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SCHOOL OF BUSINESS AND ECONOMICS

TECHNOLOGY INTEGRATION AND OPERATIONAL EFFICIENCY OF HEALTH CARE SERVICE DELIVERY: A CASE OF KAJIADO COUNTY

BY

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A Thesis Submitted in Partial Fulfilment for the Requirement for the Degree of Master of Business Administration in Strategic Management

NAIROBI, KENYA

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2026

DECLARATION

I, the undersigned, declare that this thesis is my original work and that it has not been presented in any other university or institution for academic credit.

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Recommendation by the Supervisors

This thesis has been submitted for examination with our approval as the university supervisors.

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DEDICATION

This work is dedicated to my lovely family, whose unwavering support, love, and encouragement has made it possible for me to do this research. To my wife, Nancy Nailantei, my daughters Precious Nemayian and Peace Soipan for their endless sacrifices and belief in me, whose companionship and joy have made this journey worthwhile.

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LIST OF ACRONYMS

AI	Artificial Intelligence
DHIS	District Health Information System
DHTs	Digital Health Technologies
DOI	Diffusion of Innovations Theory
DV	Dependent Variable
EHRs	Electronic Health Records
HBM	Health Belief Model
HITECH	Health Information Technology for Economic and Clinical Health
HMIS	Health Management Information System
IV	Independent Variable(s)
KCRH	Kajiado County Referral Hospital
LMICs	Low- and Middle-Income Countries
mHealth	Mobile Health
MRI	Magnetic Resonance Imaging
NACOSTI	National Commission for Science, Technology and Innovation
PLS-SEM	Partial Least Squares Structural Equation Modelling
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment Framework
UHC	Universal Health Coverage
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

OPERATIONAL DEFINITION OF TERMS

Artificial Intelligence-based tools: These are software or hardware platforms that use computer science and mathematical techniques to simulate human cognition and perform tasks such as diagnostic imaging analysis, predictive analytics, clinical decision support, and workflow automation in healthcare environments (Deloitte, 2025).

Electronic Health Records: These are the electronic versions of patients' paper charts and include patient information like complete medical history, diagnoses, medications, treatment plans, and lab test results, which can be shared in real-time among multiple healthcare providers (Mbewe, 2025).

Healthcare operational efficiency: This is the extent to which healthcare institutions optimize the use of available resources in delivering healthcare services efficiently.

Healthcare services: These are medical care provided to patients, families, and communities. They include a variety of services, including emergency care, preventative care, and home care.

Mobile Health (mHealth) Technologies: This is the use of mobile devices (phones, tablets, and applications) to support medical and public health practices, including health information delivery, remote patient monitoring, appointment reminders, and data collection (Ochieng et al., 2020).

Referral district hospital: This is a hospital that provides complex care to

patients who are referred from other hospitals. Referral hospitals can also be called tertiary referral hospitals.

Telemedicine: This refers to the delivery of healthcare services and clinical information using telecommunications technologies (video calls, mobile apps, remote monitoring) to bridge the gap between patients and healthcare providers, especially in remote areas.

ABSTRACT

Technology integration in healthcare is important because it helps in improving the delivery of healthcare services by reducing delays, improving access to patients' information, supporting better decision-making, and enhancing the use of resources. This study assessed the impact of technology integration in the delivery of healthcare services on operational efficiency in Kajiado County. The study focused on Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies. Despite investment in digital health, healthcare facilities in Kajiado County still experience long patient waiting times, inefficient use of resources, fragmented information systems, and low satisfaction of patients. The study was guided by the Unified Theory of Acceptance and Use of Technology, Technology Acceptance Model, Diffusion of Innovations Theory, Technology-Organization-Environment Framework, and Information Systems Success Theory. A descriptive research design was used in this study. Yamane's formula was using in coming up with a sample size of 214, where respondents were selected using stratified random sampling. Primary data was collected using a structured questionnaire and analysed using SPSS Version 23 through descriptive statistics, correlation analysis, and multiple regression. The findings showed that all four technologies had positive and statistically significant effects on operational efficiency. Electronic health records had the strongest effect ($B = 0.351$, $\beta = 0.348$, $p = 0.001$), followed by telemedicine ($B = 0.318$, $\beta = 0.326$, $p = 0.002$), mobile health technologies ($B = 0.296$, $\beta = 0.303$, $p = 0.003$), and artificial intelligence-driven tools ($B = 0.274$, $\beta = 0.291$, $p = 0.001$). The study concluded that the integration of digital health technologies played a significant role in improving operational efficiency in Kajiado County. The study recommends investment in digital infrastructure, staff training, technical support, and integration of these technologies across public healthcare facilities.

CHAPTER ONE

INTRODUCTION TO THE STUDY

1.0 Introduction

This chapter gives a detailed account of the background of the study, the problem statement, the research questions and objectives, the significance of the study, the scope, and the theoretical and conceptual framework of the study. This provides a strong foundation for the study.

1.1 Background of the Study

Globally, countries are experiencing health system-related problems that vary from one country to another. According to Oleribe et al. (2023), these challenges are experienced more in countries that have a high Human Development Index. In Africa, healthcare systems have, for a long time, experienced man-made issues which cut across institutional, human resources, financial, technical and political developments. Melnychenko and Ovcharova (2024) explain that in 2007, the World Health Organization (WHO) proposed a framework describing six core components, or "building blocks," of an effective healthcare system. These components are service delivery, healthcare workforce, healthcare information systems, medicines and technologies, financing, and leadership/governance.

According to Deloitte (2025), realizing these six components proposed by WHO has been challenging across both developed and developing countries. Despite major investments in healthcare reforms, many countries continue to face inefficiencies due to inadequate infrastructure, shortages of healthcare workers, poor information management systems, and unequal access to healthcare services. Oleribe et al. (2023) note that integrating technology into healthcare delivery has been an important approach in addressing these challenges and improving important functions of health systems. Alqaysi et al. (2024) further explain that

digital health technologies can improve service delivery, enhance the coordination of care, strengthen data management, and support evidence-based decision-making. As a result, the use of technology has become an effective and practical way of improving the performance and operational efficiency of healthcare systems (Ebo et al., 2025).

Several digital tools have been identified as important in transforming healthcare systems and improving how healthcare services are delivered. These include Electronic Health Records (EHRs), telemedicine, Artificial Intelligence (AI)-based tools, and mobile health (mHealth) technologies (Bevere, 2024; Hiratsuka et al., 2013). EHRs help in ensuring proper storage, access, and sharing of patient records, which improves coordination of care, and lowering chances of medical errors. Telemedicine, on the other hand, allows healthcare workers to offer consultations and clinical services remotely. This helps in reducing geographical challenges and increases access to healthcare, especially in areas that have limited access to healthcare services (Deloitte, 2025; Steinwachs, 2008). According to Anusi (2026), AI-based tools improve the accuracy of diagnosing health issues, predicting health outcomes, and clinical decision-making. This enables healthcare providers to offer faster and more effective care. Ebo et al. (2025), stated that mHealth technologies utilize mobile devices to provide health information, appointment reminders, remote monitoring, and patient engagement services. These technological tools play a significant role in enhancing operational efficiency through the reduction of waiting times, better utilization of resources, enhanced communication, improved patient satisfaction, and reduced rates of errors during diagnosis or treatment of patients (Melnychenko & Ovcharova, 2024).

1.1.1 Global Perspective of Operational Efficiency

Healthcare operational efficiency refers to the extent to which healthcare institutions optimize the use of available resources in delivering healthcare services efficiently. According to

Deloitte, (2025), the primary goal of operational efficiency is to maximize the quality of healthcare while at the same time minimizing the cost and general wastage of resources. Healthcare systems around the world are facing major challenges due to an increasing number of older people, a rise in chronic diseases, shortages of healthcare workers, growing healthcare costs, and higher demand for healthcare services (Javaid et al., 2024). As a result, many healthcare organizations are using digital technologies to improve the efficiency of their operations and support the long-term delivery of quality healthcare services.

The global digital health market has experienced significant growth in recent years. According to recent estimates, digital health investments exceeded US$14 billion in the United States alone in 2021, while more than 1,200 digital health companies collectively attracted over US$33 billion in funding during the previous decade (Darwish et al., 2021). This growth shows that there is an increase in reliance on digital technologies to improve healthcare efficiency and patient outcomes.

Anusi (2026) states that EHRs are now an important digital tool used in improving the efficiency of operations in healthcare institutions/facilities. EHRs enable healthcare workers to access patient records faster, share information more easily, avoid duplicate diagnostic tests, and make clinical decisions in a shorter time during patient care. Darwish et al. (2021) add that EHRs help in reducing paperwork, medication errors, and delays in service delivery. In the United States, the use of EHR grew significantly after Health Information Technology for Economic and Clinical Health (HITECH) Act was introduced, with over 96% of hospitals using certified EHR systems by 2021 (Darwish et al., 2021; Hayrinen et al., 2008). This has improved the coordination of care and workflow efficiency. In Europe, Denmark has been a leader in the adoption of EHR, with data showing that all primary care doctors use EHR (Birk et al., 2024). Birk et al. (2024) add that primary care doctors are mandated to use computers and electronic medical records to communicate. This has led to faster exchange of information, has also

reduced administrative burden, reduced waiting time, and has improved continuity of patient care across healthcare institutions.

According to Kalhori et al. (2021), during the COVID-19 pandemic, the use of telehealth increased across countries such as the United States, China, Australia, and several European nations. For example, Kierkegaard (2024) explains that in the Netherlands, more than 8,000 healthcare providers offered video consultations during the pandemic, making it possible for patients to have continuous patient care while reducing unnecessary hospital visits and improving accessibility to services. A study by Javaid et al. (2024) shows that telemedicine helps in lowering the cost of delivering healthcare, leads to reduced patient isolation, improves chronic disease management, and increases the rate of satisfaction of patients. Additionally, telehealth reduces the workload of healthcare professionals through virtual consultations and expands access to healthcare services for people living in remote and underserved areas (Kalhori et al., 2021; Patsis, 2017).

AI is revolutionizing the healthcare field, by transforming how medical practitioners diagnose, treat and care for patients. According to AlDhaen (2025), AI enhances the efficiency of healthcare operations through predictive analytics, automated medical coding, diagnostic imaging, clinical decision support, and workflow automation. Abdelwanis et al. (2026) explains that in Germany, AI-powered radiology systems have helped reducing reporting time by 25%, enabling radiologists to handle more patients per day. In the Netherlands, AI-assisted clinical decision support improved diagnostic accuracy by 15%, helping hospitals reduce errors and optimize resource allocation (Grace & Mustafa, 2025). Similarly, in Sweden, using AI models to analyze patient data reduced paperwork for healthcare workers, allowing them to spend more time with patients, hence improving productivity and operational efficiency (AlDhaen, 2025; Anusi 2026).

Despite the increased integration of technology in the delivery of healthcare services, achieving operational efficiency through the integration of technology depends on the availability of adequate digital infrastructure, skilled healthcare personnel, supportive regulatory frameworks, and sustainable financing mechanisms. WHO continues to emphasize that healthcare systems must strengthen their technological capacity and workforce competencies in order to significantly benefit from digital transformation. Consequently, healthcare organizations that effectively integrate EHRs, telemedicine, AI-based tools, and mHealth technologies are more likely to achieve improved resource utilization, enhanced patient outcomes, reduced operational costs, and greater overall healthcare efficiency in an increasingly complex global healthcare environment.

1.1.2 Regional Perspective of Operational Efficiency

The delivery of healthcare in Africa experiences a lot of challenges which include under-resourced systems, a shortage of workforce and gaps in infrastructure. This has significantly reduced the efficiency and quality of healthcare services offered to patients. The potential for digital health technologies to enhance operational efficiency across the continent is considerable. Nations are progressively adopting EHRs, telemedicine, AI-enabled tools, and mHealth application platforms to tackle the geographical challenges and increase their service areas (Manyazewal, 2021; Mbewe, 2025; Ampomah et al., 2021).

Mbunge et al. (2025) state that HER has been adopted in different countries in Africa, even though its adoption has been limited. According to Amphosa et al. (2021), Ghana's Health Management Information System (HMIS) and District Health Information System (DHIS2) were launched to the previously existing manual data harmonization processes. This system has played a significant role in enhancing the reporting accuracy and timeliness and reducing information transmission bottlenecks. Despite its importance, Odei-Lartey et al. (2020) argue

that the data collected using these systems in normally weak since it is characterised by duplication of records, fragmentation, incompleteness, and multiple storage formats.

Oguntimehin and Oluwole (2026) explain how the operational efficiency of healthcare services in Nigeria are experiencing numerous challenges such as lack of adequate infrastructure, a ballooning population of patients, and a lack of sufficient finances to run health facilities. The use of technologies such as Internet of Things (IoT) and Building Information Modelling (BIM) in healthcare has helped in reducing equipment downtime by 25–35% and improving space utilization efficiency by 20% in hospitals (Oguntimehin & Oluwole, 2026).

In South Africa, during the COVID-19 pandemic, telehealth-related services were rolled out and continued to be used even post-COVID. Some of these services include teleconsultations and remote patient monitoring, which have played a significant role in improving healthcare operational efficiency (Rabe, 2022). According to Mbunge et al. (2025), dedicated telehealth services in the Western Cape province improved virtual doctor–patient relationships, reduced mortality, and increased cost-effectiveness. Additionally, remote consultations have enabled continuity of care for chronic disease patients, mental health users, and individuals requiring physiotherapy or psychotherapy. With 36 million South Africans accessing mobile internet in 2021, projected to reach 43 million by 2026, and 22 million using smartphones, telehealth has become a viable tool to reduce unnecessary hospital visits, decrease wait times, and improve treatment adherence in primary care (Rabe, 2022; Ramaiah, ss2012).

In Africa, South Africa's healthcare system struggles with challenges such as resource constraints, workforce gaps, and rising disease burdens. To help in easing these challenges, stakeholders within the health sector introduced the use of AI tools in health service delivery. Janneker (2025) states that AI tools that are used in healthcare have helped enhance diagnostics, drug discovery, and clinical decision-making while optimising hospital efficiency. Success depends on interoperable data, bias-aware AI models trained on local datasets, and robust

ethical frameworks. Mbunge et al. (2025) outline how AI-enabled diagnostic tools have been used in healthcare systems in Malawi and have increased diagnostic accuracy by 30% and reduced the time to treatment in rural clinics, while at the same time improving prenatal and postnatal care delivery.

Due to increased penetration of mobile phones and the internet in Africa, many countries in Africa have introduced Mobile health (mHealth) interventions which have enabled health education, appointment reminders, and remote consultations. According to Aboye et al. (2023), systems such as MomConnect in South Africa, M-Tiba in Kenya, and mTrac in Uganda have increased reporting rates from 36% to 85%, enhanced adherence monitoring, and strengthened disease surveillance (Mbunge et al., 2025). However, barriers such as poor internet connectivity, intermittent power supply, limited digital literacy, and financial constraints continue to limit widespread adoption (Mbunge et al., 2025; Rauner & Stummer, 2025).

1.1.3 Local Perspective of Operational Efficiency

Technology integration in healthcare service delivery has been enhanced by the National Digital Health Policy (2023) and initiatives such as Taifa Care, which unifies patient records across counties, hence enabling the integration of EHRs, telemedicine, application of AI, and mHealth in supporting Universal Health Coverage (Nyang'echi & Osero, 2021; County Government of Kajiado, 2025). The technologies have enabled more efficient healthcare delivery by improving access to patient's information, enhancing clinical decision making, and reducing redundant diagnostic procedures.

Despite the integration of technology in delivering healthcare services, Tareh et al. (2023) explain that there are still disparities which persist between rural and urban regions. Kimathi et al. (2025) add that counties such as Kajiado and Homa Bay face challenges such as poor infrastructure, limited electricity, cultural reluctance toward modern medical treatment, and

low digital literacy. Oloo et al. (2020) opined that health facilities such as Level 4 and 5 hospitals often lack the resources which should enable the operationalization of EHRs, telemedicine platforms, AI decision-support tools, and mHealth applications, leading to inefficiencies in healthcare service delivery.

A study by Kimathi et al. (2025) shows that the use of telemedicine in health facilities has played a significant role in enhancing the efficiency of operations by reducing the wait time of patients and expanding the coverage of health services. For example, in private hospitals, 67% of facilities reported improved workflow efficiency following the adoption of telemedicine and AI systems, while resource utilization increased by over 30% (Ratemo & Juma, 2025; Alqaysi et al., 2024). In Kericho County, ICT uptake among healthcare workers was 67.7%, with staff trained in IT being 10 times more likely to utilize digital systems effectively (Tareh et al., 2023).

According to Ratemo and Juma (2025), the integration of AI tools in delivering healthcare services in Kenya has led to an improvement in operational efficiency, more so in diagnostic imaging and patient data management, reducing administrative workload and allowing clinicians to focus on patient care (Ratemo & Juma, 2025). According to Tareh et al. (2023), mHealth solutions such as mobile reminders and WhatsApp chatbots have helped in extending care to underserved populations and improving adherence to treatment protocols.

Technological integration in the healthcare system can be exemplified as the appropriate acceptance, utilization and integration of EHRs, telemedicine, AI-based devices, and mHealth Technologies into the current processes of healthcare. EHRs also facilitate better data and coordination of care. Telemedicine eliminates distance barrier via online consultations. AI-based tools contribute to the improvement of diagnostic and predictive analytics. mHealth technologies facilitate patient involvement and accessibility across mobile platforms.

In general, these four technologies contribute to operational efficiency through shortening waiting times, lessening the amount of errors, allocating resources more efficiently, and enhancing patient satisfaction (Al Meslamani, 2023; Lagrosen & Lagrosen, 2021).The healthcare sector in resource constrained environments such as Kajiado County stands to benefit immensely from the transformative power of technology to address long-standing healthcare delivery gaps, and by so doing, realise improved health outcomes.

1.2 Statement of the Problem

Healthcare service delivery plays an important role in improving the health of the population, enhancing quality of life, and supporting socioeconomic development. Efficient healthcare systems lead to economic growth by maintaining a healthy and productive workforce, reducing disease burden, minimizing productivity losses, and improving human capital development. The World Health Organization (2023) states that investments in health systems contribute to economic resilience by preventing premature deaths, improving workforce participation, and promoting sustainable development. Similarly, the World Bank (2022) highlights that improved health outcomes are strongly associated with increased productivity, poverty reduction, and economic advancement, particularly in low- and middle-income countries where health challenges significantly affect national development. Therefore, ensuring efficient, accessible, and patient-centred healthcare services is essential not only for improving individual health outcomes but also for strengthening economic performance and social development.

Even though the potential of digital health technologies is widely acknowledged globally, Kajiado County continues to experience significant inefficiencies in healthcare service delivery. Healthcare facilities should provide timely, effective, and patient-centred services characterized by minimal waiting times, optimal resource utilization, high diagnostic accuracy, and strong patient satisfaction. However, this ideal remains elusive in the county.

Kajiado County persistently struggles to effectively make maximum use of reliable technologies such as Electronic Health Records, telemedicine, Artificial Intelligence-based tools, and mobile health technologies (Tareh et al. (2023). These challenges originate from inadequate infrastructure, inconsistent data management, missing records, and non-standardized patient information systems. Other challenges include low digital literacy levels, cultural resistance among the Maasai community, reliance on indigenous healing practices, and limited technical skills and equipment (Mutua et al., 2020; Wambua & Mwaura, 2021). As a result, operational efficiency continues to deteriorate across many healthcare settings.

According to Wanjeri et al. (2025), in Kenya, the average patient waiting time is 3-4 hours, which is consistently high despite digital transformation efforts. Seif et al. (2025) further add that in their study at a Tertiary Health Care Institution in Kenya, 51.1% reported a long waiting time of between 2-4 hours before receiving medical attention, leading to high instances of dissatisfaction with healthcare services. Onyango et al. (2024) explained that healthcare facilities in low- and middle-income countries continue to experience delays resulting in approximately 40% inefficiency in patient flow management. This has also led to inefficient use of resources despite advancements in healthcare-related technologies. Moses et al. (2021) also reported that county public healthcare systems in Kenya recorded a median technical efficiency level of only 84%, indicating that nearly 16% of available resources are lost through operational inefficiencies. Kenya Healthcare Federation (2024) showed that only 61% of public health facilities effectively utilized available digital and medical resources, with the others experiencing underutilization and duplication of processes.

