nurses, clinicians, records officers, and frontline healthcare workers) indicated that despite awareness of national reforms, these factors did not directly shape their daily data use; their practice was more affected by

internal workflows, immediate workload, feedback loops, and on-site resource constraints. This indicates that environmental reforms must be deliberately translated into tangible operational support at the facility level, meaning national policy alone is insufficient. External digital health reforms will only increase HMIS use when paired with internal organizational reinforcement, training, investment in infrastructure functionality, routine feedback, and facility-level accountability systems that convert national direction into everyday practice

5.5 Recommendations

5.5.1 Recommendations for Practice

At the facility level, hospital management should focus on strengthening internal governance and leadership engagement in HMIS processes. Since organizational factors were the strongest predictor of HMIS utilization, the hospital leaders must actively promote a culture of data use by providing clear policies, supportive supervision, and regular performance reviews based on HMIS data. In alignment with Kwon& Kim 2025, managers should also foster multidisciplinary participation in data analysis and decision-making, ensuring that all departments are engaged in setting and monitoring health indicators.

In practice, facilities should establish functional data-use committees or units responsible for overseeing data quality checks, conducting regular data interpretation sessions, and generating actionable insights for operational planning. Additionally, reward and recognition mechanisms should be implemented to encourage consistent and accurate HMIS use among staff. Recognition programs can improve motivation and address the behavioral gaps identified in the study. Finally, facilities should prioritize capacity-building and mentorship, ensuring that all staff, not just health records officers, are trained to navigate HMIS platforms, interpret dashboards, and apply data in both clinical and administrative settings. This inclusive approach will ensure broader ownership of health information systems and ultimately lead to more effective, evidence-based healthcare delivery.

5.5.2 Recommendations for Policy

To enhance the effectiveness of HMIS in public healthcare decision-making, policymakers should prioritize harmonization and integration of digital health systems across counties and levels of care. The study revealed persistent issues of system fragmentation and limited interoperability, despite national platforms like Afya Kenya. Therefore, the Ministry of Health should enforce interoperability standards and develop a national HMIS integration framework that aligns all digital health platforms with other health information systems such as KHIS platform. In addition, policy guidelines on decentralized data use should be developed to empower frontline facilities with greater autonomy in data-driven planning and resource allocation. These guidelines should also mandate routine data review forums and institutionalize feedback loops at the facility level to close the gap between data generation and use.

Further, investment in continuous professional development should be anchored in policy. Although behavioral factors such as motivation and confidence were positively associated with HMIS use, the study showed they were insufficient without organizational support. Thus, national policy should require that all health personnel receive periodic training on digital literacy, data analysis, and health information ethics. Such training must be embedded in existing healthcare professional development curricula and funded through both national and county health budgets. Lastly, there is a need for increased and equitable budget allocation for HMIS infrastructure, including internet access, IT support, and hardware, in all public facilities. This should be enshrined in county health planning policies to ensure consistent, reliable system access across departments and regions.

5.6 Limitations of the Study

One key limitation of the study is its contextual focus on a single Level 5 public hospital (Chuka County Referral Hospital) in Tharaka Nithi County. While this allowed for an in-depth assessment, the findings may not be fully generalizable to other healthcare levels (e.g., tertiary care facilities) or to hospitals in more urban or resource-rich counties. Additionally, although the study employed a census approach targeting all clinical and departmental staff involved in HMIS use, it relied primarily on self-reported data focused on perceptions collected through Likert-scale questionnaires. This approach is susceptible

to social desirability bias, where respondents may have overstated their use or understanding of HMIS to align with perceived expectations(Adams et al., 2005; Mondal & Mondal, 2018).

Another limitation is the cross-sectional design, which captures data at a single point in time and therefore limits the ability to draw causal conclusions about the long-term effects of HMIS on decision-making. Furthermore, while the study used both quantitative and qualitative tools, the qualitative data was limited to open-ended questionnaire responses and did not include in-depth interviews or focus group discussions, which could have provided richer contextual insights, especially on behavioral and organizational dynamics.