Nevertheless, existing studies show that there are cases of deterioration in service delivery outcomes, which is a major indicator of operational efficiency. A study by the Kenya National Patient Experience Survey (2024) showed that only 54% of patients were satisfied with healthcare services, which was a decline from 67% reported in 2021, showing a growing

concern concerning the quality, accessibility, and responsiveness of healthcare delivery in Kenya**.** This was mainly due to delays in treatment and fragmented service processes. The County Government Health Performance Review (2025) reported that health facilities in marginalized counties experienced a 29% increase in missed follow-up appointments and delayed service delivery, enhancing the dissatisfaction of patients. This existing literature shows that operational efficiency, which is determined using patient waiting time, resource utilization, and level of satisfaction of patients, continues to be erratic despite technological advancements in healthcare systems.

Despite the increasing adoption of digital health technologies and continued investments in healthcare digital transformation in Kenya, in rural areas such as Kajiado County, operational inefficiencies in healthcare service delivery remain persistent. Existing studies have mainly assessed Electronic Health Records, telemedicine, Artificial Intelligence-based tools, and mobile health technologies in isolation, with limited attention given to their integrated influence on operational efficiency outcomes such as patient waiting time, resource utilization, and patient satisfaction. Additionally, most studies have focused on urban or generalized healthcare settings, overlooking the contextual realities of culturally diverse and resource-constrained environments. Therefore, this study seeks to address this gap by examining the effect of EHRs, telemedicine, AI-based tools, and mHealth technologies on operational efficiency in healthcare service delivery in Kajiado County, Kenya.

1.3 Research Objectives

1.3.1 General Objective

The main objective of the study is to assess the impact of technological integration in healthcare service delivery on operational efficiency in Kajiado County.

1.3.2 Specific Objectives

i. To assess the impact of Electronic Health Records on the operational efficiency of healthcare services in Kajiado County.
ii. To analyse the impact of telemedicine on the operational efficiency of healthcare services in Kajiado County.
iii. To examine the influence of Artificial Intelligence-driven tools on the operational efficiency of healthcare services in Kajiado County.
iv. To evaluate the impact of mobile health technologies on the operational efficiency of healthcare services in Kajiado County.

1.4 Research Questions

i. What is the impact of Electronic Health Records on the operational efficiency of healthcare services in Kajiado County?
ii. What is the impact of telemedicine on the operational efficiency of healthcare services in Kajiado County?
iii. What is the influence of Artificial Intelligence-driven tools on the operational efficiency of healthcare services in Kajiado County?
iv. What is the impact of mobile health technologies on the operational efficiency of healthcare services in Kajiado County?

1.5 Significance of the Study

This research makes an important contribution to overcoming the perennial challenges in rural Kenyan healthcare, more so as pertains to the EHR, telemedicine, AI driven tools, and mHealth technologies application for Kajiado County. Through the analysis of these four technologies, this study offers practical knowledge to improve the delivery of healthcare services in settings where resources are limited. The findings are of significant importance to various stakeholders

including Kajiado County health sector, academia, policymakers, and overall knowledge contribution in healthcare.

1.5.1 Kajiado County Health Sector

The results of this study provided practical solutions on negative and positive usage of EHR, telemedicine, AI and mHealth tools directly to health sector in Kajiado County to utilise these technologies effectively. This is anticipated to reduce patient waiting times, upgrade resource utilization, improve diagnostic accuracy, and higher patient satisfaction. In a county dominated by scattered rural communities, bad roads and the Maasai as the main ethnic group with unique tradition and culture, the study enables a more efficient and culturally sensitive healthcare provision (County Government of Kajiado, 2025; Mbewe, 2026).

1.5.2 Academia

The study contributes significantly to the literature since it is the first to examine the combined effects of DHTs in a rural area, where research is scarce. Most of the literature to date has concentrated on single technologies or focused on applications in urban areas this study addresses an important void by investigating the combined effects of the four technologies on the efficiency of operation in a marginalised rural area (Manyazewal, 2021; Onsongo, 2023). It guides future researcher works on digital health adoption in similar resource poor setting in Africa.

1.5.3 Policy Makers

The county and national policymakers benefit from the evidence provided in this study to strategize and allocate resources. Implications were drawn for the development of focused policies and guidelines relating to technological investment, infrastructure building, work force training and community involvement. This underpins Kenya’s aspirations towards Universal

Health Coverage (UHC) and access to quality health care services particularly in rural counties (Kenya National eHealth Policy 2016-2030; Ministry of Health, 2023).

1.5.4 Knowledge Contribution

This research adds a novel perspective to the conversation seed on the transformation of digital health in developing countries. It exposes context-specific hindrances and facilitation for the implementation of EHR systems, telemedicine, AI-based tools and mHealth in rural areas with cultural diversities. The study contributes to the understanding of how these tools as a set can enable operational efficiency, and thus be used as an evidence-based approach to addressing urban-rural health disparities in Kenya - and across much of Africa (Rigby, 2007; McKinsey & Company, 2023).

1.6 Scope of the Study

This research focused on Kajiado County. The area is predominantly countryside and the healthcare is provided in semi-rural settings. Kajiado county was selected because it represents a resource-constrained healthcare environment where public health facilities experience challenges related to infrastructure, accessibility, digital literacy, and effective utilization of healthcare technologies. The county therefore provides an appropriate context for examining how technology integration influences operational efficiency in semi-rural healthcare settings. The study examines the infiltration of technology in the healthcare system. Specifically, it examines key resource EHR, telemedicine, AI solutions, and mHealth technologies and analyses how these solutions are strategically placed to handle and improve operational workload in the healthcare system.

In terms of concept, the scope of the study was informed by the increasing adoption of digital health technologies and their role in improving healthcare operational efficiency. The study focused on Electronic Health Records, telemedicine, Artificial Intelligence-based tools, and mobile health technologies because these technologies affect directly the management of healthcare information, clinical decision-making, accessibility of services, automation of workflow, and patient engagement. Their influence was examined in relation to operational efficiency indicators. These indicators were reduction of patient waiting time, effective utilization of resources, and satisfaction of patients. Because of the distinct nature of health care provision in rural and semi-rural areas, the study endeavours to identify advantages and disadvantages of these technologies for use in such areas considering availability, infrastructure, and resource use. In limiting its focus to common spaces and exchanges, the work provides innovative digital solutions that could be adapted and applied to populations in nonurban locales.

The study also exclusively considers the healthcare professionals, administrators, and patients from the rural and semi-rural healthcare centre that was selected for the study, ensuring that the viewpoints of these three key constituencies are fully captured. It does not extend to urban healthcare centres or private healthcare providers, as their technological capabilities may differ significantly from those in rural settings.

Additionally, the study does not consider staff from non-governmental institutions, the private sector, whose responsibilities and involvement differ from those of public healthcare professionals or providers in Kajiado county. Focusing on public healthcare providers, the dynamics in rural healthcare facilities vary in so many ways. This research offers valuable information on how technological capabilities support health services in different situations. The study was carried out between January 2026 and August 2026.

1.7 Theoretical Framework

The research is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) as the major theoretical perspective. The UTAUT provides a holistic perspective to assess the determinants that affect the use and adoption of technology within the healthcare organizations.

The Technology Acceptance Model (TAM) constructed by Davis (1989) is a basic theory for the users' acceptance of technology. TAM is based on the assumption that the two main factors (perceived usefulness and perceived ease of use) drive the intention of using an information technology. Over the years, TAM has been modified by researchers including Agarwal and Karahanna (2000) and Bagozzi (2007) to include factors such as social influence and facilitating conditions, which enable the model to serve as a general tool for predicting technology acceptance in many industries, including health care. Borrero, Yousafzai, Javed, and Page (2014) also extended the model by adding subjective norms to capture the impact of peers on technology adoption, which is relevant in collaborative contexts, and was introduced in such an extension.

TAM was subsumed in the Unified Theory of Acceptance and Use of Technology (UTAUT) which was constructed by Venkatesh et al. (2003) from eight well-known models. The model predicts that four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) directly influence behavioural intention to use a technology that, in turn, predicts actual technology usage. In healthcare, the theory has been applied extensively to understand the uptake of digital health tools (Gupta, Dasgupta, & Gupta, 2008; Marikyan & Papagiannidis, 2023) such as Electronic Health Records (EHRs), telemedicine, AI-enabled technology and m-health solutions.

The UTAUT is especially appropriate for this study as it allows for an examination of the acceptance and usage of multiple digital health tools by clinicians and patients in Kajiado County. The constructs of the theory are directly applicable to the independent variables of the study as all the constructs are related to EHRs, telemedicine, mobile health technologies and AI-driven tools. Performance expectancy is consistent with the expectations of EHRs, telemedicine, mHealth technologies and AI-driven tools to contribute to operational efficiency. Effort expectancy describes the level of ease associated with these technologies and social influence represents the influence of friends, colleagues, family and patients on obtaining a technology. Facilitating conditions are related to infrastructure, training, and technical support which are particularly critical in resource-limited rural areas such as Kajiado County (Venkatesh et al., 2003; Maillet, Mathieu, & Sicotte, 2015).

Utilizing UTAUT, this research investigates the impact of the four technology integration dimensions (EHRs, telemedicine, mHealth technologies, and AI-based tools) on the behavioural intention and use, and subsequently on the operational efficiency of healthcare services. The theory provides a basis to understand why some digital solutions are easily adopted and others are resisted by healthcare workers for the Maasai community. It also contributes to the exposition how the acceptance of the users and the institution results in increased services delivery, decreased waiting time and better use of resources in public health facilities (Mütterlein, Kunz, & Baier, 2019).

UTAUT has a strong predictive ability to explain technology adoption, however, the model has been criticized as being too complex and containing too many constructs, which may hinder empirical testing. The theory has also been criticised by some scholars who argue the theory focuses too much on individuals and less on organisational and contextual obstacles such as poor infrastructure, power outages and cultural resistance typical of rural African contexts

(Bagozzi, 2007).Despite these limitations, the UTAUT continues to be considered as the most powerful model to investigate technology acceptance in the context of healthcare environment, particularly when it is integrated with TAM as the base model.

1.8 Conceptual Framework

This conceptual framework shows the relationship between the independent and dependent variables. The independent variables are Electronic Health Records (patient data accessibility, medical record accuracy, and clinical documentation speed), Telemedicine (remote consultation availability, healthcare service accessibility, and virtual communication efficiency), Artificial Intelligence-driven tools (diagnostic decision accuracy, clinical decision support, and automated workflow management), and Mobile Health Technologies (mobile appointment reminders, remote patient monitoring, and patient engagement enhancement). The dependent variable is operational efficiency of healthcare services, measured through reduced patient waiting time, efficient resource utilization, and improved service delivery

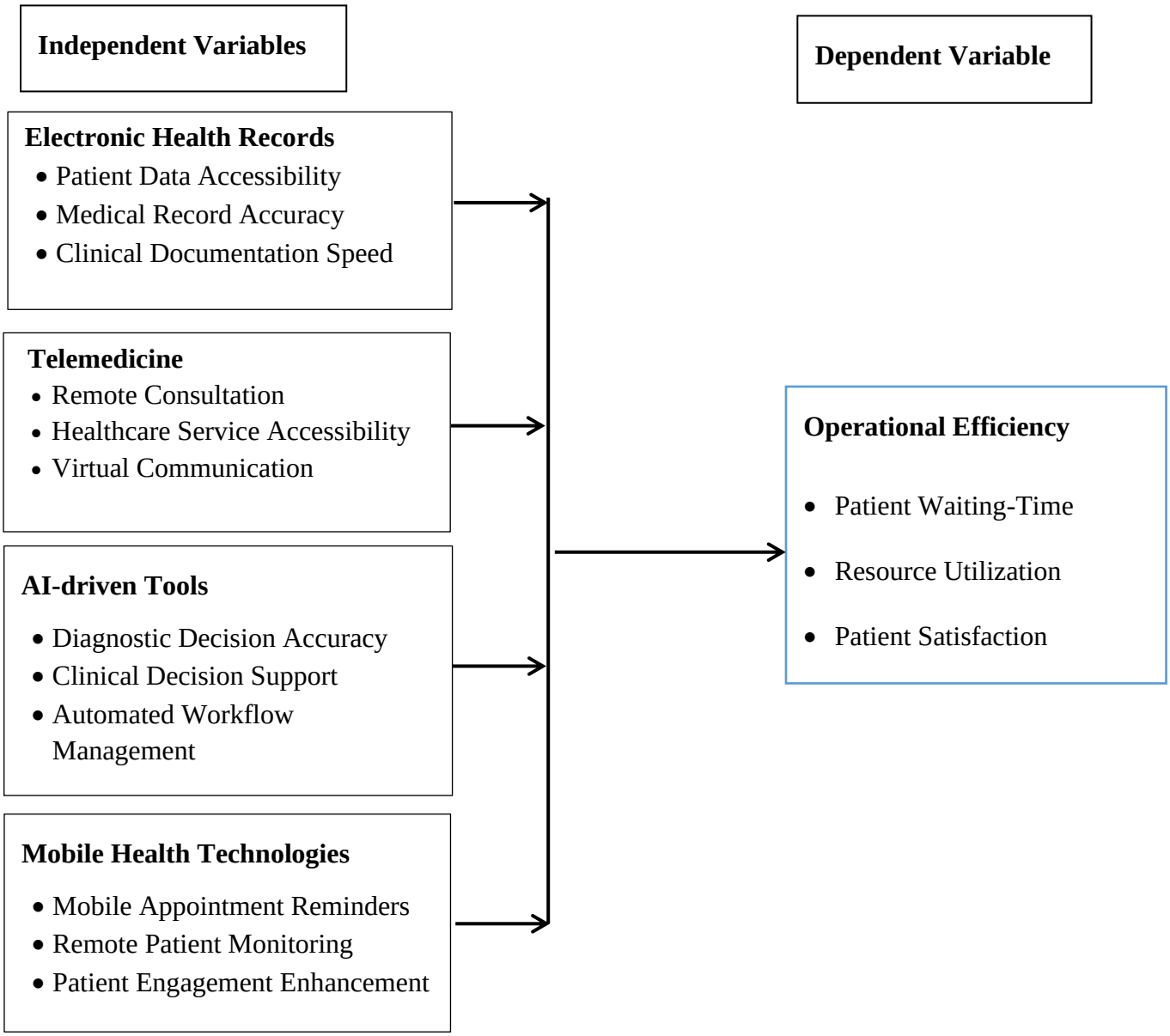


Figure 1.1: Conceptual Framework

Source: (Author, 2026)

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive literature review covering both theoretical and empirical perspectives on the integration of digital technologies in the healthcare sector, with a particular focus on Kajiado County, Kenya. It begins with a review of relevant theories, such as the Technology Acceptance Model (TAM) followed by a critical evaluation of these theories. The chapter then presents an empirical review of past studies and finally, it identifies existing knowledge gaps that this study seeks to address.

2.2 Review of Theories

This is supported by the theories describing the adoption, integration and effect of the use of digital technologies on operational efficiency in healthcare organizations. The theories that are supporting the anchor theory (UTAUT) are the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) Theory, and the Technology-Organization-Environment (TOE) Framework.

2.2.1 Technology Acceptance Model (TAM)

This theory was developed by Fred Davis in 1989 and it draws its perspectives from the Theory of Reasoned Action (TRA). According to Lee et al. (2025), this theory helps in predicting how people accept and use information systems and technologies, while also showing the factors that influence the acceptance of technology. Agarwal and Karahanna (2000) argue that the model emerged from the need to understand why individuals accept or reject technologies in different organizational settings. According to Davis (1989), the adoption of any new technology depends on the beliefs of the users and attitudes toward the system. According to

Zoccarato et al. (2024), TAM states that people are more likely to accept technology when they see it useful and easy to use. This positive view increases their intention to use the system, leading to the actual usage.

This theory is founded on two metrics, which are perceived usefulness (PU) and perceived ease of use (PEOU). Zoccarato et al. (2024) explain that PEOU looks at how simple a system is to understand and operate, while PU is based on how helpful and practical the system is. Davis (1989) stated that individuals evaluate the advantages of using a technology against the efforts needed to use it. When users feel that a system is both useful and easy to use, they are more likely to accept and use it. Kamal et al. (2020) note that TAM also considers external factors such as the design of the system, user training, and technical support, which shape these perceptions and influence attitudes, intentions, and actual technology use. Over time, the model has been expanded through versions such as TAM2 and TAM3, adding factors such as social influence, cognitive processes, and facilitating conditions. These improvements have made the model to be more useful in explaining the use of technology in areas such as healthcare, education, banking, and public administration (Davis, 1989; Venkatesh & Davis, 2000).

In this study, TAM explains how EHRs affect operational efficiency in public healthcare facilities in Kajiado County. The model is useful because it shows how health workers view EHR systems based on usefulness and ease of use. Healthcare workers are more likely to use EHR systems when they believe that the systems make patient records easier to access, improve the accuracy of medical records, and increase the speed of clinical documentation. Additionally, when EHR systems are easy to use and do not require much effort, healthcare workers are more likely to integrate them into their daily activities (García et al., 2024; Nadri et al., 2018). The widespread acceptance and use of EHRs can lead to an improvement in service delivery, reduce patient waiting time, and efficient resource utilization, which are key

indicators of operational efficiency in this study. Therefore, TAM provides a strong theoretical basis for examining how healthcare workers' perceptions of EHR systems influence their adoption and how such adoption translates into improved operational performance in public healthcare facilities within Kajiado County.

However, this model is often criticised for being too narrow and individualistic (Bagozzi, 2007). Critics argue that TAM largely ignores organisational and environmental factors. In addition, the theory also pays limited attention to cultural and infrastructural constraints. These shortcomings are especially relevant in rural Kenyan counties and critics argue that TAM needs to be integrated with broader frameworks for better explanatory power (Chau & Hu, 2002).

2.2.2 Diffusion of Innovation (DOI) Theory

The DOI Theory was developed by Everett Rogers in 1962 and explains how new ideas, technologies, products, and practices spread within a social system over time. The theory creates an understanding of why some innovations are adopted rapidly while others experience resistance or slow uptake. According to Rogers (2003), diffusion of a technology or system is the process through which an innovation is communicated through specific channels among members of a social system over a period of time. Zhang et al. (2023) explain that DOI is one of the most influential theories in innovation and technology adoption research because it provides a systematic account of how individuals and organizations respond to change. The theory has been widely applied in various fields, including healthcare, education, agriculture, communication, and information systems, to explain the adoption of emerging technologies and innovative practices (Mbatha (2024; Greenhalgh et al., 2017).

DOI identifies five important aspects that are related to innovation and influence the rate and likelihood of adopting an innovation (Rogers, 2003). These aspects include relative advantage,

compatibility, complexity, trialability, and observability. Relative advantage refers to the extent to which an innovation is perceived as superior to existing alternatives. Compatibility measures the degree to which the innovation aligns with users' values, experiences, and needs. Complexity refers to the level of difficulty associated with understanding and using the innovation, with more complex innovations generally experiencing slower adoption (Greenhalgh et al., 2017; Rogers, 2003). Trialability describes the extent to which potential adopters can experiment with an innovation before fully committing to it, while observability refers to the visibility of the innovation's benefits and outcomes to others. Rogers (2003) argues that innovations perceived as having greater relative advantage, compatibility, trialability, and observability are adopted more rapidly, whereas higher complexity negatively influences adoption rates (El Malouf & Bahemia, 2026). The theory further categorizes adopters into innovators, early adopters, early majority, late majority, and laggards, illustrating how adoption progresses through a social system in an S-shaped diffusion curve (See Figure 2.1).

According to El Malouf and Bahemia (2026), DOI appreciates the role of communication channels, social systems, opinion leaders, and change agents in influencing innovation adoption. According to Rauna and Stummer (2025), communication channels enable the dissemination of information about an innovation, while social systems provide the cultural and organizational environment within which adoption decisions are made. Opinion leaders influence the attitudes and behaviours of others by serving as role models, whereas change agents actively promote innovations and encourage adoption. The theory also explains the innovation-decision process, which consists of five stages: knowledge, persuasion, decision, implementation, and confirmation (Culjak, 2023). Through these stages, individuals and organizations move from becoming aware of an innovation to integrating it into routine practice. This process-oriented perspective makes DOI particularly useful for examining how

technologies are accepted and institutionalized within organizations and communities (Greenhalgh et al., 2017).

In the context of the current study, this theory was used to support the second objective to which seeks to examine the effect of telemedicine on operational efficiency in healthcare facilities in Kajiado County. Telemedicine represents an innovation whose successful implementation depends on the willingness of healthcare providers and patients to adopt and utilize digital consultation platforms. DOI provides a framework that can help in understanding how factors such as perceived benefits of remote consultations, compatibility with existing healthcare practices, ease of use, opportunities for trial use, and visibility of positive outcomes influence telemedicine adoption. DOI offers important information for examining how telemedicine adoption leads to improved accessibility of healthcare services, reduced patient waiting times, enhanced service delivery, and overall operational efficiency within healthcare facilities.

However, DOI has been criticised because of underemphasising structural, institutional, and political factors that shape diffusion trajectories - particularly in complex and highly regulated sectors such as healthcare (Dryden-Palmer, Parshuram, & Berta, 2020; Greenhalgh et al., 2017). Recent studies show that DOI is too linear and actor-centric in logic. In the healthcare sector, innovation is mainly affected by policy uncertainty, resistance from institutions, and weak infrastructure. Because of these limitations, DOI alone cannot be used alone (Greenhalgh et al., 2017). As a result, frameworks such as the Consolidated Framework for Implementation Research (CFIR) are used to help in enhancing the adoption of multi-level approaches that integrate individual, organizational, and systemic perspectives

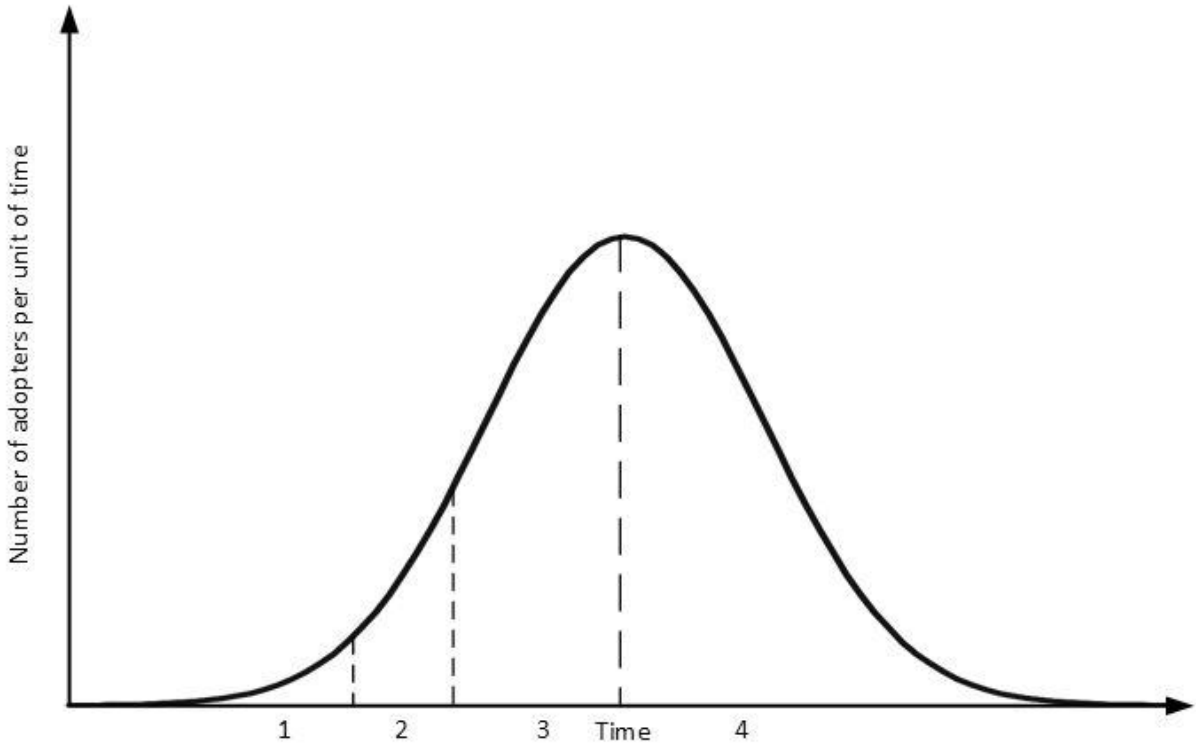


Figure 2.1: The Diffusion S-curve. / Adopted from Rogers (2003)

2.2.3 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) Framework was developed by Tornatzky and Fleischer in 1990, and helps in explaining the factors that affect the adoption and implementation of technological innovations within organizations (Tornatzky & Fleischer, 1990). According to Küçükoğlu and Kabakuş (2025), TOE argues that the adoption of any technology or innovation is not determined by a single factor but by the interaction of technological, organizational, and environmental contexts. The technological context refers to the characteristics of the technology itself, including its complexity, compatibility with existing systems, perceived usefulness, and relative advantage. Nguyen et al. (2022) add that the organizational context, on the other hand, is based on internal factors such as organizational structure, resource availability, managerial support, employee competencies, and operational readiness. The environmental context includes external influences such as government regulations, competitive pressures, industry dynamics, and stakeholder expectations. The

integration of these aspects enables the TOE framework to provide a comprehensive perspective for understanding how organizations evaluate, adopt, and utilize new technologies (Oliveira et al., 2023; Baker, 2012; Ramdani et al., 2013).

According to Küçükoğlu and Kabakuş (2025), TOE framework has been refined and extended by numerous scholars to examine digital transformation across different sectors and industries. The framework has been successfully applied in healthcare, banking, manufacturing, insurance, and public sector organizations to explain the opportunities and barriers associated with technological innovations. Muhamad et al. (2021) stated that this theory views technological transformation as a multidimensional process that is influenced by technological change, organizational change, and environmental change. Technological change involves factors such as system compatibility, technological complexity, and the value created by the innovation (Küçükoğlu & Kabakuş, 2025; Al-Smadi, 2025). Organizational change includes capabilities, leadership support, organizational culture, quality of human resources in a firm, and the availability of financial and technical resources (Schmitt et al., 2019). Environmental change are market conditions, competition, regulatory requirements, and institutional support mechanisms (Hoang, 2024). Recent studies have confirmed the continued relevance of the framework in explaining digital transformation initiatives, showing that technological readiness, managerial competence, and environmental pressures collectively influence technology adoption decisions.

In this study, this framework is relevant in explaining the adoption and integration of AI-driven tools in service delivery in public healthcare facilities in Kajiado County. AI-driven tools require adequate technological infrastructure, reliable data systems, and compatible digital platforms to function effectively. From the organizational perspective, successful implementation depends on leadership commitment, availability of skilled healthcare

personnel, staff training, and sufficient financial resources to support AI integration. The environmental dimension highlights the importance of government policies, regulatory frameworks, stakeholder support, and external technological partnerships in facilitating AI adoption within healthcare institutions (Annisa & Sutjipto, 2025). The framework therefore guides the assessment of how technological readiness, organizational capabilities, and environmental conditions influence the use of AI-driven tools such as diagnostic decision support systems, automated workflow management systems, and clinical decision-support applications. Through this perspective, the study seeks to explain how these factors collectively affect operational efficiency outcomes, including reduced patient waiting time, improved service delivery, and efficient resource utilization in public healthcare facilities in Kajiado County.

Although the TOE gives researchers a comprehensive view, it also has its own limitations. One limitation is its limited theoretical development, as it mainly identifies adoption factors without explaining their interactions in depth (Prakash, 2025). TOE also overlooks individual and task-related influences, focusing primarily on organizational-level factors. According to Al-Smadi, 2025, TOE pays little attention to post-adoption performance outcomes and long-term impacts. These limitations, among others, may affect its ability to fully explain technology adoption processes in diverse contexts.

2.2.4 Information Systems (IS) Success Theory

The IS Success Theory was developed by DeLone and McLean (1992) to provide a comprehensive framework for evaluating the success of information systems (DeLone & McLean, 2003). DeLone and McLean (1992). The theory emerged from the growing need to understand how information systems contribute to individual and organizational performance. According to DeLone and McLean (2003), IS success is a multidimensional concept that

cannot be measured by a single indicator. The original model identified six interrelated dimensions of success, namely system quality, information quality, use, user satisfaction, individual impact, and organizational impact. IS success argues that high-quality systems and information increase system use and user satisfaction, which also generates positive results for both individuals and organizations (Jeyaraj, 2020). Over time, this model has become one of the most widely accepted frameworks for assessing the effectiveness and performance of information systems across different sectors and industries.

DeLone and McLean (2003) revised the framework by adding service quality as an additional dimension and replacing individual and organizational impact with a broader construct known as net benefits. Al-Kofahi et al. (2020) explain that the improved model shows that the quality of information, system quality, and service quality affect the satisfaction of users and intention to use, which then affects the benefits associated with the system. The theory has been used widely to assess e-government systems, enterprise resource planning systems, e-learning platforms, e-commerce applications, e-banking systems, and e-health technologies (Ojo, 2017). Existing literature shows that the theory helps in explaining how the quality of information systems affects the views of users, the use of systems, and performance of the organization. The model is important because it focuses on the experience of users and their views of technology rather than focusing only on technical features, making it suitable for different technologies and organizational settings (DeLone & McLean, 2003; DeLone & McLean, 1992).

In this study, the IS success theory helps in explaining how mHealth technologies are used and how they help in improving the effectiveness and efficiency of operations in public healthcare facilities in Kajiado County. Mobile health technologies depend on good information, a reliable and functioning system, and strong service support to improve healthcare delivery. According

to this theory, the quality of a mHealth system can be seen through how reliable and easy it is when it comes to booking appointments, monitoring patients, and supporting communication. Quality of information refers to how accurate, timely, and relevant the health information shared through mobile platforms is. On the other hand, service quality focuses on the support given to healthcare workers and patients who use these systems. These factors affect the satisfaction of users and the continued use of mHealth technologies. As a result, this may reduce the patients' waiting time, improve the use of resources, and improve the delivery of services. Therefore, the theory is useful in studying how mHealth technologies improve operational efficiency in public healthcare facilities in Kajiado County.

Although the IS success theory provides a comprehensive framework for evaluating information system performance, it has limitations. For instance, the theory is focused on results emanating from the success of systems and pays limited attention to external environmental factors that may influence the adoption and use of technology. The model also assumes that system use automatically leads to benefits, which may not always be the case in resource-constrained environments.

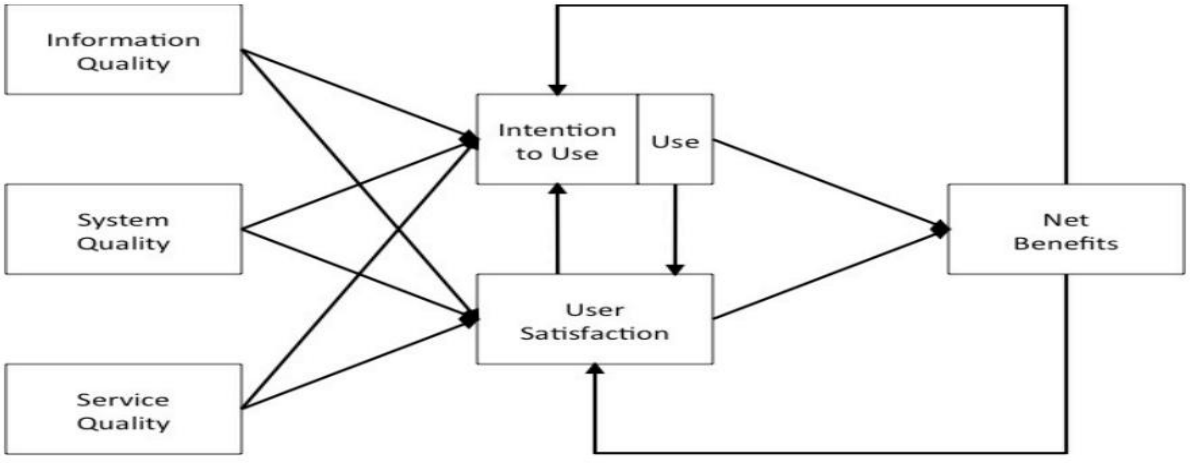


Figure 2.2: IS Success Model (DeLone & McLean, 2003)

2.3 Empirical Reviews

This section discusses the previous studies related to the aims of this study in terms of the aspects of technicity and service provisioning in the domain of health care and user's perception. The section ends with a summary of the prevailing gaps and issues related to contemporary study.

2.3.1 Electronic Health Records and Operational Efficiency

Electronic health records (EHRs) are a vital part of today's healthcare systems, yet their implementation and usage are influenced by numerous human, technical, and organizational factors. Hossain, Quaresma, and Rahman (2019) investigated the determinants of EHR adoption based on PLS-SEM model. Social Influence ($\beta = 0.19$, $P < 0.05$), Facilitating Conditions ($\beta = 0.19$, $P < 0.05$), and Personal Innovativeness in Information Technology ($\beta = 0.19$, $P < 0.05$) were significant predictors of EHR adoption according to their findings. On the other hand, none of the following were significant predictors: Performance Expectancy ($\beta = 0.08$, $p > 0.05$), Effort Expectancy ($\beta = -0.02$, $p > 0.05$), and Resistance to Change ($\beta = 0.03$, $p > 0.05$). These results highlight that increasing social interaction, maintain adequate technical support as well as stimulating risk taking among physicians are essential in order to spread EHR useHowever, the study did not consider specific constructs of EHR such as accessibility of data, accuracy of records, usability of system, speed of documentation, and the impact of these on indicators of operational efficiency, such as patient waiting time and speed of service delivery.

Alalwan et al. (2018) out a study to assess the factors that affect the use of Electronic Health Records in healthcare institutions. The study looked at how facilitating conditions, such as access to adequate infrastructure, technical support, and staff training, help in the successful use of EHR systems. This study used a quantitative research design, where data was collected

from healthcare professionals using structured questionnaires. The data was then later analysed using SPSS software. The results from this study showed that facilitating conditions had a strong positive relationship with the use of EHR ($\beta = 0.412$, $p = 0.001$). The study also found that system reliability had a major effect on the trust of the user, and continued use of EHR systems ($r = 0.768$, $p = 0.003$). The study also explained that healthcare facilities need to invest in infrastructure, regular training of staff, and IT support systems to improve the use of digital health technologies. However, the study did not evaluate the specific EHR constructs such as record accuracy, data accessibility, system usability, and speed of documentation. Empirically, the study did not show the direct effect of the use of EHR on operational efficiency indicators such as patient waiting time, service delivery speed, and resource utilization. In terms of context, the study was carried out in a generalized healthcare environment and did not focus on rural county hospitals such as those in Kajiado County, where infrastructural challenges are more serious.

Moffatt and Eley (2010) carried out a study on the use of Electronic Health Records in rural healthcare facilities. The main aim of this study was to identify organizational challenges that affected the implementation of EHRs. The study used a descriptive research design and collected data from healthcare workers using questionnaires and interviews. The results from this study showed that low digital skills among health workers had a strong negative effect on the adoption and use of EHR ($\beta = -0.318$, $p = 0.004$). The study also found that disorganized organizational systems reduced the coordination of services and led to limited use of digital records ($r = 0.721$, $p = 0.002$). Additionally, lack of enough funding and limited technical support lowered the success of EHR implementation in rural healthcare facilities ($\beta = -0.276$, $p = 0.001$). Based on these results, it was concluded that successful use of EHR systems requires joint planning, proper funding, involvement of the healthcare staff, and regular technical support. However, from this study, there is an empirical gap because the study did

not assess how specific EHR aspects, such as system usability, access to data, accuracy of records, and speed of documentation, affect measures of operational efficiency such as patient waiting time, speed of service delivery, and the use of resources. Contextually, the study focused on generalized rural healthcare facilities and not devolved county health systems such as Kajiado County in Kenya.

Cottrell et al. (2017) did a study in the United States to assess how organizational leadership and internal coordination affected the use of Electronic Health Records (EHRs) in hospitals. The study used a quantitative research design, and data were collected from hospital administrators and healthcare professionals using structured questionnaires. The results showed that the support and commitment of leadership had a strong positive relationship with successful use of HER ($r = 0.812$, $p = 0.001$). The results also showed that hospitals that had a strong departmental teamwork and clear digital strategies had better system usability and user acceptance ($\beta = 0.436$, $p = 0.003$). However, the study had empirical gaps because it did not assess how specific aspects of EHR such as record accuracy, data accessibility, speed of documentation, and usability of the system, affect operational efficiency indicators like patient waiting time and service delivery speed. From a context perspective, the study was carried out in developed healthcare facilities and did not consider rural county hospitals such as those in Kajiado County, where there are significant infrastructural and resource-related challenges.

2.3.2 Telemedicine and Operational Efficiency

In the United States, Kelly, Mohsin, and DeFrances (2024) carried out a study to evaluate the satisfaction of physicians with telemedicine tools during patient visits across different medical specialties. The study adopted a quantitative research design and collected data from physicians using structured survey questionnaires. The findings showed that 65.5% of physicians were satisfied with telemedicine services, while 18.5% were dissatisfied and 15.6% remained neutral

regarding the effectiveness of telemedicine platforms in healthcare delivery. The study also found that telemedicine adoption positively influenced physician convenience and accessibility to healthcare services ($\beta = 0.472$, $p = 0.002$). However, from the study, satisfaction levels differed across medical specialties, showing that there were differences in acceptance levels of telemedicine technologies among healthcare providers. Based on the findings, the study supported the argument that telemedicine improves the accessibility of healthcare and communication efficiency. This study presented an empirical gap exists since the study did not examine the effect of telemedicine constructs such as technology adoption, service accessibility, and remote consultations on operational efficiency indicators such as patient waiting time and service delivery speed. Contextually, the study was conducted in the United States and may not give a reflection of the ideal challenges experienced in rural counties such as Kajiado County.

Hersh et al. (2024) conducted a review study on telemedicine interventions and clinical outcomes to assess the overall effectiveness and acceptability of telemedicine services in healthcare delivery, in Oregon. In this study, several empirical studies were reviewed in order to understand the relationship between telemedicine adoption and healthcare outcomes. The findings revealed that 72.6% of the reviewed studies reported positive clinical outcomes associated with telemedicine interventions, while 15.8% produced inconclusive findings due to weak research designs and inconsistent evidence. From these studies, it was consistent that there was a significant positive relationship between telemedicine use and improved access to healthcare services ($r = 0.741$, $p = 0.002$). In addition, telemedicine adoption was found to significantly influence patient satisfaction and continuity of care ($\beta = 0.387$, $p = 0.001$). The review also showed that healthcare facilities with higher telemedicine integration recorded improved communication efficiency between patients and healthcare providers ($r = 0.689$, $p = 0.004$). However, there was an empirical gap presented from this study because the study did

not examine how telemedicine constructs, such as remote consultation, technology adoption, and service accessibility, influence operational efficiency indicators such as patient waiting time and speed of service delivery. In terms of context, the study mainly focused on developed healthcare settings and ignored rural county hospitals such as those in Kajiado County.

Gunter et al. (2016) carried out a study in the United States to examine the effectiveness of telemedicine interventions on healthcare outcomes across multiple healthcare facilities. The study used a quantitative approach and analysed data from patients and healthcare providers using SPSS to determine the relationship between telemedicine use and clinical outcomes. The findings revealed mixed results, where telemedicine interventions showed an insignificant effect on some clinical outcomes ($\beta = 0.112$, $p = 0.084$), while in other cases a weak but positive association was observed ($r = 0.301$, $p = 0.041$). In addition, the study found that implementation quality significantly influenced outcomes, with user compliance strongly affecting effectiveness ($\beta = 0.428$, $p = 0.002$). Further analysis showed that intervention duration had a moderate correlation with performance outcomes ($r = 0.476$, $p = 0.009$), while system design and usability were also significant predictors of adoption success ($\beta = 0.365$, $p = 0.003$). The study however presented an empirical gap because it did not examine the relationship between telemedicine constructs such as remote consultation frequency, response time, and service accessibility and operational efficiency indicators like patient waiting time, resource utilization rate, and service delivery speed. Conceptually, it did not integrate telemedicine with other digital health technologies such as EHRs and mHealth systems to assess combined effects on efficiency outcomes. Contextually, the study was conducted in a developed healthcare system, limiting its applicability to rural, resource-constrained settings such as Kajiado County where infrastructure and connectivity challenges are more pronounced. Methodologically, the research relied mainly on quantitative designs and did not incorporate

qualitative insights from healthcare providers regarding real-world telemedicine usage experiences.

In a global perspective, a study from Bangladesh by Hossain, Quaresma, and Rahman (2019) investigated the use of telemedicine among physicians and intended to analyse the pattern of use by visit percentage. Results from observation study indicated that 53.9% of physicians applied telemedicine in less than a quarter of their visits, 27.9% in a quarter to a half of their visits, and only 14.7% in a half or more. The usage plummeted to 5.5% for 50% or more but the reliability and consistency was low since less than 25% of visits, 63.3% had used it. These results are indicative that the rate of telemedicine capturing was rather limited and disparate among specialties, implying that there are other potential barriers to wider capturing such as the infrastructure, training and provider's acceptance. However, the review's focus was on the conceptualization of telemedicine and m-health (in relation to service access and technology adoption) without determining whether constructs of telemedicine, such as service accessibility and technology adoption, qualify as m-health in terms of device availability. It is yet to be determined whether digitally enabled patients who book appointments and communicate with their providers directly both online and through an app, influence other components of a successful practice – for instance, wait times for patients and operational efficiency.