5.7 Suggestions for Further Studies

Future research should consider conducting longitudinal studies that assess how HMIS use evolves, particularly in response to policy changes such as the implementation of the Digital Health Act or the rollout of Afya Kenya. These studies could provide deeper insights into the sustainability and long-term outcomes of HMIS interventions on healthcare decision-making and performance.

Comparative studies across multiple counties and facility levels (e.g., Levels 2, 3, 5, and 6) are also recommended to assess variations in HMIS use across different healthcare contexts. Such studies could further investigate the influence of county-level leadership, budgetary support, and digital maturity on the effectiveness of HMIS.

In addition, future research should examine tactical decision-making as a distinct category alongside strategic and operational decision-making, since it plays a crucial role in resource allocation, program implementation, and mid-level managerial oversight.

Subgroup analysis is also warranted on how various sociodemographic factors (such as age, gender, professional cadre, and years of experience) directly influence the use of HMIS data.

Lastly, future studies should explore the effectiveness of targeted interventions such as feedback loops, incentive structures, and digital literacy training in enhancing HMIS data use. Understanding how these enablers interact with organizational structures could help

inform more targeted capacity-building and system-strengthening strategies across Kenya's health sector.



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APPENDICES

Appendix A: Informed Consent Form

PARTICIPANT INFORMATION SHEET AND CONSENT FORM

Title of the Study: INFLUENCE OF HEALTH MANAGEMENT INFORMATION SYSTEMS ON DECISION-MAKING IN A LEVEL 5 PUBLIC HOSPITAL IN THARAKA NITHI COUNTY, KENYA.

Investigator:

Grace Gichohi

Strathmore Business School

SECTION 1: INFORMATION SHEET

1.1 Why is this study being conducted?

This study aims to assess the factors influencing data utilization in decision-making using the Health Management Information System (HMIS) in a level 5 public health facility in Tharaka Nithi County. The study is motivated by Kenya's Digital Health Act 2023 and the implementation of Afya Kenya, which aims to enhance data use, interoperability, and health information exchange. Despite these efforts, challenges remain in fully leveraging HMIS data for decision-making. Hence the need to study the factors affecting HMIS data utilization in decision-making.

1.2 Do I have to take part?

No. Being part of this study is completely your choice. You are free to join or opt out at any time, and doing so will not affect you in any way. Should you choose to participate, you will be asked to fill out a questionnaire that explores technical, organizational, behavioral, and environmental aspects influencing how data is used in operational and strategic decision-making.

1.3 Who is eligible to take part?

This study is open to healthcare personnel involved in decision-making and data use at Chuka County Referral Hospital in Tharaka Nithi County. Eligible participants include doctors, nurses, dentists, clinical officers, anesthetists, anesthesiologists, pharmacists, pharmaceutical technologists, lab technicians, nutritionists, procurement and HR officers, health records personnel, and administrative staff.

1.4 What will taking part involve?

If you agree to participate, you will be asked to complete a semi-structured questionnaire focusing on your experience with Health Management Information Systems (HMIS) and the use of data in making decisions. The survey should take approximately **5- 10 minutes** to complete.

1.5 Are there any risks?

There are no anticipated risks associated with this study. All the information you provide will be kept confidential and used solely for research purposes.

1.6 What are the benefits of taking part?

There are no direct or immediate personal benefits to you from participating in this study. However, the findings will help improve HMIS utilization, leading to better healthcare planning, resource allocation, and service delivery in public hospitals.

1.7 Who will have access to my information?

All information will be securely stored and accessible only to the research team. Data will be anonymized to protect confidentiality.

1.8 Who can I contact for more information?

If you have any questions, you may contact:

- **Researcher:** Grace Gichohi, Strathmore Business School, +254782070401
- **Supervisor:** Dr. Jackline Aridi, Strathmore Business School
- **Ethics Review Board:** Strathmore University Institutional Ethics Review Board, ethicsreview@strathmore.edu Tel number: +254 703 034418

SECTION 2: CONSENT FORM

Please tick the boxes that apply to you:

- ☐ I have read and understood the study details provided in this document.
- ☐ I voluntarily agree to participate in this study.
- ☐ I understand that my participation is confidential, and my identity will not be disclosed.
- ☐ I understand that I can withdraw from the study at any time without consequences.