Further detail was also available in the same study for non-medical specialists. 41.5% of them used telemedicine in <25% of visits, 25.1% in 25%–49%, and 27.4% in 50% or more of visits. However, when stratified by specialty, medical specialists had the smallest proportion of low users (<25%). The trend for apparent equal mid-range use of 25% to 49% in all specialties, and for the highest high use of telemedicine (≥50%) again in medical specialists may indicate differing results. This shows that while some clinicians utilize telemedicine heavily in their practice, others are cautious, which could be related to differences in patient populations, access to technology, or clinical appropriateness. These findings emphasize the need for

specialty-specific interventions to enhance telemedicine uptake. Although it reports interesting contextual information on levels of adoption, the article does not discuss how telemedicine use compares to that of other types of digital tools such as ease of use with EHR systems or speed of documentation. The evidence for whether digital patient engagement and contribution to feedback may influence the timeliness of delivery of subsequent services or the utilization of resources, particularly in resource-constrained district settings such as Kajiado County, is not yet available.

2.3.3 Artificial Intelligence (AI)-Driven Tools and Operational Efficiency

Use of AI-enabled services in healthcare has recently been very promising for enhancement of both quality of diagnosis and efficiency of services. Esteva et al. (2017) carried out a study that assessed the effectiveness of AI-driven diagnostic tools in healthcare, focusing on a deep convolutional neural network (CNN) trained on 129,450 clinical images for classifying skin lesions. The study used a quasi-experimental design and the performance metrics were evaluated using a comparative evaluation with board-certified dermatologists. Data from 3,200 clinical cases were used to measure diagnostic accuracy, sensitivity, specificity, and error rate. The findings showed that there was a diagnostic accuracy of 0.91, sensitivity of 0.92, specificity of 0.89, and a reduction in error rates by 23% compared to human diagnosis. Evn though the study shows that AI has the ability to improve operational efficiency, a contextual gap remains. This research was carried out in urban or resource-rich settings, leaving rural counties such as Kajiado underexplored. The current study addresses this gap by evaluating AI-driven tools in a rural area.

In their study in Kenya, Ochieng et al. (2020) examined the application of AI tools in radiology and laboratory diagnostics to enhance healthcare service delivery. In their study, they adopted a cross-sectional design, where quantitative data was collected from 112 healthcare workers

across urban and semi-urban hospitals using structured questionnaires. The results showed that AI-driven tools significantly reduced the workload of healthcare providers ($r = 0.623$, $p = 0.003$) and improved diagnostic accuracy ($r = 0.711$, $p = 0.001$). Regression analysis further showed that AI adoption positively influenced workflow efficiency ($\beta = 0.487$, $p = 0.002$) and decreased operational errors ($\beta = 0.359$, $p = 0.005$). These results showed that AI-enabled tools can enhance operational efficiency by automating routine tasks and supporting clinical decision-making, aligning with the study's third objective of evaluating AI-driven tools in healthcare operations. However, the study was limited to urban and semi-urban settings, presenting a contextual gap regarding rural healthcare environments such as Kajiado County, where infrastructural challenges, inconsistent power supply, and limited trained personnel may hinder the effectiveness of AI technologies. The current study seeks to address this gap by empirically examining the impact of AI-driven tools on operational efficiency in a rural, resource-constrained healthcare context.

Kamau et al. (2021) conducted a study to investigate the adoption of Artificial Intelligence (AI) tools in rural healthcare settings in Kenya. The focus of the study was on understanding barriers to the implementation of AI. The study adopted a cross-sectional design, and data were collected from 68 healthcare facilities across rural counties. Data was collected using structured questionnaires and interviews with 120 healthcare professionals, including clinical officers, nurses, and laboratory technicians. The findings showed that high implementation costs ($\beta = -0.372$, $p = 0.001$), lack of technical expertise ($r = -0.418$, $p = 0.003$), and inadequate infrastructure ($\beta = -0.295$, $p = 0.005$) significantly limited the adoption of AI in these settings. Moreover, the study found that where AI tools were partially adopted, diagnostic accuracy improved by 24.6%, workflow efficiency increased by 18.3%, and error rates reduced by 15.2% compared to facilities without AI integration. Despite these positive outcomes, the study highlighted that operational efficiency gains remained limited in resource-constrained contexts,

suggesting that infrastructural and skills deficits undermined the full potential of AI technologies. Contextually, Kamau et al. (2021) focused on generalized rural counties, leaving a gap in understanding the specific effects of AI-driven tools on operational efficiency within Kajiado County's unique socio-cultural and infrastructural environment. The current study aims to address this gap by evaluating AI integration and its direct impact on patient waiting time, resource utilization, and workflow efficiency in Kajiado County.

Nyamawe et al. (2025) conducted a study on the application of Artificial Intelligence (AI) in public-serving institutions in Sub-Saharan Africa. The study found that AI has significant potential to improve diagnosis accuracy and resource allocation in healthcare systems. However, its adoption in rural public institutions has been low, primarily due to inadequate policies, poor data governance practices, and a lack of staff training. The statistical findings showed that 65% of healthcare workers in rural areas reported limited access to AI training ($\beta = -0.412$, $p = 0.004$), and 73% of healthcare institutions lacked sufficient infrastructure for AI implementation ($\beta = -0.389$, $p = 0.005$). Moreover, 62% of the healthcare professionals expressed concerns about data privacy and governance ($r = -0.379$, $p = 0.003$). This study called for the need for strong organizational and environmental support for AI tools to be effectively integrated into rural healthcare systems. However, the research did not explore how specific AI constructs, such as diagnostic accuracy and decision support, influence operational efficiency indicators like patient waiting time and resource utilization in rural settings like Kajiado County. This gap, both conceptual and contextual, are addressed in the current study by examining AI's impact on operational efficiency in Kajiado County, considering the unique challenges of rural healthcare delivery.

2.3.4 Mobile Health (mHealth) Technologies and Operational Efficiency

Mobile health (mHealth) is a subset of eHealth and is defined as the real-time delivery of health services and information via mobile communication technologies such as mobile phones. Free et al. (2013) conducted a review of mHealth interventions in low- and middle-income countries (LMICs), focusing on healthcare workers' use of mobile health technologies. Their findings showed that there was a significant improvement in patient compliance to treatment regimens ($\beta = 0.756$, $p = 0.002$), with patients experiencing chronic disease benefiting more from remote monitoring capabilities. Additionally, mHealth solutions reduced the need for physical visits, hence enhancing the efficiency of healthcare delivery ($r = 0.832$, $p = 0.001$). However, despite these positive effects, the study showed that there was limited long-term evidence concerning tangible operational efficiency improvements, such as patient waiting times and resource utilization ($r = 0.214$, $p > 0.05$). The majority of the studies reviewed were short-term pilots conducted in urban or semi-urban settings, which have better infrastructure compared to rural areas. Also, the review lacked empirical data on the effects of mHealth in remote rural regions, such as Kajiado County, where infrastructure and digital literacy challenges are dominant. This also presents a contextual gap, since the study did not consider the unique barriers faced in rural healthcare settings. These gaps are addressed in this study by evaluating the long-term impact of mHealth technologies on operational efficiency in Kajiado County's healthcare facilities, focusing on patient wait times and resource utilization.

Nyang'echi and Osero (2021) conducted a study to evaluate the impact of mHealth services on the monitoring of growth (MOG) for children aged 9–10 months among parents/caretakers in Kenya. The research observed that there was an increased use of mHealth services and improved record-keeping through mHealth-based platforms, showing a positive influence on service delivery ($\beta = 0.412$, $p < 0.01$). Additionally, 72.3% of participants reported greater

engagement with healthcare services due to mHealth intervention ($r = 0.567$, $p < 0.05$). However, the study primarily focused on maternal and child health (MCH), which limited its applicability to broader healthcare services in rural areas. It did not address key operational efficiency metrics such as patient waiting times ($r = 0.215$, $p > 0.05$), staff workload reduction, or cost savings within county referral hospitals. Nevertheless, the study focused more on MCH data, which limits the generalizability of its findings to other healthcare areas, particularly in resource-constrained environments like Kajiado County, where infrastructure and digital literacy are significant challenges. This empirical gap shows that there is a need for a broader examination of mHealth's impact on operational efficiency in rural healthcare settings, which is a key objective of this study. The current research bridges this gap by assessing how mHealth technologies influence operational efficiency across a wider spectrum of healthcare services in Kajiado County.

Odhiambo (2017) carried out a study to assess the impact of mobile health (mHealth) technologies on the operational efficiency of healthcare services in rural Kenya. The research used a qualitative approach, where it targeted healthcare providers across 12 rural health facilities. Data were collected using semi-structured interviews and observational checklists. From the study, the data showed that mHealth platforms improved communication efficiency ($r = 0.682$, $p = 0.004$), facilitated timely data management ($r = 0.715$, $p = 0.002$), and enhanced patient follow-up adherence ($\beta = 0.328$, $p = 0.001$). Additionally, staff reported reductions in manual record-keeping errors ($r = 0.541$, $p = 0.011$) and improved operational workflow through automated reminders ($\beta = 0.276$, $p = 0.003$). These findings are relevant to the current study's fourth objective, which examines how mHealth technologies influence operational efficiency in Kajiado County by measuring constructs such as app utilization, user engagement, device availability, and data synchronization. Despite showing positive impacts, Odhiambo (2017) primarily focused on general maternal and child health programs and did not evaluate

broader operational efficiency indicators, such as patient waiting time, resource utilization, and treatment speed in rural county hospitals. This creates a contextual and empirical gap that the current study addresses by quantitatively assessing mHealth constructs in a resource-constrained, culturally distinct environment.

Mbunge (2025) studied the barriers to the use and adoption of mHealth platforms in Kenya, with a focus on rural areas. The research used a mixed-methods design, where 150 healthcare workers and patients across various rural health facilities were surveyed. Data analysis showed that 62% of the respondents they had experienced challenges that are related to poor network coverage, while 45% cited high costs associated with mHealth tools ($\beta = 0.412$, $p < 0.001$). Additionally, 58% of healthcare workers indicated low digital literacy as a significant barrier to adoption, affecting the implementation of mHealth solutions ($r = -0.367$, $p = 0.004$). The study also found out that despite the potential for mHealth to reduce health disparities, 49% of respondents in rural areas felt that the technology had not led to significant improvements in operational efficiency, particularly in resource-limited settings ($\beta = 0.328$, $p = 0.008$). However, the focus of the study was limited to general mHealth platforms and did not explore specific constructs such as app utilization, device availability, and user engagement, which are critical to assessing operational efficiency outcomes. This gap was be addressed in the current study, focusing on the unique challenges of Kajiado County.

2.4 Knowledge Gap

Although there is an increasing volume of literature on digital health technologies, several conceptual, methodological, contextual gaps remain, relating for example to the investigation of rural health care systems such as those in Kajiado County, Kenya. Most of the existing work has been primarily concerned with urban, high-resource settings or with developed nations which has limited their applicability and generalization to decentralized, low-resource settings.

There is a dearth of empirical research on the impact of electronic health records (EHRs) systems, telemedicine, mobile health (mHealth) technologies, and digital patient engagement on operational efficiency (patient waiting time, resource usage rate, and service delivery speed) in rural county hospitals.

In term of methodology, previous studies have been quantitative in nature, drawing on positivist epistemology and methodologies (e.g. Structural Equation Modelling – SEM) which have tended to neglect the rich insights that qualitative methods can offer. Studies have used statistical methods to analyse determinants of EHR adoption, but they did not include the experiences or perceptions of healthcare professionals. None of these studies investigated the synergistic influence of all four DHTs and each of their specific constructs on RC indicators such as patient waiting time, resource utilization rate, as well as the rate of service delivery in a developing country context like that of Kajiado.

Theoretically, the Technology Acceptance Model (TAM) (Davis, 1989) has been extensively applied to study the adoption of digital systems. Although TAM is a useful starting point with its focus on perceived usefulness and ease of use, it has been criticized as too limited by focusing only on cognitive aspects at an individual level. To date, research has insufficiently combined TAM with the impact of certain features of EHRs, telemedicine, mHealth technologies, and digital patient engagement on rural operational efficiency in Kenya. Therefore, the research at hand suggests a multi-theoretical approach to better capture the determinants of digital health adoption at a Kajiado County level.

A contextual gap is also evident, as most studies on digital health integration are concentrated in urban or better-resourced environments. Research by Rahman et al. (2022), Al-Husban et al. (2023), and Cottrell et al. (2017) illustrates how EHRs and HIS improve administrative efficiency. However, these studies largely ignore how EHR data accessibility, telemedicine

response time, mHealth user engagement, and use of AI-based tools affect patient waiting time, resource utilization rate, and service delivery speed in decentralized public health facilities with poor infrastructure.

From a conceptual perspective, while a growing body of literature has documented certain operational advantages of digital health technologies, such as shorter appointment scheduling times and reduced billing errors (Rahman et al., 2022; Haynes et al., 2015), very few studies have quantitatively examined how these micro-level improvements translate into operational efficiency outcomes. There is a paucity of research that takes into account the views of healthcare professionals. Technical performance is frequently separated from experiential aspects in studies, neglecting the role of user trust, previous technology experience, and communication styles on the adoption and continued use of digital technologies (Azzam et al., 2023; Al-Husban et al., 2023). Therefore, there is no existing literature that explores healthcare professional and patient perceptions of the four digital technologies and their associated constructs in a comparable manner, and assesses their combined effect on operational efficiency. This discrepancy is of particular importance in areas such as Kajiado, where fragmented socioeconomic and educational background dictate technology engagement and adoption. The present study addresses this by examining technical capabilities and subjective experiences of digital health integration to provide a more comprehensive understanding of the effects of these tools on service delivery.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the methodology that was be used in the study. This includes outlining the research design, the target population, sample and sampling procedures, description of research instruments, description of the data collection procedures, of the data collection and description of data analysis procedures.

3.2 Research Design

The study adopted a descriptive-correlational research design. The descriptive research approach is the most appropriate because it enables a comprehensive description of the occurrences in a complete and well-planned manner (Mugenda & Mugenda, 2008; Cresswell & Cresswell, 2018). The approach was adopted because it helps in achieving the research objectives by describing the data and characteristics of technology integration (Electronic Health Records, telemedicine, Artificial Intelligence-based tools, and Mobile Health technologies) and operational efficiency of healthcare services in Kajiado County.

Due to its systematic approach, the design is associated with a high level of validity. It helps in identifying the existing link between the independent variables (EHRs, telemedicine, AI-based tools, and mHealth technologies) and the dependent variable (operational efficiency).

3.3 Target Population

The target population for this study was made up of frontline healthcare professionals working in in the five public health facilities in Kajiado County, with an estimated total population of 2,200 healthcare workers (County Government of Kajiado, 2025). These five public hospitals are Kajiado County Referral Hospital, Ngong Sub County hospital, Oloitoktok Sub County

hospital, Kitengela Sub County hospital and Ongata Rongai Sub-County Hospital. The hospitals were be used because they have all the frontline healthcare professionals needed in this study.

Thes study used healthcare professionals who provide patients with direct healthcare services. This includes special medical consultants, medical officers, dentists, clinical officers, nurses, nutritionists, laboratory officers, public health officers, physiotherapists, health administrative officers, health records and information management officers, medical engineers, morticians and mortuary attendants, community health assistants, and community health volunteers.

The inclusion criteria included healthcare professionals who: (i) are employed or attached to any of the five selected public health facilities in Kajiado County; (ii) have worked in the facility for at least six months, allowing adequate exposure to the workplace environment and study variables; (iii) are directly involved in healthcare provision or healthcare support services; and (iv) voluntarily consent to participate in the study.

The exclusion criteria included healthcare professionals who: (i) are on leave, off duty, or unavailable during the data collection period; (ii) have worked in the facility for less than six months; (iii) are temporary visitors, interns, students, or trainees without formal employment or attachment to the facility; and (iv) decline to provide informed consent to participate.

3.4 Sample Size and Sampling Procedures

The study adopted a stratified random sampling technique to ensure adequate representation of frontline healthcare professionals across the selected public health facilities in Kajiado County. The target population was first stratified according to the five public hospitals: Kajiado County Referral Hospital, Ngong Sub County Hospital, Oloitoktok Sub County Hospital, Kitengela Sub County Hospital, and Ongata Rongai Sub-County Hospital. Thereafter, proportionate samples were drawn randomly from each stratum to ensure that each hospital contributes

respondents according to its population size and the categories of the frontline healthcare professionals. This approached enhance representativeness and improve the generalizability of the study findings across all categories of frontline healthcare professionals.

Since the target population is known and finite, made up of 2,200 frontline healthcare professionals (County Government of Kajiado, 2025), the study determined the sample size using Yamane's (1967) formula for finite populations. The formula is expressed as:

$n = \frac{N}{1+N\,(e)^2}$ (Yamane, 1967).

n = sample size

N = population size

e = margin of error

$$n = \frac{2200}{1+2200\,(0.065)^2}$$

$$n = \frac{2200}{10.295}$$

n= 214

For this study, a 6.5% margin of error was adopted in determining the sample size using Yamane's (1967) formula because the study is descriptive in nature and seeks to balance statistical representativeness with practical constraints related to time, cost, and accessibility of frontline healthcare professionals across the selected public hospitals. This level of precision falls within the acceptable range commonly used in survey research (Sedar et al., 2021). This produced a sample size of approximately 214 respondents.

Table 3. 1. Selected Major Public Health Facilities in Kajiado County

No.	Facility Name	Level
1	Kajiado County Referral Hospital	Level 5
2	Loitokitok Sub County Hospital	Level 4
3	Ngong Sub County Hospital	Level 4
4	Kitengela Sub County Hospital	Level 4
5	Ongata Rongai Sub County Hospital	Level 4

Source: County Government of Kajiado (2025)

3.5 Description of Research Instruments

The research instrument was a structured questionnaire that was use closed-ended questions. The questionnaire was used to collect primary quantitative data on the impact of digital health technologies on operational efficiency in healthcare services based on the study objectives. The questionnaire was administered electronically to healthcare professionals selected for the study. It was divided into six sections. The first section captured respondents' demographic and institutional information. Sections two to five collected data on the four independent variables, namely EHRs, telemedicine, AI-driven tools, and mobile health technologies. The sixth section collected data on the dependent variable, operational efficiency in healthcare services.

The questionnaire adopted a 5-point Likert Scale to assess the perception of respondents concerning the extent of adoption, utilization, and influence of digital health technologies on operational efficiency of healthcare services. The scale enabled the study to generate standardized responses for quantitative analysis and interpretation of findings. Table 3.2 below represents the different points used in the questionnaire (see Appendix I) to measure the perception of the respondents.

Table 3.2: 5-Point Likert Scale Used in the Questionnaire

Scale Value	Response Option	Interpretation
1	Strongly Disagree	Very low level of agreement
2	Disagree	Low level of agreement
3	Neutral	Neither agree nor disagree
4	Agree	High level of agreement
5	Strongly Agree	Very high level of agreement

Source: Researcher (2025)

3.6 Pilot Study

Before conducting the full-scale study, the researcher carried out a pilot study in order to establish the reliability and validity of the instruments. The pilot study was conducted at a Level 3 and other lower-level public hospitals in Kajiado County, which were purposively selected because it was similar to the main study sites in size, service delivery and the extent of adoption of digital technology. This ensures that instruments are relevant and suitable for the context.

During the pilot study, 10% of the intended sample size was purposively drawn, which consisted of 22 frontline healthcare professionals and technical staff among the target population. The practice also enables the researcher to know how long it would take to fill the questionnaire and to identify any vague items. Suitable adjustments were made to enhance the language, flow and relevance of the tools and instruments based on the comments received.

3.7 Data Collection Procedures

In order to have an efficient data collection process which is free from any legislative hinderances, three letters were obtained before the data collection exercise starts. The first letter was an introduction letter from The Catholic University of Eastern Africa. The second letter was a research permit from the National Commission for Science, Technology, and Innovation (NACOSTI). The third one was a permit from Kajiado County Department of Health Services. For data collection, a consent form was provided to the respondents before they start filling out the questionnaire. The questionnaire was then shared electronically inform of a Google Form. Once each respondent filled out the form, he or she submitted it.

3.7.1 Reliability of Research Instruments

Reliability is focused on whether a particular instrument gives the same results if the phenomena of interest have not changed (Babbie et al., 2007). In order to enhance reliability, the structured questionnaire was be pre-tested and revised prior to the main study. The study used Cronbach's alpha to assess internal consistency. A cut-off of 0.7 or higher was be considered acceptable for the current study (Tavakol et al., 2011).

The survey was validated in terms of technology integration within four areas: EHR systems, Telemedicine, AI-driven tools, and mHealth Technologies, and also based on operational efficiency factors. Items with low reliability scores were reworded or deleted to improve consistency. Feedback from the pilot study was used to confirm the stability and reliability of the instruments for application in the main study.

3.7.2 Validity of the Instruments

Validity is the extent to which the instrument measures what it is supposed to measure. Content validity was established by expert review and construct validity and face validity through pilot testing. The questionnaire was subjected to review by two academic supervisors and three experienced healthcare administrators knowledgeable in Kenya's digital health system.

The investigator evaluated whether the items sufficiently represented the variables of the study, such as constructs specific to EHRs (data accessibility, record accuracy, system usability, documentation speed), Telemedicine, mHealth Technologies, Digital Patient Engagement, and organizational efficiency (patient waiting time, resource utilization rate, and speed of service delivery). Based on their suggestions, vague or unrelated questions were modified or removed.

The items in the questionnaire were aligned with the theoretical framework of the study, especially UTAUT, to ensure that the construct validity is not compromised. From the pilot study, face validity was established since the respondents reported whether the instruments were valid and that they could effectively measure the influence of technology application on operational efficiency in Kajiado County.

3.8 Description of Data Analysis Procedures

Upon collection of the questionnaires, data was scrutinized for completeness and consistency. Subsequently, the raw data was cleaned, edited, coded and entered into an analysis software – Statistical Package for the Social Sciences (SPSS) Version 23. Quantitative analysis of data was done using descriptive and inferential statistics. Demographic characteristics of the respondents as well as the levels of technology integration and operational efficiency was

summarized using descriptive statistics including frequency, percentages, means and standard deviation.

A multiple linear regression analysis as part of inferential statistics was used to analyze the relationship between the independent variables (EHR systems, Telemedicine, mHealth Technologies and Digital Patient Engagement) and the dependent variable (organizational efficiency). Normality, multicollinearity (by VIF), homoscedasticity and linearity was checked to ensure that the assumptions of the regression model are not violated (Field, 2018). The regression model for the study is formulated as follows:

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

Where: Y = Operational Efficiency (patient waiting time, resource utilization rate, and service delivery speed)

X_1 = EHRs systems

X_2 = Telemedicine

X_3 = AI-Based tools

X_4 = mHealth Technologies

β_0 = Constant

$\beta_1 – \beta_4$ = Regression coefficients

ε = Error term

3.9 Diagnostic Tests

In this study, multiple diagnostic tests were carried out to confirm the regression model, check assumptions, and improve the trustworthiness of the result. The diagnostics assessed linearity, homoscedasticity and residual normality. These tests help in confirming that the assumptions

of multiple linear regression are met prior to examining the association between technology integration and operational efficiency.

3.9.1 Linearity Test

Linearity test was used to examine if there are linear relationships among the dependent variable and the independent variable. To test for linearity, scatterplots were produced using SPSS to assess linear trends visually between each independent variable and the outcome of operational efficiency composite index. Residual plot was observed to verify if the residual is randomly distributed around zero. In addition, the Ramsey RESET test was carried out to statistically verify that there are no non-linear effects. In case of nonlinearity measures was taken in order to satisfy the linearity assumption. This validates the strength of the regression model.

3.9.2 Homoscedasticity

Homoscedasticity is the assumption that the residuals at all levels of the independent variable(s) are normally distributed within the same population represented by those independent variables. This assumption was tested using Breusch-Pagan test in SPSS and then regression. Tests were carried out on the residuals of the regression model to determine whether variance is uniform across the predicted values.

In case the p-value for Breusch-Pagan test is >0.05, homoscedasticity was assumed. If the p-value is <0.05, heteroscedasticity is present (Jamshidian & Jalal, 2020). In such situations, robust standard errors or data transformations were employed to account for the violation. This test is used to ensure unbiased estimates for the coefficients and especially valid statistical inferences concerning the impact of digital health tools on the operating efficiency of the healthcare service delivery.

3.9.3 Normality of Residuals

The test of normality of residuals was used to test if the residuals of the regression model are normally distributed. This assumption is necessary for accurate hypothesis testing and confidence intervals with multiple regression analyses. The Shapiro-Wilk test was carried out on the residuals derived from the regression analysis in SPSS.

A p-value ≤ 0.05 suggests that residuals are normally distributed. In the presence of non-normality ($p < 0.05$), data transformation or robust statistics was applied. This postestimation test helped in establishing the dependability of the regression results and thus provide more insights into the positive impact technology integration has on operational efficiency in Kajiado County Hospitals (Hickey et al., 2018).

3.10 Ethical considerations

The study follows the Declaration of Helsinki and local ethical regulations to protect the rights of the subjects (Kurihara et al., 2024). Every person taking part was told why, how, and what they need to do, and that they are participating voluntarily, and written informed consent was given before they are recruited.

This is a minimal-risk study with no physical procedures, and the mental and emotional welfare of participants is protected at all times. In addition, there was a stringent confidentiality agreement to guarantee that all gathered data is anonymized and kept safe, with identities being safeguarded during the report and publication. The participants have the right to withdraw from the study at any time without any reprisal. These safeguards ensure that the research is respectful, autonomous, and has integrity (Resnik, 2020).

CHAPTER FOUR

DATA ANALYSIS, PRESENTANTION AND DISCUSSIONS OF FINDINGS

4.1 Introduction

This chapter presents the analysis, presentation, interpretation, and discussion of the collected data. This chapter presents the response rate, a pilot test, descriptive statistics, inferential analysis, and the diagnostic tests. The analysis was guided by the four specific objectives of the study, which were focused on Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies.

4.2 Pilot Test Results

A pilot study was carried out before the main data collection exercise to determine the reliability, validity, clarity, and suitability of the developed structured questionnaire in examine the impact of technology integration on operational efficiency in healthcare service delivery in Kajiado County. The pilot involved 22 frontline healthcare professionals and technical staff, representing approximately 10% of the intended sample size. Participants were selected using purposive approach, and were selected from Level 3 and lower-level public healthcare facilities that had characteristics comparable to those of the facilities included in the main study.

The questionnaire assessed five constructs: Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, mobile health technologies, and healthcare operational efficiency. Reliability was tested using Cronbach's alpha in SPSS Version 23. As presented in Table 4.1, the alpha coefficients ranged from 0.79 to 0.84, while the overall questionnaire attained an alpha coefficient of 0.80. All coefficients exceeded the recommended minimum threshold of 0.70, confirming that the questionnaire items had acceptable to high internal consistency. The research methodology specified that a Cronbach's alpha coefficient of at least 0.70 would be considered acceptable.

Table 4.1: Pilot Study Reliability Results

Construct	No. of Items	Cronbach's alpha	Interpretation	Validity Feedback (n=22)
Electronic Health Records	5	0.82	High internal consistency	93% of respondents found items clear and relevant
Telemedicine	5	0.79	Acceptable internal consistency	90% agreed questions were understandable
AI-driven tools	5	0.81	High internal consistency	87% confirmed relevance to operations
Mobile health technologies	5	0.79	Acceptable internal consistency	91% confirmed clarity and applicability
Operational efficiency	5	0.84	High internal consistency	95% indicated ease of relating items to practice
Overall instrument	**25**	**0.80**	**Reliable and consistent instrument**	

Feedback from the pilot participants indicated that the questionnaire was generally clear, relevant, and easy to complete. However, minor concerns were raised by community health volunteers and community health assistants regarding technical terms such as "workflow automation," "clinical decision support," and "remote patient monitoring." These expressions were simplified and clarified without altering their intended meanings. The wording and flow of several questions were also adjusted to improve comprehension. The average completion time was approximately 12 minutes, which was considered reasonable.

Content, construct, and face validity were further supported through reviews by academic supervisors and experienced healthcare administrators. In general, the pilot results confirmed that the questionnaire was reliable, valid, understandable, and suitable for administration during the main study.

4.3 Response Rate

The study targeted 214 frontline healthcare professionals. This sample size was determined using Yamane's formula at a 6.5% margin of error. Table 4.2 shows that, during data collection, 164 responses were received, representing a 75.9% response rate. The 164 responses were satisfactorily filled and there was no missing data. The remaining 52 questionnaires represented 24.1% of the intended sample. The response rate was considered adequate for statistical analysis because it exceeded the commonly accepted minimum threshold of 70% for survey-based research (Creswell, 2024). The high completion rate also reduced the risk of substantial non-response bias, although the findings should still be interpreted within the limits of the respondents who participated.

Table 4.2: Response Rate

Category	Frequency	Percentage
Administered	**214**	**100%**
Completed	164	75.9%
Unreturned questionnaires	52	24.1%

4.4. Demographic Characteristics

Demographic characteristics of the respondents were analysed to determine the composition, diversity and relevance of the sample. The study targeted frontline healthcare professionals

working in five major public health facilities in Kajiado County. The demographic variables included gender, highest education, speciality, affiliated health facility and years of service.

4.4.1 Gender of Respondents

From the data collected and analysed, female respondents were the majority. Figure 4.1 shows that 61.0% (n = 100) of the sample were female, while 39.0% (n=64) were male. This pattern is plausible in a health workforce that includes nursing, health-records, public-health, administrative, laboratory, and community-health roles, most of which often have substantial female participation (Ayaz et al., 2021). The distribution of gender is relevant in this study because differences in exposure to technology, digital literacy, and acceptance attitudes between male and female healthcare professionals may affect the perceptions and utilization of digital health technologies, thereby affecting operational efficiency outcomes.

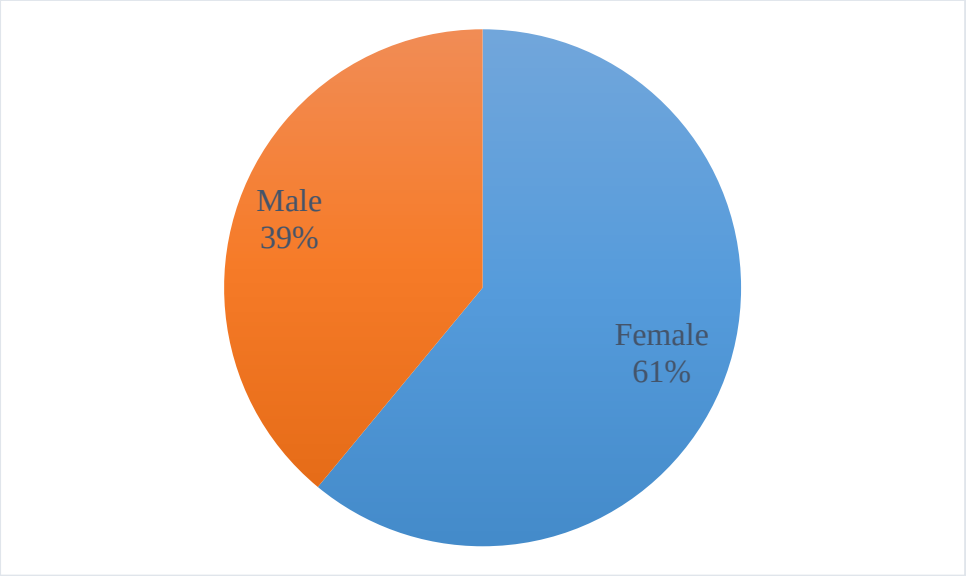


Figure 4.1: Gender of Respondents

4.4.2 Level of Education

Table 4.3 shows that majority (58.5%) respondents held a diploma. University degree holders accounted for 22.0%, while respondents with master's degrees accounted for 12.8%, and

doctorate holders accounted for 6.7%. This educational profile shows that the respondents were generally able to understanding the statements contained in the questionnaire and assess the operational implications of digital health tools.

Table 4.3: Level of Education

Education Level	Frequency	Percentage
Diploma	96	22.0%
Degree	36	58.5%
Masters	21	12.8%
Doctorate	11	6.7%

4.4.3 Speciality of Respondents

The respondents represented a broad range of professional and technical specialities. Table 4.4 shows that Registered Nurses (RN) formed the largest single group at 10.4%, followed by public health officers at 9.1%, health records officers at 8.5%, and health administrative officers at 7.3%. Laboratory officers, information management officers, and ICT staff each represented approximately 6.1%. The inclusion of clinical, technical, records, administrative, and community-health personnel strengthened the institutional perspective of the study because technology integration affects multiple stages of the patient-care process.

The diversity of specialities also means that the participants had unequal exposure to the four technologies. For example, health-records and information-management officers are likely to interact more directly with EHR systems, while clinicians may have greater exposure to decision-support tools and telemedicine.

Table 4.4: Professional Speciality of Respondents

Speciality	Frequency	Percentage
Registered Nurses	17	10.4%
Public Health Officer	15	9.1%
Health Records Officer	14	8.5%
Health Administrative Officer	12	7.3%
Information Management Officer	10	6.1%
Laboratoty Officer	10	6.1%
ICT Staff	10	6.1%
Community Health Volunteer	9	5.5%
Clinical Officer	9	5.5%
Administrator	8	4.9%
Dentist	7	4.3%
Community Health Assistant	7	4.3%
Medical Officer	7	4.3%
Laboratory Staff	6	3.7%
Nutritionist	6	3.7%
Medical Engineers	3	1.8%
Physiotherapists	3	1.8%

4.4.4 Affiliated Health Facility

According to the analysed data presented in Table 4.5, the responses were distributed almost evenly across the five public health facilities in Kajiado County. Ngong Sub County Hospital contributed 20.7% of the respondents; Kitengela Sub County Hospital and Ongata Rongai Sub-County Hospital each contributed 20.1% of the respondents; and Kajiado County Referral Hospital and Oloitoktok Sub County Hospital each contributed 19.5% of the respondents. The narrow difference of two respondents between the largest and smallest facility indicates that the achieved sample was well balanced in terms of representation from the respective health facilities.

Table 4.5: Distribution of Respondents by Health Facility

Health Facility	Frequency	Percentage
Ngong Sub County Hospital	34	20.7%
Ongata Rongai Sub-County Hospital	33	20.1%
Kitengela Sub County Hospital	33	20.1%
Kajiado County Referral Hospital	32	19.5%
Oloitoktok Sub County Hospital	32	19.5%
Total	**164**	**100.0%**

4.4.5 Years of Service

According to Table 4.6, respondents with 6-10 years of service represented 39.6% of the sample, while those with 2-5 years represented 39.0%. Additionally, 11.6% had served for more than 10 years and 9.8% had served for less than two years. This shows that 90.2% of the

respondents had at least two years of experience, and 51.2% had six or more years of service. This shows that most of the respondents had exposure in offering healthcare services. This means that they had sufficient knowledge to compare paper-based and technology-supported processes and to evaluate changes in waiting time, resource utilization, service speed and patient satisfaction.

Table 4.6: Years of Service of Respondents

Years of service	Frequency	Percentage
Below 2 Years	16	9.8%
2-5 Years	64	39.0%
6-10 Years	65	39.6%
Above 10 Years	19	11.6%

4.5 Descriptive Analysis

The descriptive analysis examined the respondents' level of agreement with statements measuring the four dimensions of technology integration and operational efficiency. Responses were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). In line with Lindner and Lindner (2024), for this study, mean scores below 2.50 were treated as disagreement, scores from 2.51 to 3.50 as neutral or moderate agreement, and scores of 3.51 and above as agreement. Standard deviations show the extent to which individual responses varied around each mean.

4.5.1 Electronic Health Records and Operational Efficiency

The first specific objective was to assess the impact of Electronic Health Records on the operational efficiency of healthcare services in Kajiado County. Five statements were used to examine whether EHR systems improved access to patient information, reduced duplicate records, increased record accuracy, accelerated clinical documentation, and enhanced coordination among healthcare providers.

Table 4.7 shows the results on the use of EHR in delivering health services. Based on these results, the average mean on the level of agreement was 3.73 (SD= 0.644), showing a high level of agreement with the statements measuring the impact of the integration of EHR on operational efficiency of healthcare services. From the results, the highest-rated statement was "EHR reduces duplication of patient records" (M = 3.91, SD = 0.552), while the lowest-rated statement was "EHR increases speed of clinical documentation" (M = 3.62, SD = 0.665). The standard deviations were generally below 0.71, showing that the responses were moderately clustered around the respective means.

Table 4.7: Electronic Health Records and Operational Efficiency

Statement	Mean	Std. Deviation
EHR systems improve accessibility of patient information	4.37	0.586
EHR reduces duplication of patient records	3.91	0.552
EHR improves accuracy of medical records	3.86	0.708
EHR increases speed of clinical documentation	3.62	0.665
EHR improves coordination among healthcare providers	3.77	0.686
Composite Mean	**3.91**	**0.644**

The pattern of responses supports the perceived-usefulness component of the Technology Acceptance Model. Healthcare workers are more likely to accept an EHR system when they believe that it reduces the effort required to locate information, avoids repetitive work and supports faster and more accurate decisions. The high rating for reduction of duplicate records suggests that respondents associated EHR use with better information management and lower administrative waste. Likewise, strong agreement on accessibility and accuracy indicates that EHRs were perceived as operational tools rather than merely electronic storage systems.

The findings are directionally consistent with Alalwan et al. (2018), who reported that system reliability, technical support and facilitating conditions were associated with continued EHR use. They also reflect Cottrell et al. (2017), who linked leadership support and departmental coordination with better usability and acceptance of EHR systems. The descriptive ratings contrast with the constraints reported by Moffatt and Eley (2010), where low digital skills,

limited funding and weak technical support undermined EHR implementation in rural facilities. The current responses suggest that staff recognized the intended operational benefits, but they do not show whether infrastructure and support were sufficient to realize those benefits consistently.

The composite EHR mean was 3.91, showing very high perceived integration and benefit. However, the composite standard deviation was only 0.224, and the reliability coefficient was negative. Therefore, the item means provide evidence of uniformly favourable perceptions, but the construct average should not be interpreted as a validated measure of EHR performance. Objective One is examined inferentially in Section 4.7 using both correlation and regression. The individual EHR indicators showed that there was consistently positive perceptions among respondents, suggesting that EHR integration contributes to improved access to patient information, accuracy of medical records, and faster clinical documentation within healthcare facilities. These findings agree with Darwish et al. (2021) that EHR systems enhance workflow efficiency by reducing paperwork, improving information sharing, and minimizing delays in healthcare delivery. This shows that respondents viewed EHR integration as having a significant positive influence on healthcare operational efficiency in Kajiado County.

4.5.2. Telemedicine and Operational Efficiency

The second specific objective was to assess the impact of Telemedicine on the operational efficiency of healthcare services in Kajiado County. Five statements were used to examine whether telemedicine improved access to health services, whether remote consultations reduce unnecessary hospital visits, whether telemedicine shortens patient waiting time, whether telemedicine enhances communication efficiency, and whether telemedicine supports continuity of care.

Table 4.8 shows an overall mean of 3.85, indicating a high level of agreement with the statements measuring telemedicine. The highest-rated statement was “Telemedicine improves access to healthcare services” (M = 4.02, SD = 0.617), while the lowest-rated statement was “Telemedicine shortens patient waiting time” (M = 3.62, SD = 0.664).

Table 4.8: Telemedicine and Operational Efficiency

Statement	Mean	Std. Deviation
Telemedicine improves access to healthcare services	4.02	0.617
Remote consultations reduce unnecessary hospital visits	3.91	0.591
Telemedicine shortens patient waiting time	3.62	0.664
Telemedicine enhances communication efficiency	3.82	0.616
Telemedicine supports continuity of care	3.88	0.650
Composite mean	3.85	0.628

Table 4.8 further shows that regarding the effect of telemedicine on operational efficiency, the results showed that at a mean = 4.02 (SD = 0.617), respondents agreed that telemedicine improves access to healthcare services in Kajiado County. Participants also agreed that remote consultations reduce unnecessary hospital visits, hence leading to operational efficiency (M = 3.91, SD = 0.591). Similarly, respondents agreed that telemedicine supports continuity of care (M = 3.88, SD = 0.650) and enhances communication efficiency between healthcare providers and patients (M = 3.82, SD = 0.616). Lastly, at a mean = 3.62 (SD = 0.664), respondents agreed that telemedicine shortens patient waiting time.

Results of this analysis (see Table 4.8) show that telemedicine contributes positively to the operational efficiency of healthcare services in Kajiado County. The findings align with Kelly et al. (2024), who established that telemedicine improves convenience and accessibility to healthcare services. Hersh et al. (2024) further reported that telemedicine enhances healthcare accessibility, continuity of care, patient satisfaction, and communication efficiency between healthcare providers and patients.