☐ I agree to have my questionnaire responses stored for future data analysis.

Participant's Name: _____

Signature: _____

Date: // _____

Investigator's Name: _____

Signature: _____

Date: // _____



Appendix B: Research Budget

Category	Details	Estimated Cost (KES)
1. Ethical Approval	NACOSTI Approval	1,000
2. Travel & Logistics	Travel to the study site	15,000
3. Data Collection	Enumerator support, printing, and stationery	24,000
4. Data Analysis	Software (SPSS, Excel), Biostatistician fees	20,000
5. Report Writing	Printing and binding of final report	10,000
6. Findings Dissemination	Stakeholder briefing, venue	10,000
7. Miscellaneous	Unforeseen expenses	10,000
TOTAL		90,000

Appendix C: Questionnaire

Self-Administered Questionnaire

Date:

Introduction

I am a student from Strathmore University, and I am researching the factors influencing the utilization of health management information systems for decision-making among public healthcare workers in Chuka County Referral Hospital, Tharaka Nithi County, Kenya. The feedback on findings will contribute to informing strategies and identifying opportunities for improving data utilization in healthcare. Please express your honest opinion; your identity remains anonymous, and your responses will be kept confidential. It can only be used to drive a research conclusion.

Your participation and assistance in completing this study is highly appreciated.

Section A: Sociodemographic Factors

(Please tick or circle the most appropriate option.)

1. Age of the respondent

- ☐ 18-30
- ☐ 31-40
- ☐ 41-50
- ☐ 51-60
- ☐ 60 above

2. Gender

- ☐ Male
- ☐ Female

3. What is your professional background?

- ☐ Medical Officer/ General Practitioner
- ☐ Consultant/Specialized Doctor
- ☐ Dentist
- ☐ Clinical Officer
- ☐ Nurse (Registered/Enrolled)
- ☐ Pharmacist/ Pharmaceutical Technician
- ☐ Laboratory Technician

- Public Health Officer
- Nutritionist
- Health Records Officer
- Procurement Officer
- Other (Specify) _____

4. What is your highest level of education attained?

- Certificate
- Diploma
- Higher Diploma
- Degree
- Masters
- PhD

5. How long have you worked in the healthcare sector in Tharaka Nithi County?

- 1-6 months
- 6-12 months
- 1-2 years
- More than 2 years

Section B: Factors Influencing HMIS Data Utilization

Instructions: Please rate the following statements based on your level of agreement.

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

Here's your questionnaire structured for clarity and readability:

Section 1: Organizational Factors Influencing Data Use in Decision-Making

Scale:

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

Statement	1	2	3	4	5
1. The hospital has clear and standardized policies and guidelines for using HMIS and follows well-defined processes for data collection, analysis, and reporting.	☐	☐	☐	☐	☐
2. The facility encourages staff to regularly review and use data to monitor health service indicators and promotes a culture of	☐	☐	☐	☐	☐

accountability by documenting and following up on data-driven decisions.					
3. Facility leadership actively supports and encourages using HMIS data for evidence-based decision-making, and supervisors provide constructive feedback on improving data collection and utilization.	☐	☐	☐	☐	☐
4. The facility has sufficient IT resources (e.g., computers, internet access, data collection tools) and provides adequate training opportunities to improve staff data management skills.	☐	☐	☐	☐	☐
5. I have the authority to use HMIS data to make decisions related to patient care, resource allocation, and service improvement.	☐	☐	☐	☐	☐
6. I can make HMIS-based decisions without unnecessary external influence or interference.	☐	☐	☐	☐	☐

Section 2: Behavioral Factors Influencing Data Utilization

Scale:

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

1. I have the necessary skills to retrieve, analyze, and interpret HMIS data, including calculating percentages, rates, and trends for decision-making.	☐	☐	☐	☐	☐
2. I can effectively plot health data by months or years and use the trends for informed decision-making.	☐	☐	☐	☐	☐
3. Collecting and using HMIS data is meaningful, contributes to better health service delivery, and helps identify gaps to improve patient care.	☐	☐	☐	☐	☐
4. In my facility, data collection is often done as a routine activity rather than for actual decision-making.	☐	☐	☐	☐	☐

5. I feel motivated to use HMIS data because my colleagues, supervisors, and management appreciate and encourage its use in decision-making.	☐	☐	☐	☐	☐
6. Lack of incentives and recognition discourages staff from actively using HMIS data for decision-making.	☐	☐	☐	☐	☐

Section 3: Technical Factors Influencing HMIS Utilization

Scale:

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

Statement	1	2	3	4	5
1. My facility has adequate IT infrastructure, including computers, internet access, printers, and backup systems, and provides technical support for troubleshooting HMIS-related IT issues.	☐	☐	☐	☐	☐
2. The IT equipment in my facility is well-maintained and regularly serviced to support smooth HMIS operations.	☐	☐	☐	☐	☐
3. I have received formal training on data management and the use of HMIS tools, which has improved my ability to handle and utilize HMIS data effectively.	☐	☐	☐	☐	☐
4. The HMIS system is user-friendly, easy to navigate, and does not hinder efficient data entry, retrieval, or analysis.	☐	☐	☐	☐	☐
5. The complexity of the HMIS system makes it difficult for staff to efficiently enter, retrieve, and analyze data.	☐	☐	☐	☐	☐
6. The HMIS is well integrated with other health information systems (e.g., laboratory, pharmacy, patient records), allowing for seamless data exchange and decision-making.	☐	☐	☐	☐	☐

Section 4: Environmental Factors Influencing HMIS Data Utilization

Scale:

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

For Frontline & Mid-Level Managers (e.g., doctors, nurses, clinicians, records officers, department heads)

Statement **1 2 3 4 5**

1. My facility has reliable internet access, and power outages rarely disrupt the consistent use of HMIS for decision-making. ☐ ☐ ☐ ☐ ☐

2. The current infrastructure (e.g. power backup, and server access) supports effective HMIS data entry and utilization. ☐ ☐ ☐ ☐ ☐

For Top Management (e.g., Medical Superintendent, Hospital Administrator, Heads of Department, Head, Head of Records, Nursing Officer in Charge, Accountant, Procurement Officer)

Statement **1 2 3 4 5**

3. Government funding and budget allocations are sufficient to support HMIS infrastructure, operations, and staff capacity-building in my facility. ☐ ☐ ☐ ☐ ☐

4. National and county-level health information policies provide clear guidance and support for effective HMIS data collection, analysis, and use. ☐ ☐ ☐ ☐ ☐

5. External regulations, reporting demands from development partners, and the broader political environment influence how HMIS data is prioritized and used in decision-making. ☐ ☐ ☐ ☐ ☐

What is your role in the healthcare system?

- Administrative (SKIP TO Section A: Strategic DM)
- Routine service provider (SKIP TO Section B: Operational DM)

Decision-Making

Group 1: Departmental Heads & Top Management

This section will be answered by key hospital administrators, including the medical superintendent, the hospital administrator, the departmental heads (Head of H/R, Head of Procurement, Accountant, Health Records in Charge, Nursing Officer in charge), wards in charge, etc. This section will cover strategic decision-making related to resource allocation, budgeting, service delivery and long-term planning.

Section A: Use of HMIS Data in Strategic Decision-Making

Instruction: Please rate the extent to which HMIS data is used in the following areas.

Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Statement	1	2	3	4	5
1. HMIS data has been used to conduct a situation analysis to assess the status of various health services in this facility.	☐	☐	☐	☐	☐
2. HMIS data is used to prioritize resource allocation based on the most prevalent diseases or pressing public health needs.	☐	☐	☐	☐	☐
3. HMIS data is used to monitor medicine consumption, predict stock needs, and reduce drug stockouts.	☐	☐	☐	☐	☐
4. HMIS data is used to evaluate hospital performance indicators (Quality of health services, Resource mobilization and utilization, Inventories and consumables availability) and address service delivery gaps.	☐	☐	☐	☐	☐
5. HMIS data is used to assess staff workload, staff skills mix, recruitment needs, attrition rate and performance monitoring.	☐	☐	☐	☐	☐
6. The HMIS is used in pricing services, reducing billing errors, waiving bills and ensuring timely payments to suppliers.	☐	☐	☐	☐	☐
7. HMIS data is utilized in developing multi-year strategic plans (e.g., 3–5-year plans) at the facility level.	☐	☐	☐	☐	☐
8. HMIS data is used to share evidence with partners, inform policy formulation, and support decision-making in executive meetings.	☐	☐	☐	☐	☐

Group 2: Routine Health Service Providers

This section is to be answered by doctors, nurses, pharmacists, health records officers, public health officers, clinical officers, nutritionists, laboratory technicians, anesthetists and other frontline healthcare workers, responding to sections on operational decision-making.

Section B: Use of HMIS Data in Operational Decisions

Instruction: Please rate the extent to which HMIS data is used in the following areas.

Scale: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always

Statement	1	2	3	4	5
1. HMIS data is used to support clinical decisions such as patient treatment, diagnosis follow-ups, and referrals	☐	☐	☐	☐	☐
2. HMIS is used in managing patient appointments, reducing wait times, and optimizing clinic schedules.	☐	☐	☐	☐	☐
3. HMIS data is used to track drug inventory, request supplies, and prevent stockouts to ensure uninterrupted patient care.	☐	☐	☐	☐	☐
4. HMIS data is used to plan and conduct community health outreach programs and disease surveillance activities.	☐	☐	☐	☐	☐
5. HMIS data is used to identify service gaps and enhance department operations by guiding Continuous Medical Education (CME) programs in the hospital.	☐	☐	☐	☐	☐
6. HMIS data is used during departmental meetings for planning, reporting, and hospital day to day operational discussions.	☐	☐	☐	☐	☐

- What are the biggest challenges affecting the use of HMIS for decision-making in your hospital?
- What enablers have supported HMIS utilization in your hospital? And how can they further be strengthened?
- What recommendations would you give to improve HMIS utilization for better decision-making in Tharaka Nithi County?

Thank you for your participation.

Appendix D: Ethics review board approval

 REPUBLIC OF KENYA	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
Ref No: 328542	Date of Issue: 15/May/2025
RESEARCH LICENSE	
	
This is to Certify that <u>Dr. Grace Wangari Gichohi</u> of <u>Strathmore University</u>, has been licensed to conduct research as per the provision of the <u>Science, Technology and Innovation Act, 2013 (Rev.2014)</u> in <u>Tharaka-Nithi</u> on the topic: <u>Influence Of Health Management Information Systems On Decision Making In A Level 5 Public Hospital In Tharaka Nithi County, Kenya</u>. for the period ending: <u>15/May/2026</u>.	
License No: NACOSTI/P/25/4173619	
328542	
Applicant Identification Number	Deputy Director NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
	Verification QR Code
	

24th April 2025

Ms Gichohi Grace,
Grace.Gichohi@strath
more.edu

Dear Ms Gichohi,

RE: Influence of Health Management Information Systems on Decision-Making in a Level 5 Public Hospital in Tharaka Nithi County, Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-Masters** proposal. Your application reference number is **SU-ISERC2853/25**. The approval period is from **24th April 2025 to 23rd April 2026**.

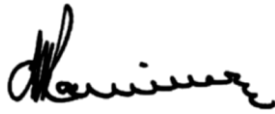
This approval is subject to compliance with the following requirements:

- 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 SU-ISERC.
- 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 SU-ISERC within 72 hours of notification.
- iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU- ISERC within 72 hours.

- v. Clearance for the 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 the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
- vii. Submission of an executive summary report within 90 days of completion of the study to SU- ISERC.

Before 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 obtain other clearances needed.

Yours sincerely,



**Mr Ambrose
Rachier,
Chairperson; SU-
ISERC**