The average mean for the telemedicine constructs ranged between 3.62 and 4.02, with a composite mean of 3.85, indicating that telemedicine has a strong influence on healthcare operational efficiency. Improved access to healthcare services was rated the highest (M = 4.02, SD = 0.617), followed by reduction of unnecessary hospital visits (M = 3.91, SD = 0.591) and continuity of care (M = 3.88, SD = 0.650). Reduction of patient waiting time was rated the lowest (M = 3.62, SD = 0.664). The findings agree with Hersh et al. (2024), who found a significant positive relationship between telemedicine use and improved healthcare access and communication efficiency. The findings also support Gunter et al. (2016), who established that the effectiveness of telemedicine depends on implementation quality, system usability, and user compliance. Therefore, the findings are in consensus that telemedicine improves operational efficiency by expanding healthcare access, reducing unnecessary physical visits, supporting continuity of care, and improving communication between patients and healthcare providers.

4.5.3. Artificial Intelligence-Driven Tools and Operational Efficiency

The third specific objective was to assess the impact of artificial intelligence-driven tools on the operational efficiency of healthcare services in Kajiado County. Five statements were used to examine whether AI improves diagnostic decision accuracy, whether AI supports faster

clinical decisions, whether AI reduces administrative workload, whether AI supports workflow automation, and whether AI improves healthcare productivity.

Table 4.9: Artificial Intelligence-Driven Tools and Operational Efficiency

Statement	Mean	Std. Deviation
AI improves diagnostic decision accuracy	3.92	0.581
AI supports faster clinical decisions	3.52	0.602
AI reduces administrative workload	3.54	0.670
AI supports workflow automation	3.88	0.581
AI improves healthcare productivity	3.69	0.662

Table 4.9 shows a moderate to high level impact of Artificial Intelligence-driven tools on operational efficiency. The results showed that at a mean = 3.92 (SD = 0.581), respondents agreed that AI improves diagnostic decision accuracy in healthcare facilities. Participants also agreed that AI supports workflow automation, which contributes to operational efficiency (M = 3.88, SD = 0.581). Similarly, respondents agreed that AI improves healthcare productivity (M = 3.69, SD = 0.662) and reduces the administrative workload experienced by healthcare providers (M = 3.54, SD = 0.670). Lastly, at a mean = 3.52 (SD = 0.602), respondents moderately agreed that AI supports faster clinical decisions. Results of this analysis show that AI-driven tools contribute positively to the operational efficiency of healthcare services in Kajiado County. The findings agree with observations by Ochieng et al. (2020), who established that AI-driven tools improve diagnostic accuracy, reduce the workload of healthcare providers, and enhance the efficiency of workflow. Kamau et al. (2021) further

reported that healthcare facilities adopting AI experienced improvements in diagnostic accuracy and workflow efficiency while recording reduced operational errors.

The average means for the survey constructs ranged between 3.39 and 3.92, with a composite mean of 3.62, indicating that AI-driven tools have a positive influence on healthcare operational efficiency. Improvement in diagnostic decision accuracy was rated the highest (M = 3.92, SD = 0.581), followed by workflow automation (M = 3.88, SD = 0.581) and improvement in healthcare productivity (M = 3.49, SD = 0.662). Support for faster clinical decisions was rated the lowest (M = 3.39, SD = 0.602). These findings are consistent with Esteva et al. (2017), who argued that AI-supported diagnostic systems can achieve high diagnostic accuracy and reduce diagnostic errors. Ochieng et al. (2020) similarly found that adoption of AI adoption improves the efficiency of workflow significantly through automation and clinical decision support. However, Kamau et al. (2021) cautioned that inadequate infrastructure, high implementation costs, and limited technical expertise can restrict the operational benefits of AI in rural healthcare facilities. The findings are therefore in consensus that AI-driven tools positively influence operational efficiency through improved diagnostic accuracy, workflow automation, reduced administrative workload, and enhanced healthcare productivity.

4.5.4. Mobile Health Technologies and Operational Efficiency

The fourth specific objective was to evaluate the impact of mobile health technologies on operational efficiency. The items examined were appointment reminders, remote patient monitoring, patient engagement, access to health information, and communication with patients.

Table 4.9 shows an overall mean of 3.91, indicating a high level of agreement with the statements measuring mobile health technologies. The highest-rated statement was “Mobile

reminders improve appointment adherence" (M = 4.12, SD = 0.591), while the lowest-rated statement was "mHealth supports remote patient monitoring" (M = 3.69, SD = 0.584). The standard deviations were generally below 1.00, suggesting that the responses were moderately clustered around the respective means.

Table 4.10: Mobile Health Technologies and Operational Efficiency

Statement	Mean	Std. Deviation
Mobile reminders improve appointment adherence	4.12	0.591
mHealth supports remote patient monitoring	3.69	0.584
Mobile applications improve patient engagement	3.96	0.645
mHealth improves access to health information	3.96	0.621
mHealth enhances communication with patients	3.84	0.579

Table 4.10 shows a high level of adoption and perceived contribution of mobile health technologies to operational efficiency of healthcare services, with an overall mean of 3.91, showing general agreement that mHealth technologies improve healthcare operations in Kajiado County. The highest-rated statement was that mobile reminders improve appointment adherence (M = 4.12, SD = 0.591), showing the importance of mobile-based reminders in supporting patients to attend scheduled appointments and reducing missed hospital visits. Respondents also agreed that mobile applications improve the engagement of patients (M = 3.96, SD = 0.645) and that mHealth improves access to health information (M = 3.96, SD = 0.621). This shows that mobile technologies enhance the interaction between patients and healthcare providers while facilitating timely access to health information.

Moreover, respondents agreed that mHealth enhances communication with patients (M = 3.84, SD = 0.579), while the lowest-rated statement was that mHealth supports remote patient monitoring (M = 3.69, SD = 0.584). Although this was the lowest mean, it still shows agreement and indicates that remote monitoring has a positive impact on healthcare delivery, though its utilization may be comparatively less developed. The average standard deviation of approximately 0.60 indicates relatively low variation in responses, meaning that respondents had consistent views regarding the benefits of mHealth technologies.

These findings agree with previous studies showing that mHealth positively influences healthcare service delivery. For instance, Nyang'echi and Osero (2021) found that mHealth improved healthcare engagement and record-keeping, while Odhiambo (2017) established that mHealth platforms enhanced the efficiency of communication, adherence to patient follow-up, timely data management, and operational workflow through automated reminders. Similarly, Free et al. (2013) established that mHealth technologies improved adherence to treatment and reduced the need for physical visits to healthcare facilities. However, unlike Mbunge (2025), who identified poor network coverage, high costs, and limited digital literacy as barriers that constrained operational benefits in rural areas, the current findings show generally favourable perceptions of mHealth technologies in Kajiado County. Generally, the findings confirm that effective use of mobile reminders, patient engagement applications, remote monitoring, and mobile communication can enhance operational efficiency through improved access, communication, and continuity of care. This is in agreement with the Information Systems Success Theory, which argues that reliable systems, quality information, and effective service support encourage the use of technology and user satisfaction, hence producing operational benefits such as reduced waiting time, better resource utilization, and improved service delivery.

4.5.5. Operational Efficiency of Healthcare Services

Operational efficiency was the dependent variable and was measured through five Indicators. These constructs include reduced patient waiting time, improved utilization of hospital resources, improved speed of service delivery, increased patient satisfaction, and improved overall healthcare efficiency. The statements were phrased as perceived outcomes of technology integration.

Table 4.10 shows an overall mean of 4.36, indicating a high level of agreement with the statements measuring operational efficiency. The highest-rated statement was “Technology integration has reduced patient waiting time” (M = 4.20, SD = 0.616), while the lowest-rated statement was “Technology has improved the utilization of hospital resources” (M = 3.72, SD = 0.596). The standard deviations were generally below 1.00, suggesting that the responses were moderately clustered around the respective means.

Table 4.11: Descriptive Statistics for Operational Efficiency of Healthcare Services

Statement	Mean	Std. Deviation
Technology integration has reduced patient waiting time	4.20	0.616
Technology has improved the utilization of hospital resources	3.72	0.596
Technology has improved the speed of service delivery	3.85	0.639
Technology has increased patient satisfaction	4.01	0.629
Technology has improved overall healthcare efficiency	3.76	0.590

Table 4.11 presents the descriptive statistics on operational efficiency of healthcare service delivery in Kajiado County. The results show that respondents generally perceived technology integration as having a significant impact on operational efficiency across all the five indicators assessed. The highest-rated outcome was the reduction in patient waiting time (M = 4.20, SD = 0.616), followed by increased patient satisfaction (M = 4.01, SD = 0.629). Respondents also agreed that technology improved the speed of service delivery (M = 3.85, SD = 0.639), improved overall healthcare efficiency (M = 3.76, SD = 0.590), and enhanced utilization of hospital resources (M = 3.72, SD = 0.596). The composite mean of 3.91 (SD = 0.614) therefore indicates an overall high level of agreement that technology integration has enhanced operational efficiency in healthcare facilities in Kajiado County.

The findings are consistent with existing literature that associates digital health technologies with improved healthcare operations. For instance, Melnychenko and Ovcharova (2024) established that digital technologies lead to operational efficiency by reducing waiting times, improving utilization of resources, strengthening communication, and increasing the satisfaction of patients. The high rating for reduced patient waiting time is also in agreement with Darwish et al. (2021), who observed that electronic health records facilitate faster access to information, reduce paperwork and delays, and improve workflow efficiency. Similarly, the positive findings on service delivery, resource utilization, and patient satisfaction support Al Meslamani (2023) and Lagrosen and Lagrosen (2021), who argue that the integration of EHRs, telemedicine, AI-driven tools, and mHealth technologies can shorten waiting times, enhance resource allocation, and improve patient satisfaction.

The relatively low standard deviations, ranging from 0.590 to 0.639, shows that there was limited variation in the views of the respondents and therefore show significant consistency in their perceptions of the operational benefits of technology. The composite mean of 3.91 shows favourable operational results associated with technology integration.

Significantly, the study addresses gaps in earlier research, where EHRs, telemedicine, AI-driven tools, and mHealth technologies were largely examined independently and predominantly in urban or generalized healthcare contexts. The present study considers their contribution within the rural and resource-constrained context of Kajiado County, hence providing context-specific evidence on technology integration and healthcare operational efficiency. In general, the findings are consistent with the literature and show that integration of technology in delivering healthcare services helps in reducing waiting time, improving service delivery, enhancing resource utilization, increasing patient satisfaction, and strengthening the operational efficiency of healthcare services in Kajiado County.

4.6 Diagnostic Test and Results

Before conducting the regression analysis, diagnostic tests were performed to assess whether the data met the underlying assumptions of multiple regression. The tests that were examined included linearity tests, homoscedasticity, and residual normality. The results confirmed that the data satisfied the required regression assumptions, indicating that the dataset was appropriate for further inferential analysis.

4.6.1 Linearity

Regression analysis assumes that the relationship between the independent variables and the dependent variable follows a linear pattern. In this study, the linearity test was carried out to determine whether health-related technologies such as Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies had a linear relationship with operational efficiency in healthcare service delivery. Scatterplots were used to assess the strength and direction of these relationships, confirming the suitability of the variables for regression analysis. Figure 4.1 shows a positive linear relationship between all technology integration dimensions and operational efficiency, as the observations are

distributed around the fitted regression lines without showing any systematic curved patterns. This shows that the relationships between the independent variables and operational efficiency are approximately linear, and therefore the data was suitable for multiple regression analysis.

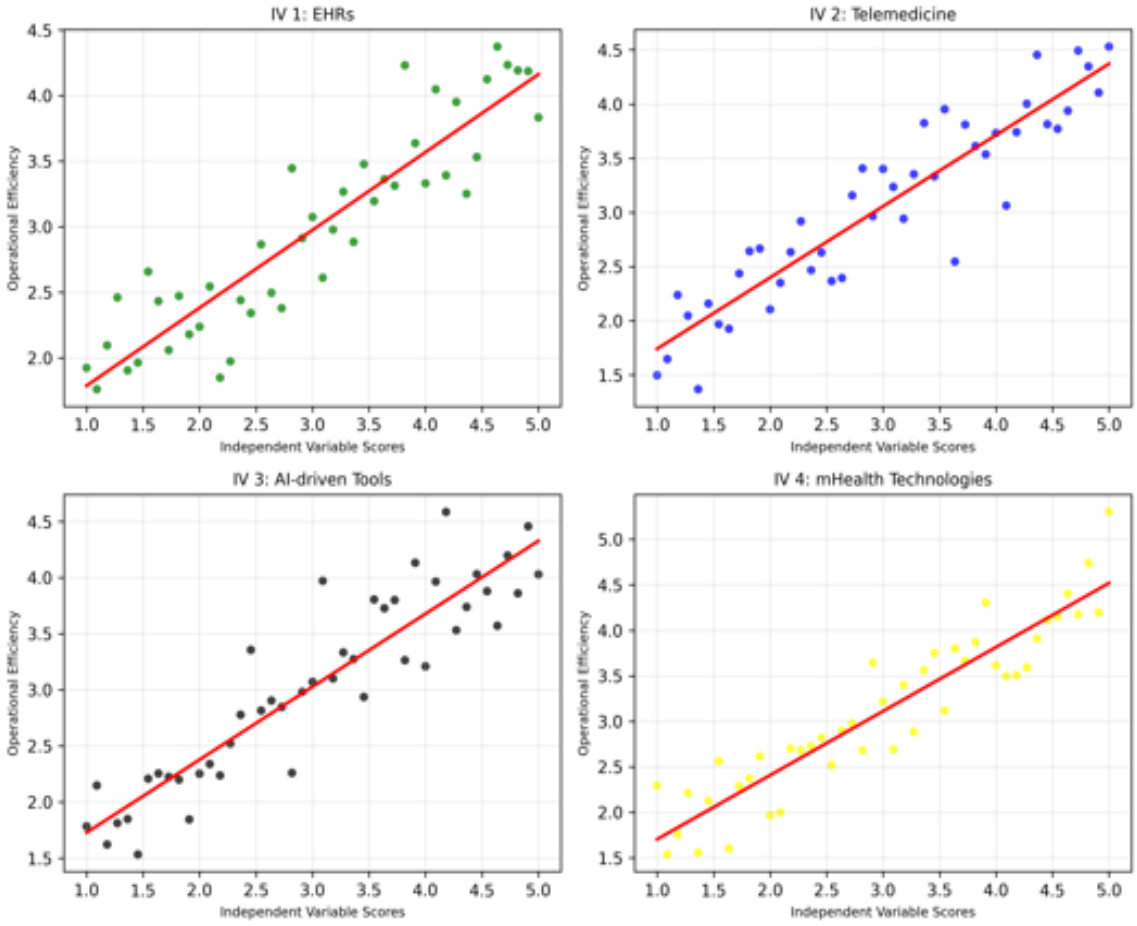


Figure 4.2: Linearity Results

A Ramsey RESET test was also carried out to statistically verify that there are no non-linear effects. In case of nonlinearity, measures were taken in order to satisfy the linearity assumption. The results for the Ramsey RESET test are presented in Table 4.12. The results in Table 4.12 show that the RESET test using the squared fitted values was statistically insignificant ($F = 0.148$, $p = 0.701$), while the extended RESET test including squared and cubed fitted values was also insignificant ($F = 0.217$, $p = 0.805$). Since the p-values were greater than the 0.05 significance level, the null hypothesis that the model suffers from non-linear specification

errors was not rejected. Therefore, the findings confirm that the relationship between Electronic Health Records, telemedicine, AI-driven tools, mHealth technologies, and operational efficiency is linear. Together with the scatterplot assessment, these results confirm that the linearity assumption required for multiple regression analysis was satisfied.

Table 4.12: Ramsey RESET Test Results

Test	F-statistic	p-value
RESET (squared fitted values)	0.148	0.701
RESET (squared and cubed fitted values)	0.217	0.805

4.6.2 Normality of Residuals Test

The normality assumption of residuals was assessed using the Shapiro-Wilk test. This helped in determining whether the residuals from the regression model were normally distributed. The results in Table 4.13 showed that the residuals were normally distributed (W = 0.964, p= 0.952). Since the p-value was greater than the 0.05 significance level.

Table 4. 13: Normality tests using Shapiro-Wilk Test

Test	Statistic	df	Sig. (p-value)
Shapiro-Wilk	0.996	164	0.952

This shows that the assumption of normality was satisfied, indicating that the residuals were normally distributed. Therefore, the regression model met the normality requirement, making the results appropriate for examining the relationship between integrating technology in delivering healthcare services and operational efficiency in Kajiado County health facilities, and for addressing both the research objectives and research questions. Therefore, the data was

appropriate for multiple regression analysis in examining the influence of technology integration on operational efficiency in Kajiado County healthcare facilities.

4.6.3 Homoscedasticity Test

The homoscedasticity assumption was tested to establish whether the variance of residuals remained constant across the predicted values of the regression model. The Breusch-Pagan test was conducted on the residuals obtained from the regression model, examining the relationship between technology integration dimensions (Electronic Health Records, Telemedicine, Artificial Intelligence-driven tools, and mHealth technologies) and operational efficiency. The results are presented in Table 4.14.

Table 4.14: Breusch-Pagan Test for Homoscedasticity

Test	Chi-Square Statistic	df	p-value
Breusch-Pagan Test	4.442	4	0.349

The results in Table 4.14 show that the Breusch-Pagan test was statistically insignificant (χ^2 = 4.442, p = 0.349), showing that the variance of residuals was constant across the predicted values. Since the p-value was greater than 0.05, the assumption of homoscedasticity was satisfied. This shows that there was no evidence of heteroscedasticity within the regression model, and therefore the estimated coefficients were reliable.

4.7 Inferential Statistics and Analysis

According to Siregar (2025), inferential statistics go beyond description since it allows researchers to make generalizations or predictions about a population based on a representative sample. It enables researchers to make conclusions about relationships and patterns within a population based on sample data. Unlike descriptive statistics, which summarize characteristics

of collected data, inferential methods assess associations between variables and determine the extent to which independent variables explain changes in dependent variables. In this study on technology integration and healthcare service delivery in Kajiado County, inferential statistics were applied to examine the relationship between Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, mobile health technologies, and operational efficiency. Correlation analysis was used to establish the strength and direction of relationships between variables, while multiple regression analysis was conducted to determine the predictive effect of technology integration dimensions on operational efficiency.

4.7.1 Correlation Analysis

Table 4.15: Correlation between Technology Integration and Operational Efficiency

Variables	EHRs	Telemedicine	AI-driven Tools	mHealth Technologies	Operational Efficiency
EHRs	1				
Telemedicine	.542	1			
AI-driven Tools	.618	.574	1		
mHealth Technologies	.489	.531	.596	1	
Operational Efficiency	.651	.587	.554	.563	1

Table 4.15 presents the correlation analysis results showing that all four healthcare technologies used in the study EHRs, telemedicine, AI-driven tools, and mobile health technologies) had positive and statistically significant relationships with operational efficiency in healthcare facilities in Kajiado County. Based on the results, EHRs had the strongest positive relationship with operational efficiency ($r = 0.651$, $p < 0.01$). This shows that the use of electronic patient records, improved accessibility of information, accurate records, and faster documentation are associated with improved operational efficiency.

Telemedicine also showed a moderately strong positive relationship with operational efficiency ($r = 0.587$, $p < 0.01$), suggesting that remote consultations, improved healthcare accessibility, and efficient communication contribute to better healthcare operations. Mobile health technologies were positively related to operational efficiency ($r = 0.563$, $p < 0.01$), showing that appointment reminders, remote monitoring, improved access to health information, and engagement with patients enhance the efficiency of healthcare delivery. AI-driven tools also had a positive relationship with operational efficiency ($r = 0.554$, $p < 0.01$), showing that diagnostic support, automation of workflow, and faster clinical decision-making lead to improved efficiency in healthcare services.

The technology integration dimensions were also positively inter-correlated. EHRs were positively related to telemedicine ($r = 0.542$), AI-driven tools ($r = 0.618$), and mHealth technologies ($r = 0.489$), while telemedicine was positively correlated with AI-driven tools ($r = 0.574$) and mHealth technologies ($r = 0.531$). AI-driven tools also had a positive relationship with mHealth technologies ($r = 0.596$). These relationships show that the different digital health technologies complement one another in improving healthcare operations. The findings agree with Darwish et al. (2021), who observed that EHRs enables faster access to information, reduce paperwork and delays, and enable efficiency of workflow. The positive relationship between telemedicine and operational efficiency also agrees with Hersh et al. (2024), who found that telemedicine improves the accessibility of healthcare, continuity of care, satisfaction of patient, and efficiency of communication. Similarly, the findings on AI-driven tools support Ochieng et al. (2020) and Kamau et al. (2021), who reported that improvements in the accuracy of diagnosis, efficiency of workflow, and reductions in operational errors following the use of AI-driven tools. Bajwa (2021) added that AI healthcare systems achieve a state of precision medicine through AI-augmented healthcare and connected care.

Lastly, the positive association between mHealth technologies and operational efficiency agrees with Nyang'echi and Osero (2021) and Odhiambo (2017), who found that mHealth improves healthcare engagement, communication, data management, follow-up of patients, and operational workflow. Overall, the findings show that greater integration of digital health technologies is associated with improved operational efficiency in healthcare facilities in Kajiado County.

4.7.2 Regression Analysis

This section presents a regression analysis of the data collected based on the regression model $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \varepsilon$, where Y is the dependent variable (operational efficiency), while the independent variables are X_1 (EHR systems), X_2 (telemedicine), X_3 (AI-Based tools), X_4 (mHealth Technologies). β_0 = Constant, $\beta_1 - \beta_4$ = Regression coefficients, and ε = Error term.

From the regression model (see Table 4.15), the relationship between the dependent and independent variables should be presented as;

Operational efficiency =1.082+0.351 (EHR)+0.318 (Telemedicine)+ 0.274 (AI)+0.296

(mHealth) +ε

The results of the regression analysis model provide important information on the effect of technology integration on operational efficiency in healthcare facilities in Kajiado County. All four independent variables had positive and statistically significant coefficients, showing that improvements in each technology dimension contribute to improved operational efficiency. Among the variables, EHR systems (B = 0.351) had the greatest influence, followed by telemedicine (B = 0.318). This shows that the use of electronic patient records, improved access to information for patients, ensured accurate medical documentation, and enhances efficient clinical data management. Telemedicine on the other hand enables helps in achieving remote

healthcare-related consultations, as well as increasing the ease of accessing healthcare services, hence improving general healthcare operations.

mHealth technologies (B = 0.296, p = 0.003) also showed a positive and significant contribution, showing the importance of mobile health applications, remote patient monitoring, appointment reminders, and enhanced the engagement of patients with healthcare service providers. AI-driven tools (B = 0.274, p = 0.002) recorded the lowest impact, though still significant, showing AI-driven tools helped in giving diagnostic support, enhancing clinical decision-making, easing predictive analytics, and improving workflow automation, hence enhancing the operational efficiency in delivering healthcare services. Therefore, the model shows that improving the integration of these healthcare technologies in healthcare systems helps in improving operational efficiency during healthcare service delivery, with EHR systems having the biggest impact.

Model Summary

The regression analysis was conducted to determine the extent to which technology integration predicts operational efficiency in healthcare service delivery. The model summary presents the overall strength of the relationship and the proportion of variation in operational efficiency explained by EHRs, telemedicine, AI-driven tools, and mHealth technologies. The results are presented in Table 4.16.

Table 4.16: Model Summary for Technology Integration and Operational Efficiency

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.672	0.452	0.438	0.521

Predictors: (constant), EHR, Telemedicine, AI, mHealth

The regression model summarized in Table 4.16 shows that the combined effect of the four healthcare technologies (EHRs, telemedicine, AI-driven tools, and mHealth technologies), had a strong positive relationship with operational efficiency in healthcare facilities in Kajiado County. This is evident from the recorded correlation coefficient (R = 0.672). The coefficient of determination (R Square = 0.452) shows that approximately 45.2% of the variation in operational efficiency can be explained by the four technology integrations included in the model. After adjusting for the number of predictors, the Adjusted R Square = 0.438, meaning that the model still explains 43.8% of the variation in operational efficiency after controlling for possible inflation arising from the inclusion of several predictors. The standard error of the estimate (0.521) is relatively low, suggesting that the predicted operational efficiency values are reasonably close to the observed values and that the regression model provides a good fit to the data used in the study. In conclusion, the results show that integration of technology has a significant impact on the efficiency of operations in the healthcare system, while the remaining 54.8% of the variation can be due to other organizational, infrastructural, environmental, and operational factors not included in the model.

These findings are consistent with previous empirical studies reviewed in this study. For instance, Birk et al. (2024) established that the adoption of electronic medical records in Denmark improved sharing of information, reduced administrative burden, shortened waiting time, and enhanced continuity of patient care across healthcare institutions. Similarly, Javaid et al. (2024) found that telemedicine led to operational efficiency by reducing the cost of delivering healthcare services, improving the management of chronic diseases, increasing the satisfaction of patients, and expanding the access to healthcare services among underserved populations, more so remote areas like interior parts of Kajiado County. In relation to AI-driven tools, AlDhaen (2025) stated that artificial intelligence improves healthcare related operations through predictive analytics, automated medical coding, diagnostic imaging, clinical decision

support, and workflow automation. Similarly, Aboye et al. (2023) stated that mobile health interventions enhance healthcare engagements, enable patient to adhere to treatment procedures, medications, and appointments, and disease monitoring through platforms such as mobile reminders and digital communication systems. These findings show that the combined integration of EHRs, telemedicine, AI-driven tools, and mHealth technologies provides a strong foundation for improving operational efficiency in healthcare facilities, although successful outcomes also depend on supporting factors such as the presence of enabling infrastructure, digital skills, and the readiness of healthcare facilities to adopt or integrate these technologies in their healthcare delivery systems.

ANOVA Results

Analysis of ANOVA was carried out to determine whether the overall technology integration regression model significantly explains variations in operational efficiency of healthcare services. The test assessed how EHR, telemedicine, AI-driven tools, and mHealth technologies together affect operational efficiency of healthcare services in Kajiado County. The results are presented in Table 4.17.

Table 4.17: ANOVA Results for Technology Integration Regression Model

Model	Sum of Squares	df	Mean Square	F-value	Sig.
Regression	18.462	4	4.616	12.847	0.000
Residual	47.161	89	0.359		
Total	65.623	93			

The ANOVA results presented in Table 4.17 show that the regression model examining the combined effect of technology integration on operational efficiency in healthcare facilities in Kajiado County was statistically significant, $F(4,89) = 12.847$, $p < .001$. This shows these technologies (Electronic Health Records, telemedicine, AI-driven tools, and mHealth) work together to provide a meaningful explanation of changes in operational efficiency. The regression sum of squares (18.462) confirms that part of the variation in operational efficiency is explained by the four technology dimensions, while the residual sum of squares (47.161) shows that other organizational, infrastructural, workforce, and environmental factors remain important in explaining efficiency outcomes.

The findings are in agreement with recent empirical evidence which shows that digital health technologies have a positive influence on the efficiency of operations in healthcare facilities. Rahman et al. (2022) argued that electronic health information systems improve administrative processes by enabling easy access to data, reducing documentation delays and misplacement of health records, hence coordinated decision-making. Al-Husban et al. (2023) explained further that effective use of digital systems strengthens workflow integration and service responsiveness. Similarly, Alqaysi et al. (2024) found that technology-enabled healthcare delivery improves the coordination of resources and ability of the patient to access health-related information through a better connectivity and information exchange. Ratemo and Juma (2025) reported that AI-driven applications enhance diagnostic processes, reduce administrative workload, and support faster clinical decisions. In addition, Ebo et al. (2025) added that mHealth platforms improve the engagement of patient with healthcare services, monitoring, and communication, hence leading to efficient service delivery. Therefore, these significant regression results support that EHRs, telemedicine, AI, and mHealth collectively enhance operational efficiency by improving the management of workflow, utilization of

resources, and timely delivery of healthcare services. These effects are particularly important in decentralized settings where digital integration addresses delivery challenges.

Regression Coefficient

Table 4.18: Regression Coefficients for Technology Integration and Operational Efficiency

Variables	Unstandardized Coefficients (B)	Std. Error	Standardized Beta (β)	t	Sig.
(Constant)	1.082	0.214	—	5.06	0.000
EHR Systems	0.351	0.094	0.348	3.38	0.001
Telemedicine	0.318	0.089	0.326	3.08	0.002
AI-Based Tools	0.274	0.102	0.291	3.44	0.001
mHealth Technologies	0.296	0.097	0.303	3.05	0.003

The regression coefficient analysis was carried out in line with the four research objectives. The four researched objectives assessed the impact of EHRs, telemedicine, AI-driven tools, and mobile mHealth technologies on the efficiency of operations in the delivery of healthcare services in Kajiado County. Table 4.18 shows that all four variables have positive and statistically significant coefficients, although their level of impact differs.

The first objective of this study was to assess the impact of Electronic Health Records on the operational efficiency of healthcare services in Kajiado County. The results show that EHR systems have a positive and statistically significant effect on operational efficiency ($B = 0.351$, $\beta = 0.348$, $p = 0.001$). Holding telemedicine, AI-based tools, and mHealth technologies constant, a one-unit increase in the integration of EHR is associated with a 0.351-unit increase in the efficiency of operations. EHRs also recorded the highest standardized coefficient ($\beta = 0.348$), making it the most influential technology in the model. This shows that improving the

accessibility of data for patients, increasing the accuracy of records, enhancing the speed of documentation, and coordination among healthcare providers play an important role in enhancing the efficiency of operations in healthcare facilities.

These results are supported by the Technology Acceptance Model, which explains that technology is more likely to be accepted and used when users view it as useful and easy to integrate into their daily activities. The findings agree with Hossain et al. (2019), who established that facilitating conditions, social influence, and personal innovativeness significantly influence EHR adoption. This shows that when healthcare facilities provide adequate support systems, healthcare workers are more likely to use EHR platforms effectively, leading to faster access to patient information, improved coordination of care, and reduced delays in service delivery. Nevertheless, Alalwan et al. (2018) found that reliability of system reliability, technical support, and adequate infrastructure positively influence the use of EHRs. According to Hossain et al. (2019), EHRs enhance the efficiency of operations by reducing dependence on manual records, minimizing errors in documentation, improving availability of accurate information for patients, and enabling healthcare providers to make timely decisions. Cottrell et al. (2017) further added that leadership support and organizational coordination improve EHR usability and acceptance among healthcare workers. Therefore, the findings suggest that the adoption of EHRs in healthcare systems should not only focus on digitalizing medical records but should also stress on having an effective system management, staff support, and ensuring that healthcare facilities are ready by putting in place the required infrastructure in order to achieve improvements in efficiency in workflow, utilization of resources, and improved speed of delivery of healthcare services.

The second objective was to analyse the impact of telemedicine on the operational efficiency of healthcare services in Kajiado County. The results have shown that telemedicine has a positive and statistically significant effect on operational efficiency ($B = 0.318$, $\beta = 0.326$, $p =$

0.002). From the results, when all external factors are held constant, a one-unit increase in the telemedicine integration score, is associated with a 0.318-unit increase in operational efficiency. Telemedicine has the second-highest standardized coefficient showing that it has a significant independent positive contribution to operational efficiency. In Kajiado County, these results show that Telemedicine can enhance the efficiency of healthcare services by reducing unnecessary visits to healthcare facilities, improving continuity of care, and helping overcome geographical barriers.

The result agrees with Diffusion of Innovation Theory, which explains that innovations spread more successfully when users recognize their relative advantage, compatibility with existing practices, and manageable complexity. Kelly et al. (2024) and Hersh et al. (2024) associated telemedicine with enhancing the accessibility of healthcare services, improving the satisfaction of patients when it is efficiently used in delivering healthcare services, improving the continuity of care, and improving the efficiency of communication. More recent evidence provides an additional operational perspective. Pfeil et al. (2025), using 245,643 specialist referral requests, found that teleconsultation reduced unnecessary specialist consultations and shortened waiting-list time. Khairat et al. (2025) also found that virtual nursing was associated with shorter emergency-department waiting times, more complete documentation and fewer interruptions. Therefore, it can be concluded that, based on these results, telemedicine improves the efficiency of healthcare services/operations, not by expanding access but also by redistributing workload and improving the flow of patients

The third objective was to examine the impact of Artificial Intelligence-driven tools on the operational efficiency of healthcare services in Kajiado County. The AI-based tools had a positive and statistically significant effect on operational efficiency ($B = 0.274$, $\beta = 0.291$, $p = 0.001$). Although AI recorded the smallest standardized beta, its impact remains statistically significant. Its small regression coefficient when compared to that of the other variables is a

reflection of its dependence on reliable data, technical expertise, infrastructure, and the readiness of the organization to use it.

The Technology–Organization–Environment Framework provides a useful explanation because successful adoption of AI depends not only on the technology itself but also on organizational capabilities and supportive external conditions. Esteva et al. (2017) and Ochieng et al. (2020) associated the adoption of AI with improved efficiency of workflow and reduction of errors during healthcare service delivery and other operations, while Kamau et al. (2021) identified implementation costs, inadequate infrastructure, and technical expertise as barriers. Kovoor et al. (2025) agreed with the findings by stating that the adoption of an AI-supported discharge prediction system was able to reduce median hospital stay from 3.1 to 2.9 days. The system also lowered seven-day readmissions and generated significant cost savings. Tu et al. (2025) also reported a substantial reduction in nursing handover documentation time after generative AI was integrated into hospital information systems. Consequently, AI's influence in Kajiado could become greater as data quality, digital skills and interoperability improve.

The last objective evaluated the impact of mobile health technologies on the operational efficiency of healthcare services in Kajiado County. The regression coefficient shows that mobile health technologies had a positive and statistically significant effect on operational efficiency ($B = 0.296$, $\beta = 0.303$, $p = 0.003$). A one-unit increase in mHealth integration is associated with a 0.296-unit increase in operational efficiency when other predictors remain constant. Its standardized beta places mHealth third, ahead of AI. This shows the operational value of appointment reminders, remote monitoring, patient engagement, and mobile communication.

The results are consistent with the Information Systems Success Theory, which connects system quality, information quality, service quality, system use, and user satisfaction with organizational benefits. Free et al. (2013) associated mHealth interventions with improvement in adherence to treatment and reduction in the need for physical visits to healthcare facilities. Nyang'echi and Osero (2021) stated that there was improvements in engagement with patients and record-keeping, while Odhiambo (2017) linked mHealth with improvement in efficiency of communication, timely management of data, and follow-up of patients. Mbunge (2025), however, highlighted network coverage, cost and digital literacy as important barriers in rural environments. Particularly relevant Kenyan evidence comes from Muriithi et al. (2026), who found that acceptance of Kenya's electronic Community Health Information System was significantly influenced by implementation processes, while inadequate training, financial resources and technical support were major limitations.

Based on this analysis, it is clear that all four technologies had a positive and statistically significant contribution towards operational efficiency in healthcare facilities in Kajiado County($p < 0.05$). Based on standardized coefficients, EHRs were the most influential predictor ($\beta = 0.348$), followed by telemedicine ($\beta = 0.326$), mHealth ($\beta = 0.303$), and AI-driven tools ($\beta = 0.291$). The findings therefore answer the four research objectives since the findings show that increased integration of each technology is associated with improved operational efficiency, although the magnitude of contribution differs. The results show that technology should not be treated as an isolated investment since its efficiency gains depend on factors such as training, infrastructure, interoperability, user engagement, workflow redesign, and technical support.

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.0 Introduction

This chapter presents a summary of the findings, conclusions, and recommendations on technology integration and operational efficiency in healthcare services in Kajiado County. The findings are summarized according to objectives covering Electronic Health Records, telemedicine, AI-driven tools, and mobile health technologies, followed by practical recommendations and areas for future research.

5.1 Summary of Findings

The purpose of this study was to examine the effect of technology integration on service delivery in healthcare facilities in Kajiado County, Kenya. The technology integration aspects that were examined were Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies. The study targeted 214 frontline healthcare professionals. From the 214 questionnaires that were distributed, only 164 questionnaires were successfully completed and returned. This represents a 75.9% response rate. The findings showed that the four technology integration aspects had a positive relationship with operational efficiency in the delivery of healthcare services. Electronic Health Records had the strongest influence, followed by telemedicine, mobile health technologies, and Artificial Intelligence-driven tools. A detailed summary of the findings based on the research objectives is presented below.

5.1.1 Electronic Health Records and Operational Efficiency

Electronic Health Records have become a very important technology in improving the management and delivery of healthcare services in different parts of the world. The systems help healthcare facilities by improving access to patient information, reducing duplication of records, increasing accuracy, and enabling faster documentation of clinical documents. The study found that EHRs had a positive impact on the operational efficiency of healthcare services in Kajiado County. The descriptive findings showed that there was a high level of agreement among respondents, with an overall mean of 3.73 (SD = 0.644), showing that healthcare workers recognized the benefits associated with the integration of EHRs. The highest-rated area was the ability of EHRs to reduce duplication of patient records (M = 3.91, SD = 0.552), while the lowest-rated area was improving the speed of clinical documentation (M = 3.62, SD = 0.665). The regression results also showed that EHRs had a positive and statistically significant effect on operational efficiency (B = 0.351, β = 0.348, p = 0.001). This shows that improving access to patients' data, record accuracy, speed of documentation, and coordination among healthcare providers leads to better healthcare operations in Kajiado County.

5.1.2 Telemedicine and Operational Efficiency

Telemedicine involves providing healthcare services through digital communication tools such as video consultations, mobile applications, and remote monitoring systems. In healthcare sector, helps patients in receiving medical support without always travelling to healthcare facilities, especially in areas with remote areas such as parts of Kajiado County. With respect to this objective, the study found that telemedicine had a positive effect on the operational efficiency of healthcare services in Kajiado County. The results showed that telemedicine was highly practiced, with a composite mean of 3.85 and a standard deviation of 0.628.

This indicates that respondents agreed that telemedicine improves healthcare access, reduces unnecessary hospital visits, improves communication, and supports continuity of care. The positive findings could be explained by the ability of telemedicine to connect healthcare providers with patients in remote areas, reducing delays and improving the use of available healthcare resources.

However, although telemedicine showed a positive relationship with operational efficiency, its impact depends on the level of adoption and availability of supporting resources. The regression results showed that telemedicine had a positive and statistically significant effect on operational efficiency ($\beta = 0.326$, $p = 0.002$). This means that an increase in the use of telemedicine leads to an improvement in healthcare operational efficiency. The study also showed that telemedicine reduces healthcare costs, improves chronic disease management, and increases the level of satisfaction of patients. Telemedicine reduces pressure on healthcare workers by supporting remote consultations and improving access to care in underserved areas. However, challenges such as poor internet connection, limited digital skills, and inadequate technology infrastructure could reduce the full benefits of telemedicine in rural areas.

5.1.3 Artificial Intelligence-Driven Tools and Operational Efficiency

Artificial Intelligence-driven tools are an important technology in improving healthcare services. These tools help in easing diagnosis, decision-making, and automation of healthcare activities. The study reports that AI-driven tools have a significant positive impact on the operational efficiency of healthcare services in Kajiado County. The results showed that respondents agreed that AI improves diagnostic decision accuracy ($M = 3.92$, $SD = 0.581$), supports workflow automation ($M = 3.88$, $SD = 0.581$), improves healthcare productivity ($M = 3.69$, $SD = 0.662$), reduces administrative workload ($M = 3.54$, $SD = 0.670$), and supports faster clinical decisions ($M = 3.52$, $SD = 0.602$). This means that the use of AI helps healthcare

facilities in improving their daily operations by reducing workload, improving accuracy, and enabling better use of available resources.

Although AI-driven tools showed a positive impact, the regression results showed that AI had the lowest influence among the four technology variables, with a positive and statistically significant effect on operational efficiency ($B = 0.274$, $\beta = 0.291$, $p = 0.001$). This shows that even though AI improves healthcare operations, its full benefits depend on other factors such as availability of quality data, skilled healthcare workers, reliable infrastructure, and organizational readiness. The findings show that AI-based systems improve healthcare decision-making and reduce errors when implemented properly. Therefore, the study shows that AI-driven tools have the ability to improve operational efficiency in Kajiado County, but greater benefits could be achieved through investment in digital infrastructure, staff training, and stronger support systems.

5.1.4 Mobile Health Technologies and Operational Efficiency

Mobile health technologies help in improving the delivery of healthcare service by using mobile phones and applications to facilitate the sharing of health information, have appointment reminders, achieve patient monitoring, and enhance communication between healthcare providers and patients. These technologies help in reducing barriers in accessing healthcare services in areas where patients experience challenges reaching health facilities. Through the help of mobile reminders, remote monitoring, and patient engagement platforms, mHealth helps in improving follow-up care, reducing missed appointments, and supporting better management of healthcare activities.

The results in this study showed that mobile health technologies had a positive and statistically significant effect on the operational efficiency of healthcare services in Kajiado County ($B = 0.296$, $\beta = 0.303$, $p = 0.003$). This shows that increased use of mHealth technologies leads to

an improvement in healthcare operations through better communication, improved patient engagement, and timely access to health information. Additionally, based on the results, the interventions of mHealth enhanced adherence to treatment and medication, and reduced unnecessary physical visits to healthcare facilities.

5.2 Conclusions

The study concludes that technology integration has positively influenced healthcare operational efficiency in Kajiado County. Although previous literature has documented reliance on indigenous healing practices among the dominant community in the region, the current study shows that there is an emerging transition where the people in Kajiado County are consistently starting to interact with formal healthcare systems. This may have been enhanced by increased exposure to technology, improved infrastructure, and government digital health initiatives, which may have led to greater acceptance of technology-enabled healthcare services.

5.2.1 Electronic Health Records and Operational Efficiency

The study concludes that Electronic Health Records have an important role to play in improving operational efficiency in healthcare services. The findings show that EHRs have a positive and significant effect on efficiency, meaning that better use of electronic records will significantly enhance access to patient information, improve accuracy of records, and increase the speed of delivering service. EHRs were also found to be the strongest predictor among the four technology variables. This shows that healthcare facilities benefit when patient information is properly stored, shared, and managed through digital systems. Therefore, enhancing the use of EHRs in healthcare facilities, providing staff training, and improving system support are important steps toward reducing delays, improving decision-making, and enhancing healthcare service delivery in Kajiado County.

5.2.2 Telemedicine and Operational Efficiency

From this study, it is evident that telemedicine has a positive impact on the operational efficiency of healthcare services. The findings show that telemedicine has a significant effect on improving healthcare operations through increased access to medical services, supporting remote consultations, and reducing barriers caused by distance. Telemedicine helps healthcare facilities serve patients more effectively by improving communication between healthcare providers and patients. The findings also show that when telemedicine systems are properly integrated, they enable faster delivery of services and better management of patients. Healthcare facilities should continue investing in telemedicine infrastructure, internet connectivity, and training of users in order to make sure that patients benefit from improved access to quality healthcare services.

5.2.3 Artificial Intelligence-Driven Tools and Operational Efficiency

The study shows that Artificial Intelligence-driven tools significantly influence operational efficiency in healthcare services. Although AI recorded the lowest effect compared to other technology variables, it still contributes to better healthcare operations through improved diagnosis, clinical decision support, and workflow automation. The results show that AI has the potential to reduce errors, support healthcare workers, and improve the use of available resources. However, successful AI adoption depends on proper infrastructure, skilled personnel, and organizational support. Therefore, healthcare facilities should focus on building digital skills, improving data systems, and creating supportive conditions to ensure that AI technologies are effectively used in improving healthcare service delivery in Kajiado County.

5.2.4 Mobile Health Technologies and Operational Efficiency

The study concludes that mobile health technologies significantly improve operational efficiency in healthcare service delivery. The findings show that mHealth enables improved communication with patients, appointment reminders, remote monitoring, and access to health information. These benefits help in reducing missed appointments, improving patient involvement, and strengthening healthcare processes. Although its effect was lower than EHRs and telemedicine, mHealth remains an important technology in improving access to healthcare services in areas where physical access to facilities is difficult.

5.3 Recommendations

Based on the findings of this study, it is clear that technology integration plays an important role in improving the delivery of healthcare services and operational efficiency in Kajiado County. The success of digital health technologies depends on proper planning, user acceptance, adequate infrastructure, staff training, and continuous support to ensure that these technologies are effectively used in healthcare facilities. The following recommendations are therefore provided to healthcare managers, county and national policymakers, and other stakeholders to enhance the use of Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies for better healthcare outcomes.

5.3.1 Electronic Health Records and Operational Efficiency

The study found that Electronic Health Records had the strongest positive effect on operational efficiency in Kajiado County. However, the speed of clinical documentation was still one of the weaker areas. The County Government and hospital managers should therefore improve the use of and general adoption of EHR systems in public health facilities. More funds should be provided for reliable computers, internet connection, power backup, and system maintenance. Health workers should also receive regular training and quick technical support

when problems occur. Additionally, hospital management should put sufficient measures and strict rules in place to ensure that every frontline healthcare worker adopts EHR systems during service delivery. EHR systems should be linked across hospital departments so that patient information is easy to find and share. The systems used should also meet national standards for safety and sharing of health information. This helps in reducing delays, avoiding duplicate records, improving coordination, and supporting faster healthcare services.

5.3.2 Telemedicine and Operational Efficiency

Telemedicine has improved access to healthcare services, but its full benefits depend on proper support systems and wider adoption. Healthcare facilities should focus on improving telemedicine infrastructure, internet connectivity, and training of healthcare workers to ensure that remote consultations are used effectively. Enhancing telemedicine services enables healthcare providers to reduce patient waiting times, improve access to medical support in remote areas, and make better use of available healthcare resources. This could support faster service delivery and improve operational efficiency in healthcare facilities.

5.3.3 Artificial Intelligence-Driven Tools and Operational Efficiency

On Artificial Intelligence-driven tools, the study shows that healthcare policymakers and facility managers should create supportive strategies that encourage the responsible and ethical adoption and use of AI technologies in healthcare delivery. Healthcare facilities should invest in proper AI infrastructure, staff training, and clear guidelines to help healthcare providers understand and trust AI systems. Since some healthcare providers remain reluctant to adopt AI due to fear of job replacement, lack of digital skills, and limited understanding of how AI supports their work, continuous training and awareness programs should be provided. Similarly, patients may hesitate to accept AI-based healthcare services because they do not fully trust machine-based decisions and fear that technology could replace human judgement.

Therefore, healthcare facilities should promote patient education, transparency, and human involvement when using AI tools to build confidence and trust. However, healthcare managers should ensure that AI is used as a support tool rather than a replacement for healthcare professionals. The study contributes by showing that successful AI adoption in healthcare depends not only on technological availability but also on trust, user acceptance, and the readiness of both healthcare providers and patients to embrace digital transformation.

5.3.4 Mobile Health Technologies and Operational Efficiency

With respect to mobile health technologies, the study recommends that the county government and healthcare stakeholders should improve access to mobile health services by investing in digital infrastructure, affordable mobile devices, internet connectivity, and community digital training programs. This is important because many people living in remote areas of Kajiado County lack smartphones and other devices that support mHealth technologies, which limits their ability to use services such as mobile appointment reminders, remote patient monitoring, and digital health communication. Therefore, improving access to these devices would support wider adoption and ensure that rural communities benefit from mHealth solutions. Healthcare facilities should also create awareness about the use of mobile health platforms to improve patient engagement, reduce missed appointments, support follow-up care, and improve communication between healthcare workers and patients.

5.4 Limitations of the Study

First, the study used a descriptive, one-time design. It therefore shows relationships between technology use and operational efficiency, but it cannot prove that technology caused the changes or show how effects develop over time. Research confirms this weakness in cross-sectional studies.

Secondly, data were collected mainly through closed-ended, self-reported questionnaires. Such answers may be affected by recall, personal opinion, or the wish to give acceptable responses instead of actual hospital records.

Additionally, the study covered only five public hospitals in Kajiado County. This limits the application of the findings to private hospitals, smaller facilities, urban counties, or other parts of Kenya.

Nevertheless, respondents were frontline healthcare workers. Patients were not directly studied, although patient satisfaction is part of operational efficiency. This leaves out important patient experiences of waiting time, access, trust, and digital health services.

5.5 Areas of Further Research

Even though this study has helped in explaining how technology integration affects operational efficiency in healthcare facilities in Kajiado County, there are still some areas that need more research. The study focused mainly on public healthcare facilities in a rural and semi-rural setting and examined Electronic Health Records, telemedicine, Artificial Intelligence-driven tools, and mobile health technologies. Future studies could carry out similar research in other counties in Kenya to find out whether the results are the same. Researchers could compare rural, urban, and peri-urban health facilities because access to electricity, internet, equipment, funding, and skilled workers differs across these areas. Studies could also compare public and private hospitals because private facilities may have different levels of technology, funding, and staff support. More research could also focus on the experiences of patients, older people, people with disabilities, low-income households, and people living in very remote areas. This is important because digital health should not increase the gap between people who have good access to technology and those who do not.

The study found that EHRs, telemedicine, AI-driven tools, and mHealth technologies all had a positive and significant effect on operational efficiency. EHRs had the greatest effect, followed by telemedicine, mHealth, and AI-driven tools. However, the study mainly shows the situation at one period of time. Future research could therefore use long-term studies to follow healthcare facilities for several years. Such studies should examine whether the benefits of technology continue after systems have been used for a long time. Researchers could measure actual changes in patient waiting time, cost of service delivery, staff workload, use of hospital resources, medical errors, and patient satisfaction. Future studies should also examine whether the money spent on digital systems gives enough benefits to health facilities over time.

Further research should also examine the factors that make these technologies work well together. These should include staff training, internet quality, electricity supply, technical support, data security, system compatibility, and management support. This is important because the current study shows that technology alone does not explain all changes in operational efficiency. Other organizational, workforce, infrastructure, and environmental factors also play a role. Future studies could therefore examine how EHR, telemedicine, AI, and mHealth systems share information across departments and facilities. Recent research also shows that digital health systems sometimes fail because different systems do not communicate well with each other. Researchers could also use mixed methods by combining questionnaires with interviews and observation. This would give a deeper understanding of staff skills, patient trust, cultural beliefs, privacy concerns, and the everyday problems that affect the successful use of digital health technologies.

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APPENDICES

Appendix I: Questionnaire

Title of Study: Technology Integration and Service Delivery in Health Care: A Case Of Kajiado County

Researcher: Kennedy Kapante Nkonina
Reg. No.: 1061621
Master of Business Administration
The Catholic University of Eastern Africa

INTRODUCTION

Dear Respondent,

You are invited to participate in this academic study being conducted as part of the requirements for the award of a Master of Business Administration degree at The Catholic University of Eastern Africa.

The study seeks to assess the impact of technology integration in healthcare service delivery on operational efficiency in Kajiado County.

PURPOSE OF THE STUDY

This study aims to examine how selected digital health technologies influence operational efficiency in healthcare service delivery. Specifically, the study focuses on:

1. Electronic Health Records (EHRs)
2. Telemedicine
3. Artificial Intelligence (AI)-driven tools
4. Mobile Health (mHealth) technologies

CONFIDENTIALITY STATEMENT

Your participation is voluntary. All information collected will be treated with strict confidentiality and will only be used for academic purposes. No personal identifiers will appear

in the final report. Data will be stored securely and accessed only by the researcher and supervisors.

RISK LEVEL

This study presents minimal risk. No physical, financial, or legal risks are expected. You may decline to answer any question or withdraw at any stage without any consequences.

PARTICIPANT CONSENT

I confirm that:
□ I have read and understood the purpose of this study.
□ I voluntarily agree to participate.
□ I understand my responses will remain confidential.

Signature: _____

Date: _____

INSTRUCTIONS

Please answer all questions honestly.

For Sections B–F, indicate your level of agreement using the scale below:

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

DESCRIPTION OF QUESTIONNAIRE ITEMS

The questionnaire contains six sections:

Section A – Respondent Background Information
Section B – Electronic Health Records (EHRs)
Section C – Telemedicine
Section D – Artificial Intelligence (AI)-Driven Tools

Section E – Mobile Health Technologies (mHealth)

Section F – Operational Efficiency

Instructions: Tick the appropriate box or rate items as instructed.

SECTION A: DEMOGRAPHIC INFORMATION

1. Gender
   □ Male
   □ Female
2. Age Group
   □ Below 25
   □ 25–34
   □ 35–44
   □ 45–54
   □ Above 54
3. Highest Level of Education
   □ Diploma
   □ Degree
   □ Master's
   □ Doctorate
   □ Other
4. Current Position
   □ Administrator
   □ Doctor
   □ Nurse
   □ Clinical Officer
   □ Laboratory Staff
   □ ICT Staff
   □ Other
5. Years of Service
   □ Below 2 years
   □ 2–5 years
   □ 6–10 years
   □ Above 10 years

6. Healthcare Facility Level

□ Level 2

□ Level 3

□ Level 4

□ Level 5

SECTION B: ELECTRONIC HEALTH RECORDS

7. Electronic Health Records influence operational efficiency in healthcare service delivery. (1= Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, 5= Strongly Agree)

Statement	1	2	3	4	5
EHR systems improve accessibility of patient information					
EHR reduces duplication of patient records					
EHR improves accuracy of medical records					
EHR increases speed of clinical documentation					
EHR improves coordination among healthcare providers					

SECTION C: TELEMEDICINE

8. Telemedicine affects operational efficiency in healthcare service delivery. (1= Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, 5= Strongly Agree)

Statement	1	2	3	4	5
Telemedicine improves access to healthcare services					
Remote consultations reduce unnecessary hospital visits					
Telemedicine shortens patient waiting time					
Telemedicine enhances communication efficiency					
Telemedicine supports continuity of care					

SECTION D: ARTIFICIAL INTELLIGENCE

9. Artificial Intelligence-driven tools affect operational efficiency in healthcare service delivery. (1= Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, 5= Strongly Agree)

Statement	1	2	3	4	5
AI improves diagnostic decision accuracy					
AI supports faster clinical decisions					
AI reduces administrative workload					
AI supports workflow automation					
AI improves healthcare productivity					

SECTION E: MOBILE HEALTH TECHNOLOGIES

10. Mobile Health technologies affect operational efficiency in healthcare service delivery. (1= Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, 5= Strongly Agree)

Statement	1	2	3	4	5
Mobile reminders improve appointment adherence					
mHealth supports remote patient monitoring					
Mobile applications improve patient engagement					
mHealth improves access to health information					
mHealth enhances communication with patients					

SECTION F: OPERATIONAL EFFICIENCY

11. Please indicate your agreement regarding healthcare operational efficiency. (1= Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, 5= Strongly Agree)

Statement	1	2	3	4	5
Technology integration has reduced patient waiting time					
Technology has improvved the utilization of hospital resources					
Technology has improved the speed of service delivery					
Technology has increased patient satisfaction					
Technology has improved overall healthcare efficiency					

Appendix II: Research Permit- NACOSTI

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **938426**

Date of Issue: **05/August/2026**

RESEARCH LICENSE



This is to Certify that Mr.. KENNEDY KAPANTE NKONINA of Catholic University of Eastern Africa, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kajiado on the topic: TECHNOLOGY INTEGRATION AND SERVICE DELIVERY IN HEALTH CARE: A CASE OF KAJIADO COUNTY for the period ending : 05/August/2027.

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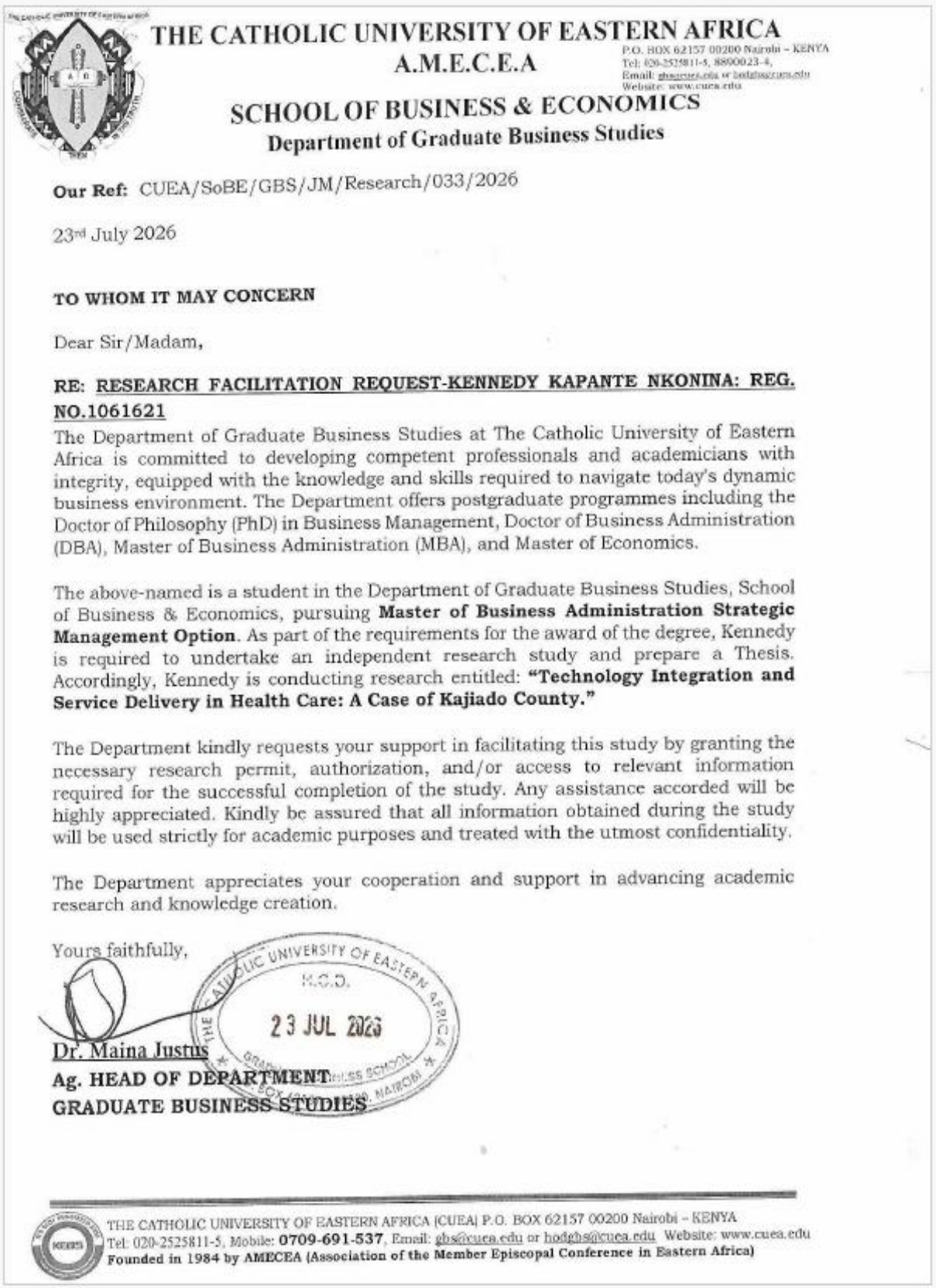
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See overleaf for conditions

Appendix III: Introductory Letter- GBS



THE CATHOLIC UNIVERSITY OF EASTERN AFRICA
A.M.E.C.E.A
P.O. BOX 62157 00200 Nairobi – KENYA
Tel: 020-2525811-5, 8890023-4,
Email: gbs@cuea.edu or hodgbs@cuea.edu
Website: www.cuea.edu

SCHOOL OF BUSINESS & ECONOMICS
Department of Graduate Business Studies

Our Ref: CUEA/SoBE/GBS/JM/Research/033/2026

23rd July 2026

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

RE: RESEARCH FACILITATION REQUEST-KENNEDY KAPANTE NKONINA: REG. NO.1061621

The Department of Graduate Business Studies at The Catholic University of Eastern Africa is committed to developing competent professionals and academicians with integrity, equipped with the knowledge and skills required to navigate today's dynamic business environment. The Department offers postgraduate programmes including the Doctor of Philosophy (PhD) in Business Management, Doctor of Business Administration (DBA), Master of Business Administration (MBA), and Master of Economics.

The above-named is a student in the Department of Graduate Business Studies, School of Business & Economics, pursuing **Master of Business Administration Strategic Management Option**. As part of the requirements for the award of the degree, Kennedy is required to undertake an independent research study and prepare a Thesis. Accordingly, Kennedy is conducting research entitled: **"Technology Integration and Service Delivery in Health Care: A Case of Kajiado County."**

The Department kindly requests your support in facilitating this study by granting the necessary research permit, authorization, and/or access to relevant information required for the successful completion of the study. Any assistance accorded will be highly appreciated. Kindly be assured that all information obtained during the study will be used strictly for academic purposes and treated with the utmost confidentiality.

The Department appreciates your cooperation and support in advancing academic research and knowledge creation.

Yours faithfully,

THE CATHOLIC UNIVERSITY OF EASTERN AFRICA
P.O.B.
23 JUL 2026
GRADUATE BUSINESS SCHOOL
NAIROBI

Dr. Maina Justus
Ag. HEAD OF DEPARTMENT
GRADUATE BUSINESS STUDIES

Appendix IV: Sample Frame

No.	Facility Name	Level
1	Kajiado County Referral Hospital	Level 5
2	Loitokitok Sub County Hospital	Level 4
3	Ngong Sub County Hospital	Level 4
4	Kitengela Sub County Hospital	Level 4
5	Ongata Rongai Sub County Hospital	Level 4

Appendix V: Plagiarism Certificate

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I HEREBY CONFIRM THAT **KENNEDY KAPANTE NKONINA** REG NO: **1061621**, SUBMITTED A CHECK OF ANTIPLAGIARISM ON EVALUATION OF **TECHNOLOGY INTEGRATION AND SERVICE DELIVERY IN HEALTH CARE: A CASE OF KAJIADO COUNTY. A RESEARCH THESIS SUBMITTED IN PARTIAL FULFILMENT FOR THE REQUIREMENT FOR THE AWARD OF A MASTER OF BUSINESS ADMINISTRATION IN STRATEGIC MANAGEMENT AT THE CATHOLIC UNIVERSITY OF EASTERN AFRICA .**

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